DEVELOPMENT OF AN INTELLIGENT SYSTEM FOR QUALITY ASSURANCE IN THE GARMENT INDUSTRY

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Development of an Intelligent System for Quality Assurance in the Garment Industry

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CERTIFICATE OF ORGINALITY

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Abstract

Garment manufacturing is a traditional industry with a global outlook. In general, better product quality is used as a product differentiation strategy in the marketplace. However, due to the error-prone nature of the garment manufacturing processes, it is challenging to assure that the garment products are of good quality. In addition, garment products are ephemeral goods which may no longer be attractive to consumers if they fail to arrive at the retail stores before the fashion trends change. Therefore, garment manufacturers are expected not only to assure the quality of their products, but also to enhance the production efficiency. Furthermore, with the pressure brought by the rapidly changing fashion trends in recent decades, traditional inspection-oriented quality assurance (QA) strategies are no longer sophisticated enough for the garment industry to cope with the challenges posed by this new generation.

Considering how process parameters are set in production is a critical factor affecting both the product quality and production efficiency, this research paves the way for a novel approach to analyze the quality problems at the parameter level. An intelligent system, termed the Fuzzy Rule-based Recursive Mining System (FRRMS), is developed for determining optimal process parameter settings which lead to improvement in product quality. The system is equipped with a process mining feature to recursively discover the hidden relationships between production process parameters and the resultant product quality. There are three modules that constitute the system: the Fuzzy Association Rule Mining Module (FARMM), the Slippery Genetic Algorithm-based Optimization Module (sGAOM), and the Decision Support Module (DSM). The FARMM collects data from the production shop floor and represents the relationships between the process parameters and product quality features in terms of fuzzy association rules. The sGAOM optimizes the fuzzy association rules obtained with the use of a novel algorithm, namely the slippery genetic algorithm in fuzzy association rule mining (sGA-FARM). The major feature of the sGA-FARM is that it produces variable-length chromosomes by imitating and transcribing the biological slippage commonly found in DNA replication. Based on the optimized rules, the DSM estimates the resultant product features when a set of process parameters are given. The output of the DSM allows the garment manufacturers to determine the appropriate process parameter settings in order to achieve the desired product features.

The feasibility of the proposed system has been validated by means of case studies. By following a generic methodology designed for the development and implementation of the system, the system was implemented in a garment manufacturing company. Through a pilot run of the system in the case company, improvement in production efficiency and product quality was observed.

The major contribution of this research is in the design and implementation of an intelligent system that facilitates appropriate decision making in the formulation of effective QA strategies, addressing the current needs of the garment industry. Furthermore, the deliverables of this research not only provide a means for developing the FRRMS, but also include the use of the novel nature-inspired sGA-FARM for industrial process parameter optimization, in general.

Publications Arising from the Thesis

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Lists of International Journal Papers

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5. **<u>Lee, C.K.H.</u>**, Choy, K.L., Ho, G.T.S., Chin, K.S., Law, K.M.Y. & Tse, Y.K. (2013), "A hybrid OLAP-association rule mining based quality management system for extracting defect patterns in the garment industry", *Expert Systems with Applications*, Vol. 40, No. 7, pp. 2435-2446.

6. **<u>Lee, C.K.H.</u>**, Choy, K.L., Ho, G.T.S. & Law, K.M.Y. (2013), "A RFID-based Resource Allocation System for Garment Manufacturing", *Expert Systems with Applications*, Vol. 40, No. 2, pp. 784-799.

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4. **Lee, C.K.H.**, Choy, K.L., Law, K.M.Y. & Ho, G.T.S. (2012), "Decision support system for sample development in the Hong Kong garment industry", *Proceedings of Portland International Center for Management Engineering and Technology: Technology Management for Emerging Technologies, PICMET'12*, August 2012, Canada, pp. 754-761.

Book Chapter

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List of Abbreviations

AI	Artificial intelligence
ALChyper-GA	Adaptive length chromosome hyper-genetic algorithm
ANN	Artificial neutral network
AQL	Acceptable quality level
CBR	Case-based reasoning
CRM	Customer relationship management
DM	Data mining
DSM	Decision support module
ERP	Enterprise resource planning
EU	European Union
FARRM	Fuzzy association rule mining module
FRRMS	Fuzzy rule-based recursive mining system
GA	Genetic algorithm
ISO	International Organization for Standardization
KPI	Key performance indicator
PDCA	Plan-Do-Check-Act
QA	Quality assurance

QC	Quality control
RBR	Rule-based reasoning
RFID	Radio frequency identification
SD	Standard deviation
sGA-FARM	Slippery genetic algorithm in fuzzy association rule mining
sGAOM	Slippery genetic algorithm-based optimization module
WTO	World Trade Organization
XML	Extensible markup language

Chapter 1 Introduction

1.1 Research Background

With increasing concerns about product quality, garment manufacturers are urged to achieve better quality in their products so as to stay competitive in the market. Unfortunately, variance in product quality is unavoidable as it can be induced by many factors during production. One of these critical factors is the workmanship which commonly exists in labor-intensive industries where many production processes are performed manually. The garment industry is viewed as very representative of a labor-intensive industry. Due to the error-prone nature of garment manufacturing processes, it is difficult to predict the resultant quality of the finished garments, making quality assurance (QA) a challenging task.

In addition, the garment industry has been under transformation since the emergence of the trend for fast fashion, the objective of which is to design and manufacture garment products quickly and economically. Under the pressure brought by the fast fashion trend, garment manufacturers have to shorten their production time so as to bring the most up-to-date fashion styles into the retail stores within the shortest time possible. However, challenges arise when the manufacturers need to achieve both high production efficiency and high product quality. Some manufacturers adopt a set of process parameters to increase their production efficiency without considering the product quality that may result. On the other hand, some aim to produce high-quality products by having their operators manufacture the products with lower efficiency.

In fact, how process parameters are set in production not only affects the production efficiency, but also exerts a positive or negative impact on the quality of the products. Traditionally, however, garment defects are identified by human inspection which fails to consider both the product quality and production efficiency concurrently. To respond to the market changes in this new era, this research provides an alternative approach to ensure quality by revealing the relationships between the production process parameters and product quality.

Many QA tasks require the collection and analysis of data to support the various functions. The evolution of data mining (DM) and artificial intelligence (AI) techniques have contributed to significant achievements in the field of QA, playing an important role in transforming the conventional QA approaches. Nevertheless, how the use of DM and AI can specifically achieve QA goals in the garment industry remains to be explored.

Motivated by the abovementioned situations, this research aims to develop an intelligent system for supporting QA in the garment industry. The proposed system integrates and hybridizes various DM and AI techniques to determine appropriate process settings while at the same time takes the quality of the products into consideration.

1.2 Problem Statements

In view of improved standards of living, consumers nowadays have higher expectations on products during purchasing. To remain competitive in the market, manufacturers are urged to improve their product quality while at the same time to lower the costs and increase the speed to market. This is of greater importance in the garment industry as it is a time-sensitive industry. Garment products are ephemeral items which may no longer be saleable or attractive to consumers if the fashion trend changes. As a consequence, both product quality and production efficiency are the major concerns in the garment industry. Any product quality problem or delay in garment production may also hinder customers from accessing their desired products, lowering the customer satisfaction.

Though the capabilities of DM in solving quality problems are well proven, Köksal et al. (2011) revealed in their recent survey that DM applications for quality management have still not been observed in a number of industries, including the garment industry. Therefore, a generic methodology for QA in the garment industry is still an area that requires more in-depth study and investigation. Major issues, remaining to be solved, are summarized as follows:

(i) How to design a generic infrastructure for an intelligent system with the objective of providing knowledge support in the determination of process parameters for QA in the garment industry;

(ii) Ho to design a mining algorithm to analyze data for solving quality related problems in the garment industry;

(iii) How to determine the optimal parameters involved in the garment production processes while the quality of products is taken into consideration;

(iv) How to discover the relationships between the process parameters and garment product quality at the parameter level; and

(v) How to achieve continuous improvement of processes and product quality for the long-term development of a garment manufacturing company.

1.3 Research Objectives

To tackle the abovementioned problems, this research has five objectives, which are:

(i) To develop an intelligent system for supporting QA at the parameter level in the garment industry;

(ii) To design a recursive process mining algorithm for discovering relationships between the process parameters and resultant product quality in terms of fuzzy rules;

(iii) To design a novel nature-inspired mechanism for optimizing the fuzzy rules;

(iv) To provide decision support for operators in their attempts to determine process parameters for achieving high quality products; and

(v) To allow continuous improvement of the processes and product quality with the recursive mining feature of the designed system.

1.4 Significance of the Research

According to the literature, traditional intelligent systems for quality management have focused on the manufacturing sector as a whole, without considering the specific needs of the garment industry. However, in practical situations, the quality management of the garment industry is more challenging than other manufacturing industries because of the error-prone nature of the processes involved in garment manufacturing. Therefore, instead of developing a generic system architecture for the manufacturing sector, this research aims to develop an intelligent system that specifically considers the needs of the garment industry in order to support QA activities.

Another significant aspect of the research includes the design and development of a novel nature-inspired algorithm, namely Slippery Genetic Algorithm in Fuzzy Association Rule Mining (sGA-FARM). In the past decades, more and more researchers have suggested that the laws of nature are good sources for inspiration of effective meta-heuristic algorithms that can provide solutions to complicated problems and develop intelligent systems. This has stimulated many researchers to develop novel algorithms which are inspired by natural phenomenon. For instance, genetic algorithms (GAs) and differential evolution algorithms were inspired by biological evolutionary processes; particle swarm optimization algorithms, artificial bee colony algorithms and ant colony optimization algorithms were inspired by animal behavior. These nature-inspired algorithms have been widely applied in various fields. Because of their proven efficiency and merit in discovering novel and better solutions to hard problems, nature-inspired algorithms attracted more and more attention from researchers and engineers in various fields of engineering. The sGA-FARM proposed in this research is inspired by the biological slippage phenomenon commonly found in DNA replication. Unlike conventional fixed-length GAs, it allows changes to the length of each chromosome and thus different combinations of parameters can be considered in a fuzzy rule. This is considered as having remarkable significance in this research since results of previous related research applying GA in fuzzy rule optimization have been inherently limited by the chromosome length. Meanwhile, the results obtained in the two case studies in this research have shown that the sGA-FARM is effective in generating good fuzzy rules with better diversity, and are capable of improving the quality of the finished products and the production efficiency.

1.5 Thesis Outline

The dissertation is divided into six chapters and is outlined as follows.

(i) Chapter 1 states the research background, problems that occur in the garment industry, and the objectives and significance of the research.

(ii) Chapter 2 is an academic review related to the research. The first section reviews the current situation and the potential causes affecting product quality in the garment manufacturing processes. The second section presents the fundamental concepts of QA, followed by a survey of different QA tasks involved in the garment industry. The third section provides a survey of available DM and AI techniques for QA. The final section explores some existing mobile technologies for automatic data collection.

(iii) Chapter 3 describes the proposed system, namely, the Fuzzy Rule-based Recursive Mining System (FRRMS), for QA in the garment industry. There are three modules involved in the FRRMS, and details of each are presented in this chapter. The Fuzzy Association Rule Mining Module (FARRM) integrates fuzzy set concepts with association rules mining. It is used to discover the relationships between process settings and product quality at the parameter level in terms of fuzzy rules. The Slippery Genetic Algorithm-based Optimization Module (sGAOM) is then used to optimize the obtained fuzzy rules by the use of the sGA-FARM. Since the sGA-FARM is inspired by the biological slippage phenomenon in DNA replication, the background of biological slippage is also presented. Finally, the Decision Support Module (DSM) applies fuzzy logic to provide decision support in the determination of the process parameters for achieving better garment product quality.

(iv) Chapter 4 introduces the implementation procedures of the FRRMS in the garment industry. There are four phases involved in the implementation, and details of each are explained in this chapter. These four phases start from the preparation of a pilot run of the system in a garment manufacturing company, through the structural formulation of each module, to the evaluation of the system.

(v) Chapter 5 describes two case studies in which the FRRMS is developed and implemented in a garment manufacturing company. The first case study deploys the FARMM and DSM. It involves the use of fuzzy association rule mining for QA. In the second case study, the sGAOM is included to optimize the rules obtained in the first case study. The aim of the second case study is to investigate the performance of the sGA-FARM on QA after rule optimization.

(vi) Chapter 6 discusses the results and major findings of the research. The system performance for supporting QA in the garment industry is presented, followed by the experimental results and discussion in the two case studies. By comparing the two case studies, the role of the sGA-FARM in optimizing fuzzy rules for QA purposes can also be investigated.

(vii) Chapter 7 concludes the work undertaken in the research. Contributions made by the research and areas for future research are also highlighted.

Chapter 2 Literature Review

2.1 Introduction

The focus of this research is on the design and development of an intelligent system for providing decision support to the garment industry when determining appropriate process parameters for the assurance of better product quality. The aim of this chapter is to provide a comprehensive review on the current research areas as revealed in academic publications. This chapter is divided into four main sections. The first two sections give overviews of the garment industry and QA. The third section is a literature review conducted on the existing DM and AI techniques used in QA. The fourth section covers some existing mobile technologies supporting automatic data collection. Finally, a summary on the literature review is presented, providing an insight on the direction of this research.

2.2 Overview of the Garment Industry

The garment industry is characterized by a number of factors, including short product life cycles, high volatility, high-impulse purchases, rapid fluctuations in postmodern consumer behavior, high product proliferation, and seasonality (Bruce & Daly, 2006; Christopher et al., 2004; Cagliano et al., 2011; Pal & Torstensson, 2011).

Compared with other manufacturing industries, it is more complicated in nature as it consists of a variety of machines and workers, and thousands of bundles of cutting pieces producing different styles simultaneously (Gunesoglu & Meric, 2007). In response to the special needs of the garment industry, the system proposed in this research is specifically focused on the QA of garment products.

In this section, the current situation in the garment industry is firstly presented, followed by the potential causes affecting product quality in the garment manufacturing processes.

2.2.1 Current Situation in the Garment Industry

Nowadays, China manufactures and exports large quantities of garments annually. Whilst having their headquarters stationed in Hong Kong, many Hong Kong manufacturers have also relocated their production-related activities from Hong Kong into the Pearl River Delta region to leverage lower labor and land costs and to gain better access to markets in Mainland China. However, after the Chinese government stepped up measures to protect labor rights in 2010, such as imposing labor laws and democratic management ordinances in some regions in China, it is now more challenging for Hong Kong-owned manufacturers in China to operate their production base. China’s increasing concern on labor rights has also made China lose her attractiveness and competitive advantage as the most preferred sourcing country, and attention has been directed to other countries with lower labor costs, such as Bangladesh, India, Indonesia, Pakistan and Vietnam. In addition, as China's accession to the World Trade Organization (WTO) has lead to a further opening up of China's markets, Chinese garment manufacturers have to face increasingly intense competition from foreign-invested enterprises (Chen & Shih, 2004). On the other hand, the Multi-Fibre Arrangement, which established quotas for different categories of apparel and textile imports to the European Union (EU), ended on January 1, 2005. The quota system resulted in the global dispersion of apparel and textile production by restricting imports to developed countries from developing countries. It is expected that China has benefited most from the elimination of quotas (Tower & Peng, 2005). Furthermore, the EU garment industry is struggling to exclude China from the EU markets by the use of the Textiles-Specific Safeguard Clause under China's Accession Protocol to the WTO. The existence of this trade agreement was viewed as the biggest factor in weakening the impact of quotas and tariffs (Tower & Peng, 2005). Under this trade agreement, Chinese's textile exports to the EU were limited to the agreed growth level until 2008. After the expiry of the agreement, a double-checking surveillance system between EU and China was established to monitor the latter's EU imports of textile and clothing products. This system ended on 1 January 2009, and following its expiry, textile and clothing products originating in China no longer require any import license or surveillance document before entering the EU (Hong Kong Trade Development Council, 2008). Likewise, the re-imposition of quotas between China and the United States were phased out on 1 January 2009. Textile and clothing shipments to the United States made on or after 1 January 2009 are therefore no longer subject to any quotas (Hong Kong Trade Development Council, 2010).

Meanwhile, increasing the speed to market has become of greater importance in the garment industry since the emergence of the fast fashion trend in recent years (Barnes & Lea-Greenwood, 2006; Zülch et al., 2011). The objective of fast fashion is to bring the most up-to-date fashion styles into stores at a lower cost and within the shortest time possible (Bruce & Daly, 2006). Technologies are now being applied to minimize both cost and manufacturing time. For example, virtual sampling is used to reduce the lead time of the product development cycle through 3D visualization of garments, allowing users to test the quality of the pattern drafts without incurring the real cost of physical sampling. These kinds of technologies which can minimize costs in the sample development process are popular, especially when the costs of physical sampling are now uncertain due to the increase in prices of raw materials. However, these technologies are mainly focusing on the sample development processes. More attention has to be placed on the bulk production processes of garments. Besides, poor product quality, arising from the bulk production processes, will cause hundreds or even thousands of garments to be wasted. In this sense, garment manufacturers, who are facing the challenges brought by fast fashion, have to shorten their production lead time while at the same time to guarantee the quality of their products during their manufacture.

Nevertheless, due to the error-prone nature of garment manufacturing operations, it is challenging to assure the quality of products. In current practice, quality inspection of garments is performed manually (Wong et al., 2009; Yuen et al., 2009). Such inspection-based QA activities are reactive to the product quality and thus fail to prevent the re-occurrence of the same quality problems (Lou & Huang 2003; Liu et al., 2009). Any occurrence of quality problems may require the reworking and discarding of products, hindering customers from accessing the latest products before the fashion trend changes. In view of this, it is important to have an intelligent system to assist the garment manufacturers in their attempt to increase production efficiency and improve the quality of their products.

2.2.2 Potential Causes Affecting Product Quality in Garment Manufacturing

Processes

Garment manufacturing is a traditional industry with a global perspective. It is traditionally labour-intensive because of the extensive styles and fabric variations of the products (Wesley & Poojitha, 2010). It is also more complicated than other manufacturing industries as it consists of various types of machines, workers and thousands of bundles of cutting pieces producing different styles simultaneously (Gunesoglu & Meric, 2007). Therefore, the product quality in the garment industry can be affected by various causes, such as the habits, skills and experience of individual workers, as well as the use of different machine settings.

In general, quality means different things to different people, depending on their perception of the value of the product under consideration and their expectations of performance and durability for that product (Mehta, 1992; Basu, 2014; Chen & Luo, 2014). It is a reflection of customer opinion on the value seen in the product compared to that in other products. Hence, better product quality can be used as a product differentiation strategy in the marketplace. In the garment industry, product quality can be assessed in terms of the quality and standard of fibers, yarns, fabric construction, color fastness, designs and the final finished garments. It is not only defined through its aesthetic and functional properties, but also as mechanical and physiological aspects of wearing, for example, the feeling of well being in wearing, its proper drape and fit (Geršak, 2002). Solinger (1988) defined garment quality into two dimensions: (i) Physical features, and (ii) Performance features. The physical features, including the design, materials, construction and finish, provide the tangible form and composition of a garment while the performance features, in terms of both aesthetic and functional performance, determine the standards fulfilled by a garment and how a garment benefits the consumer (Brown & Rice, 2001).

In order to improve product quality, garment manufacturers have to develop a means of assessing their performance in meeting the desired level of quality. To achieve this, it is important to understand the potential product defects which could arise from the garment manufacturing processes.

Major manufacturing processes include spreading, cutting, sewing, and finishing (Lee, Choy, Ho & Law, 2013). Spreading is the action of laying multiple plies of fabrics on a table before the fabrics are cut. When a roll of fabric has been spread, the operators have to carefully splice in the new roll of fabrics to ensure no partial panels are cut. They must also watch for fabric flaw flags attached by the fabric mills and remove full widths of any fabrics containing large flaws. Some companies cut many plies or layers of fabrics at one time to save time and reduce costs. However, they have to consider the cutting resources they use. For instance, lays can be stacked as high as 14 inches and contain nearly 500 plies because of the development of vacuum cutting tables (Brown & Rice, 2001). Solinger (1988) identified various factors that can affect spreading, which include ply alignment, ply tension due to slackness, bowing (i.e. the distortion of filling yarns from a straight line across the width of a fabric) and splicing (i.e. the overlapping of two ends of fabric in a ply). Lowe and Lowcock (1975) listed some examples of spreading defects such as mismatching of checks, and not having all plies facing in the correct direction.

After the fabrics have been spread, cutting can begin. Cutting quality is the prerequisite for quality in a finished garment (Mehta, 1992). If a manual cutter cuts a garment inaccurately, it cannot be sewn accurately and any poor cutting plagues the entire sewing process. Furthermore, cutting is one of the production processes that is performed on many garments simultaneously. Thus, cutting affects not just one garment but many garments. Possible defects arising from the cutting process include frayed edges, fuzzy, ragged, or serrated edges, ply-to-ply fusion, pattern imprecision, notches and drilling (Dunlap, 1978).

After cutting, sewing is undertaken to assemble different garment parts into a finished garment. Chen et al. (2012) claimed that sewing is the most critical garment manufacturing process as it generally involves a large number of operations. For instance, a man's tailored jacket, generally considered the most complex garment to construct, requires at least 115 individual operations while a simple T-shirt requires as few as 8 operations (Garment Construction Guide, 1983). According to Lowe and Lowcock (1975), Westley and Poojitha (2010) and Lee, Choy, Ho, Chin et al. (2013), examples of sewing defects include skipped stitches, broken stitches, seam puckering, pleated seams, and staggered stitches.

In addition, the finishing process refers to the final steps in the production of a garment. It includes adding finishing details, trimming and inspecting, repairing or reworking any defects, pressing, and folding and packing. For some garments, pressing is required to enhance the workmanship, and help the garment fit smoothly (Brown & Rice, 2001). Poor pressing can make even well-made garments appear to be low quality, while well-executed pressing can hide poor construction. Possible defects caused by pressing and finishing include burned or scorched garments, flattened naps or surfaces, broken zippers or buttons, and shrinkage due to heat and moisture (Mehta, 1992). Table 2.1 summarizes some examples of possible defects which can occur in the abovementioned manufacturing processes.

In fact, garment defects can be classified as (i) Critical defects, (ii) Major defects, and (iii) Minor defects. According to Kadolph (1998):

Table 2. 1 – Examples of defects occurring in different manufacturing processes

Process	Examples of possible defects		Reference(s)
Spreading	- Inconsistent fabric alignment - Fabric not thoroughly flattened	- Plies not all facing in the correct direction - Mismatching of checks	Lowe and Lowcock (1975)
Cutting	- Frayed edges - Fuzzy, ragged, or serrated edges - Ply-to-ply fusion	- Pattern imprecision - Notches - Drilling	Dunlap (1978)
Sewing	- Skipped stitches - Broken stitches - Staggered stitches	- Seam puckering - Pleated seams	Lowe and Lowcock (1975); Westley and Poojitha (2010); Lee, Choy, Ho, Chin et al. (2013)
Pressing/Finishing	- Burned or scorched garments - Flattened nap or surface - Broken zippers or buttons	- Garment not thoroughly dried - Shrinkage due to heat and moisture - Pockets not smooth	Mehta (1992)

(i) A critical defect is a defect resulting in hazardous or unsafe conditions for individuals using, maintaining, or depending on the product, or a defect that prevents performance of a tactical function of a major end-use item.

(ii) A major defect is a defect that is likely to result in product failure or to reduce potentially the usability of the product in its purpose. It is a defect which adversely affects the appearance, and the garment's performance, including fit or customer satisfaction, to a degree that would provide a discerning customer with justification for no purchase, a return or complaint.

(iii) A minor defect is a defect that is not likely to reduce materially the usability of a product for its intended purpose, or a departure from established standards having little bearing on the effective use or operation of the product.

Considering the fact that a number of defects can occur during the garment manufacturing processes, research interest has been aroused in regard to achieving better quality control (QC) and assuring the quality of garments. However, it is found that existing studies are limited to investigating the possibilities of automatic detection of defects which exist on textile fabrics. Dorrity et al. (1996) developed an online real-time monitoring system for identifying and detecting defects on textile fabrics. Ngan et al. (2005), Mak et al., (2009) and Tabassian et al. (2011) introduced wavelet-based methods for defect detection on fabrics. Wong et al. (2009) and Yuen et al. (2009) proposed hybrid models to detect and classify fabric stitching defects. Baykasoglu et al. (2011) applied heuristic approaches to classify defect factors in fabric production. Nevertheless, little effort has been paid to defects on garments.

2.3 Overview of Quality Assurance

Quality assurance (QA) is the implementation of processes which aim to ensure that concern for quality is designed and built into products or services (Collins, 1994). The purpose of QA is the conformance of products, services, and processes with given requirements and standards (Moreno-Lonzo & Peris, 1998). This conformance is achieved through systematic measurement and control to detect special causes of variation, to achieve defect prevention and to standardize processes. Through the pursuit of quality, QA provides confidence to customers that their requirements for the quality of products or service are met continuously (Karapetrovic & Willborn, 2000).

In this section, some existing QA approaches applied in the manufacturing sector are reviewed, followed by the existing approaches for ensuring quality in the garment industry.

2.3.1 Existing Quality Assurance Approaches

In fact, QA has arisen from QC as an evolution from a more operational perspective to a more global and systematic perspective (Moreno-Lonzo & Peris, 1998). Jabnoun (2002) proposed five processes involved in QA:

- Setting the standards
- Providing the inputs that will enable workers to conform to standards
- Measuring performance
- Analysis of the measured performance data
- Taking corrective action

The abovementioned processes put emphasis on the role of management to provide the inputs that enable workers to conform to the standards and that the measured performance is analyzed to find special causes of variation (Mehta et al., 2014; Baronienė & Neverauskas, 2015). In order to assure the quality of products, QA systems have been designed and developed for the manufacturing sector.

Although different manufacturing industries may have many features in common, their requirements in QA systems can be significantly different, depending on factors that include the products to be produced, the complexity of the production processes, the production rate and the size of the company (Nookabadi & Middle, 2001). In the following sections, existing QA approaches are discussed. They include

ISO 9000, Plan-Do-Check-Act (PDCA), Acceptable Quality Level (AQL), and Kaizen.

2.3.1.1 ISO 9000

ISO 9000, introduced by International Organization for Standardization (ISO), is a series of international standards dealing with quality systems that can be applied for QA purposes (Stevenson & Barnes, 2002). It provides not only quality system models for QA covering development, production and final inspection, but also guidelines for selecting and adopting these models (Bénézech et al., 2001). Since 1994, the implementation of ISO 9000 has been associated with a certification process. Organizations having their procedures meeting the international quality standards can seek ISO 9000 certification by hiring a third party, accredited by ISO, to perform a quality audit and to grant ISO 9000 certification. Under the ISO 9000 standards, controls must be established for every aspect of the production processes and all operational procedures and managerial actions must be documented. Although ISO 9000 does not regulate or control product quality, the stringent documentation requirements serve to identify deficiencies in processes or QC leading to the implementation of improvement (Withers & Ebrahimpour, 2000).

Despite the fact that ISO 9000 has become the most commonly used QA system in the world (Lipovatz et al., 1999; Naveh & Marcus, 2005), the standard is still subject to controversy for individual organizations and supply chains. A widespread criticism is that the ISO 9000 is not connected directly enough to product quality because the ISO 9000 certification does not inform an organization on how to design more efficient and reliable products (Sroufe & Curkovic, 2008). In addition, studies investigating the effects of ISO 9000 on performance have shown mixed results (Martínez-Costa et al., 2008). For example, Koc (2007) compared ISO 9000 certified and non-certified organizations and found that there were no significant differences with respect to defective part production and manufacturing cost between the two groups. In parallel with their finding, Arauz and Suzuki (2004) and Brown et al. (1998) also found no significant differences between the two groups in relation to rework and waste. On the contrary, Flynn et al. (1995) discovered that the top contributor to competitive advantage for certified organizations was the percentage of products that passed final inspection without rework.

2.3.1.2 Kaizen

Kaizen is a Japanese word meaning continuous improvement. It is a method for applying continuous incremental improvement of business processes, involving the engagement of all employees in a company in identifying possible improvement areas (Scyoc, 2008). For quality management, Japanese enterprises favor gradual improvement while western enterprises favor large jumps involving innovation (Radharamanan et al., 1996). From the QA standpoint, Kaizen helps to motivate workers to pay attention to housekeeping, proper work procedures and machinery maintenance so as to improve productivity and product quality (Mano et al., 2014).

The 5S techniques are commonly used for maintaining good housekeeping in a manufacturing environment. According to Ortiz (2010) and Titu et al. (2010), the 5S are:

- Sort: Remove all unnecessary items from the work area
- Straighten: Organize what is needed such that all the items have a home and are clearly marked with their identity and location
- Scrub: Clean everything and detect disturbances in the working areas and equipment
- Standardize: Maintain consistency in the visual workplace
- Sustain: Maintain the improvements and continually improve upon them

On the other hand, when defects occur, extra costs are incurred reworking the parts. These include additional labor costs, and more time in work-in-progress. In Kaizen, the activities that add cost to the production systems are recognized as waste.

Kaizen aims to improve quality, cost and delivery by the elimination of waste (Scyoc, 2008). In some cases, production interruptions could result when eliminating or deducting waste. Therefore, it is recommended that adequate provision in inventory is made so as to provide assurance that customer deliveries are unaffected. According to Aoki (2008), there are two different processes for the identification of waste: (i) identification by operators; and (ii) identification by others, such as team leaders and supervisors. The former process requires the operators to have self-initiative so as to participate in Kaizen activities.

In addition, Scyoc (2008) stated that Kaizen is an adaptation of the Plan-Do-Check-Act (PDCA) cycle. The basic mechanism is to make any possible improvements under the PDCA cycle, standardize the improvements and continue for another PDCA cycle (Lyu Jr, 1996). Details of the PDCA are introduced in the next section.

2.3.1.3 Plan-Do-Check-Act

One of the key ideas to improve product quality was termed as Shewhart cycle but became more renowned as the Plan-Do-Check-Act (PDCA) cycle. Dr. Edwards Deming was the one who first coined the term “Shewhart cycle” for PDCA (Jin et al., 2012). After Walter Shewhart in 1939 applied the scientific method with his cycle: (i) specification, (ii) production, and (iii) inspection, Dr. Deming in 1950 modified the Shewhart cycle into (i) design of the product, (ii) make it, (iii) put it on the market, (iv) test it through market research, and (v) redesign the product (Johnson, 2002). The Japanese interpretation of the "Deming wheel" leads to the PDCA cycle. The PDCA cycle was embedded in a model for continual improvement (Kondo, 1990). There are four phases involved in a PDCA cycle (Johnson, 2002):

- Plan: Recognize an opportunity and plan the change
- Do: Test the change
- Check: Review the test, analyze the results and identify learning
- Act: Take action based on the learnt results in the Check Phase

In the phase of planning, an organization has to analyze information, solicit ideas and select the best plan for improvement (Scyoc, 2008). After that, in the phase of doing, the plan is implemented, either as a pilot or fully deployed. The third phase is checking, in which data are gathered to evaluate the effectiveness of the plan (Srivannaboon, 2009). Finally, in the fourth phase, Act, corrective actions are taken based on the findings and user feedback (Garratt, 2007).

The PDCA cycle is viewed as a closed loop for quality improvement as it encourages continual improvement and verifies that improvement is retained. This is the process of learning in which evaluation and knowledge gained are included in the new PDCA circle. Piskar and Dolinsek (2006) stated that organizations could adopt a quality system as a business model and implement the system under the four phases of the PDCA cycle.

2.3.1.4 Acceptable Quality Level

Acceptable quality level (AQL) is the maximum number of defects or defective products based on a specified number of units or products allowed within the sample before the lot is rejected. For instance, if the AQL is set to be 1%, then a lot containing 1% defective products is being classified as a good lot. On the other hand, it is tempting to say that a lot containing more than 1% defective products is a bad lot. In the manufacturing industry, an inspector will examine a representative sample of the entire number of products in a production lot. If it is found that the lot contains more than the allowed number of defective products, the entire lot is sent back for 100% inspection and repair. According to Brown and Rice (2001), production lines or organizations with consistent AQLs of over 95% would be considered high performers.

In order to determine a reasonable AQL, there are several factors that have to be considered, for example, the harmful consequence of a nonconforming product, the industry standards, the previous history of a specific supplier, vendor, or production unit, and the type of defects that may occur, the type of inspection used, and the current quality level (Kadolph, 1998; Joglekar, 2010).

2.3.2 Existing Approaches for Ensuring Quality in the Garment Industry

If the quality of garments is assessed after production, the implications of this approach can be expensive when resources, such as labor and materials, are invested in manufacturing a garment that possesses unacceptable quality features. Therefore, it is suggested that QA has to be performed not only on finished garments, but also on materials, such as fabrics, and partially finished garments. According to Kadolph (1998), there are two basic types of defects related to materials and products: patent defects and latent defects. Patent defects are those flaws and irregularities that can be perceived during inspection of the materials while latent defects are hidden problems that are not apparent no matter how carefully the materials or products are examined. Patent defects can be identified by inspection while latent defects can only be detected by testing, for example, testing the fabric’s performance characteristics. In the following sections, testing and inspection used in the garment industry are presented, followed by sampling and product zoning.

2.3.2.1 Testing

Testing is the analysis and evaluation of a material or product to assess its characteristics, quality or performance. Garment manufacturers test to verify the quality performance of incoming raw materials, such as fabrics, so as to meet the consumers' needs and to determine the impacts on the manufacturing processes.

Considering that fabric, on average, makes up 70% of the material cost of a garment (Moon & Ngai, 2010), fabric testing plays a crucial role in gauging product quality in the garment industry. Due to the complexity of a fabric, the scope of fabric testing is broad. According to Hu (2008), the scope of fabric testing, as shown in Fig. 2.1, include physical testing, chemical testing, biological testing, visual examination, physiological testing and intelligence testing.

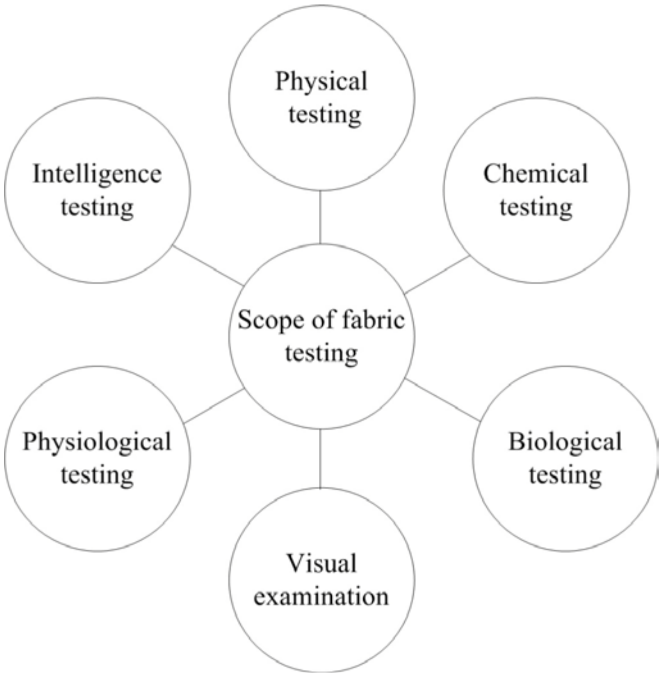

Fig. 2. 1 – Scope of fabric testing

For fabric testing, garment manufacturers cut fabric swatches at random and send them to the laboratory for testing during production. Laboratory testing is defined as evaluating the characteristics of the performance of materials using standard procedures in a specialized facility. In the current situation, there are large commercial organizations that have set up their own laboratories and standards to assess the quality of their products to satisfy customers. On the other hand, there are a vast number of private testing organizations that take up testing of fabrics on a commercial basis for the garment industry, testing their products as per the standards. Furthermore, there are governmental and approved research organizations that test and certify the fabric testing results to meet the standards. Hence, the whole scenario of fabric testing is not integrated in a particular area and the testing is not completely standardized and integrated (Hu, 2008).

2.3.2.2 Inspection

Inspection is defined as the measurement and quality assessment of materials, semi-finished parts, and finished products on the basis of their adherence to some standards, specifications or requirements (Kadolph, 1998; Tirkel & Rabinowitz, 2014). The objective of inspection is the detection of defects and nonconformance in the manufacturing processes so as to avoid investing extra time and money on correcting defects or writing off defective garments (Mehta, 1992). Because of the error-prone nature of labor-intensive manufacturing processes in the garment industry, inspection of semi-finished garments and finished garments is of great importance (Yuen et al., 2009; Wong et al., 2009). Inspection in the garment industry can be broadly divided into three processes: fabric inspection, in-line inspection, and final inspection.

(i) Fabric inspection

Various studies have shown that there is a direct correlation between fabric quality and garment quality, and fabrics with poor quality will result in excess cost in garment manufacturing (Mehta, 1992). Therefore, fabric inspection is recommended as a means of increasing overall product quality and decreasing production costs. In usual practice, fabric inspection is performed on fabric inspection machines. Defects in a fabric can be seen readily with these machines and inspectors locate, mark and record the fabric defects in terms of major defects and minor defects. Nevertheless, these traditional manual operations are easily influenced by subjective view of the inspectors, and the detection rate of defects is up to 70% only (Wen et al., 2014). In view of this, there has been extensive discussion in the literature about the automation of defect detection on fabrics (Convery et al., 1994; Ngai et al., 2014). If the fabric being examined contains more than the specified number of defects, the fabric will be rejected and returned to the mill, or the manufacturers will negotiate a discount to be subtracted from the next fabric order.

(ii) In-line inspection

In-line inspection means the visual evaluation or checking of parts during production before they are assembled into a complete product. One of the important issues in in-line inspection is the allocation of quality checkpoints (Rakiman & Bon, 2013). The decision on the location of quality checkpoints is influenced by factors that include the importance of inspection before irrevocable operations are performed, and the incidence of natural breaks in the sequence of operations. As in all quality assessment procedures, the cost impact of a defect can be greatly reduced by detecting it as early as possible in the production life cycle (Munden & Norton-Wayne, 1988).

In the garment industry, in-line inspection is performed at various points in the garment manufacturing processes from fabric spreading to finishing. The goal is to identify and correct defects during production, thereby making it possible for the garments to meet the established set of standards at each stage in production. A simple garment style might have only one quality checkpoint while a complicated garment style might have more quality checkpoints (Brown & Rice, 2001). In-line inspection in sewing involves the inspection of work from each operator based on the specifications and standards developed for the operation. For instance, a visual check is required to determine whether the buttonholes are correctly sewn and the thread ends have been trimmed away.

(iii) Final inspection

After all manufacturing processes have been completed, final inspection is conducted to ensure that a finished garment meets the required standards and specifications related to design, size, fit, appearance, construction and function. It is worth noting that some product defects would only be visible when the garment is put on a proper-size manikin or a live model. Final inspection can be based on 100% of the products or on a statistical sample. 100% inspection is the inspection of all products (Duffuaa & El-Ga'aly, 2013). Its advantage is that it gives a better idea of product quality than other inspection alternatives. However, the drawbacks are that its direct cost is high and it does not guarantee detection of all defects. In usual practice, statistical sampling is preferred if in-line inspection, training, and other QA practices have been implemented.

2.3.2.3 Sampling

Sampling is used when less than 100% inspection occurs. Special efforts are required to ensure that the sample represents a range of problems that may be present and the general quality of the lot. To select a sampling plan, garment manufacturers have to determine the lot size and the average percentage of defective products they are willing to accept in the shipments. The selection of a sampling plan also depends on the previous history of a supplier, vendor or production unit.

A lot-by-lot sample is commonly used for garment products because materials, styling, and assembly change frequently. The lot-by-lot acceptance sampling by attribute is the procedure commonly used in the garment industry. With this practice, a sample from each lot is inspected according to attributes such as size, appearance, and color matching (Kadolph, 1998). The adherence to standards and specifications of each product is assessed and this type of sampling is used to identify differences among lots where the product is supposed to be uniform.

According to Schilling (1999), the advantages and disadvantages of sampling are summarized as follows:

(i) Advantages

- Economy due to inspecting only part of the product
- Less handling damage during inspection

- Fewer inspectors, thereby simplifying the recruiting and training problem
- Upgrading the inspection job from piece-by-piece decisions to lot-by-lot decisions
- Applicability to destructive testing, with a quantified level of assurance of lot quality
- Rejections of entire lots rather than mere return of the defective products, thereby providing stronger motivation for improvement

(ii) Disadvantages

- There are risks of accepting nonconforming lots and of rejecting conforming lots
- There is added planning and documentation
- The sample usually provides less information about the product than that in 100% inspection

2.3.2.4 Product Zoning

When inspecting garments for cleanliness and fabric flaws, the location of a defect and its effect on the appearance and performance of a garment must be taken into consideration. Parts or zones that are most visible are of greater importance in maintaining higher levels of quality. For instance, Dastoor et al. (1994) classified the locations of defects on trousers, as shown in Fig. 2.2, into pocket, front opening, main panels, band, and belt loops. Garment manufacturers recognize that some parts of a garment are more crucial in terms of appearance than other parts. When a defect occurs in a garment, acceptance or rejection of the defective garment is prioritized by the zone in which it occurs. Defects which are noticeable on a garment but are not located in the focal area of the garment may not be a cause for garment rejection if the garment’s performance, fit or general appearance is not impaired. For example, areas closest to the front of the garment are of higher priorities while areas that are not likely to be seen, such as under the arms, are of lower priorities.

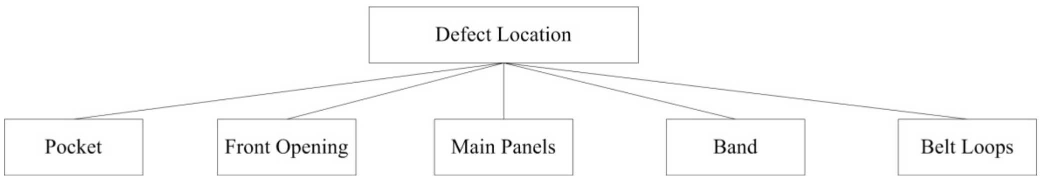

Fig. 2. 2 – Defect locations of trousers

It is found that the abovementioned applications for ensuring the quality in the garment industry are in the category of QC. These inspection-oriented approaches may not be sophisticated enough to solve the garment quality problems effectively as they do not help alter the overall product quality. A more proactive approach, such as

QA, is thus required. The differences between QA and QC are summarized in Table 2.2.

Table 2. 2 – Differences between QA and QC

QA	QC
A set of activities for ensuring quality in the processes by which the products are developed	A set of activities for ensuring quality in products
Process-oriented	Product-oriented
Defect prevention	Defect identification
Proactive (identify the weaknesses in the processes)	Reactive (detect, identify and correct defects)
Managerial tool	Corrective tool

QA is process-oriented as it identifies weaknesses of the processes by which the products are developed (Crosby, 1996; Moreno-Lonzo & Peris, 1998). It focuses on defect prevention and is thus a more proactive approach to ensure the quality of products. It also puts the emphasis on the role of management. On the other hand, QC is product-oriented, focusing on the identification of defects of the products (Deming, 1981; Feigenbaum, 1983). In QC, defects are detected, identified, and corrected. Nothing has been done to the underlying processes (Mandroli et al., 2006).

In view of this, compared with QA, QC is a reactive approach, solely adopted as a corrective tool. This highlights the needs to develop intelligent systems to transform the conventional QA approaches. In this research, an alternative QA approach is provided to investigate the garment quality problems at the parameter level. In the next section, different techniques from the areas of DM and AI, which have been adopted for QA in the general manufacturing sector, are reviewed.

2.4 Existing DM and AI Techniques Used in Quality Assurance

DM is the extraction of implicit, valid and potentially useful knowledge from a large set of raw data (Han & Kamber, 2001). It is useful in identifying patterns within data and transforming them into human-understandable knowledge (Forcht & Cochran, 1999; Çiflikli & Kahya-Özyirmidokuz, 2012). It has been widely applied in the provision of decision support in a number of manufacturing industries such as the paper industry (Milne, Drummond & Renoux, 1998), semiconductor industry (Dabbas & Chen, 2001; Hsu & Chien, 2007), carpet industry (Çiflikli & Kahya-Özyirmidokuz, 2010), and the electronics industry (Zhou et al., 2001; Tsai, 2012). In the following sections, various DM applications, including the applications of DM as a branch of applied AI, in the field of QA are reviewed.

2.4.1 Clustering

Clustering is the unsupervised classification of patterns into groups based on the similarity of objects such as high intra-cluster similarity and low inter-cluster similarity (Jain et al., 2000; Köksal et al., 2011). The similarity among objects is usually measured by distance measures. There are two major distance-based clustering methods, namely partitional clustering and hierarchical clustering.

Partitional clustering classifies the data into k parts in such a way that observations in each part are closely related to each other. It produce clusters by iteratively reassigning objects to clusters to optimize some pre-selected criteria by, for example, maximizing the between-cluster variation and minimizing the within-cluster variation. These methods produce a single clustering result, but the number of clusters must be pre-specified (Hess et al., 2001). One of the most popular algorithms for partitional clustering is the k-means algorithm (Chan et al., 2006). Using k-means does not create a tree structure to describe the groupings in the observed data, but creates a single level of clusters (Elango et al., 2011). It uses the actual observations of objects or individuals in the observed data, and not just their proximities, indicating that k-means is more suitable for clustering large amounts of data. It finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. In the field of QA, Chien et al. (2007) considered k-means clustering to infer possible causes of faults and manufacturing process variations in semiconductor manufacturing. The extracted information and knowledge is helpful to engineers as a basis for trouble shooting and defect diagnosis. Cheng and Leu (2011) applied k-means methods to classify construction defects so as to improve the quality in bridge construction.

On the other hand, hierarchical clustering groups the data into a tree of clusters by either using bottom- up (agglomerative) or top-down (divisive) approaches. It has been used for investigating the relationships between machines used in the wafer fabrication process and the yield (Hu & Su, 2004), for determining the causes of low yield (Skinner et al., 2002), and for improving yield (Baek et al., 2005).

2.4.2 Case-based Reasoning

Case-based reasoning (CBR) is a knowledge-based AI technique which solves a new problem case by reusing the knowledge and experience gained from solving a previous problem in a similar situation (Kolodner, 1991). Processes involved in a CBR cycle, as shown in Fig. 2.3, can be generally described by the four “REs” (Aamodt & Plaza, 1994):

- Retrieve the most similar case or cases;
- Reuse the knowledge provided in the case for problem solving;

- Revise the proposed solution;
- Retain the new experience as a new case for future problem solving.

Because of the abovementioned processes, it is believed that CBR is a good candidate for solving problems in experience-rich domains (Chi & Kiang, 1993) in which problem solving is not necessarily the finding of a concrete solution to an application problem (Aamodt & Plaza, 1994). It does not require strong domain knowledge and representation and is thus more useful when decision problems are difficult to define and structure (Haque et al., 2000).

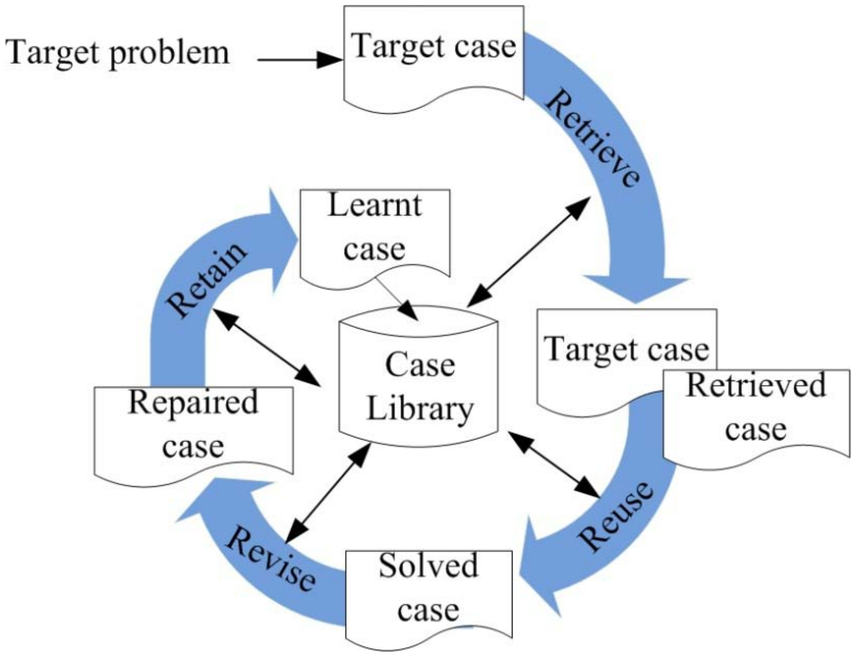

Fig. 2. 3 – CBR cycle

In order to develop an effective CBR system, the most critical issue is the design of a case retrieval mechanism (Qi et al., 2009). In general, CBR retrieval methods can be broadly categorized into two types, which are the inductive indexing and the nearest neighbor approaches (Chow et al., 2005; Tsai et al., 2005). The inductive indexing approach determines which features best discriminate cases and generates a tree-like structure to organize cases while the nearest neighbor approach is an exhaustive searching method which evaluates the dissimilarity between all past cases and the new case. Though the inductive indexing approach is useful when a single case feature is dependent upon others, it can be impossible to retrieve cases when a case feature is missing or unknown. On the other hand, the nearest neighbor approach is simple to use but time-consuming, as it makes comparisons with every case. It compares the similarity value (S) between the target case and the retrieved case by the following equation (2.1):

$$S = \frac{\sum_{i=1}^{n} w_i \times sim(f)}{\sum_{i=1}^{n} w_i} \tag{2.1}$$

where w_i is the weighting of the feature i, and *sim(f)* is the similarity function between the target case and the retrieved case. Cases with high similarity values are regarded as significant cases for the generation of the final solution.

In fact, to compose the niches of these two approaches, one of the most popular methods is to apply the inductive indexing approach to retrieve a set of matching cases, followed by the nearest-neighbor approach to rank the cases in the set according to the similarity to the new case (Wess et al., 1994; Shin & Han, 2001; Choy et al. 2005).

In the field of QA, CBR has been applied in generating customized operating procedures for handling food receiving operations in warehouses so as to guarantee the quality of food (Lao et al., 2012). It has also been used to assure the quality of personal care products by solving the ingredient formulation problems with reference to how similar past problems have been solved (Lee, Choy & Chan, 2014). Apart from the assurance of product quality, CBR has also been applied in the assurance of service quality. For instance, it has been used to enhance the quality of treatment in Intensive Care Units based on the knowledge gained from solving past patient cases (Kumar et al., 2009). In a similar vein, it has been employed to support the quality of prescription determined by general practitioners when diagnosing a wide range of health conditions and diseases (Ting et al., 2010). It is believed that CBR is a possible candidate for solving problems when assuring the quality of products or services is an experience- rich task.

2.4.3 Rule-based Reasoning

Rule-based reasoning (RBR) is a popular reasoning paradigm used in AI that expresses and stores knowledge in the form of rules for problem solving. In general, a rule-based system consists of a knowledge base and an inference engine, as shown in Fig. 2.4. The knowledge base stores two kinds of data, namely rules and facts. To represent knowledge, rules usually comprise two parts, namely, the IF and THEN parts. The IF part contains information on the facts or conditions that permit the rule to be applied, whereas the THEN part contains information on the outcome of the application of such a rule (Pal, 1999). When the condition of a rule in the knowledge base is satisfied by the input problem, intermediate results are generated by the chosen inference mechanism, such as forward or backward chaining, and the process is repeated until a desired solution state is reached (Dutta & Bonissone, 1993). On the other hand, facts express assertions about properties, relations, and propositions. In contrast to rules, facts are static and inactive regarding the pragmatic values and dynamic utilization of the knowledge.

In addition to the static memory for facts and rules, a rule-based system uses a working memory to store temporary assertions which record earlier rule-based inferences. In this sense, the contents of the working memory can be regarded as problem-solving state information.

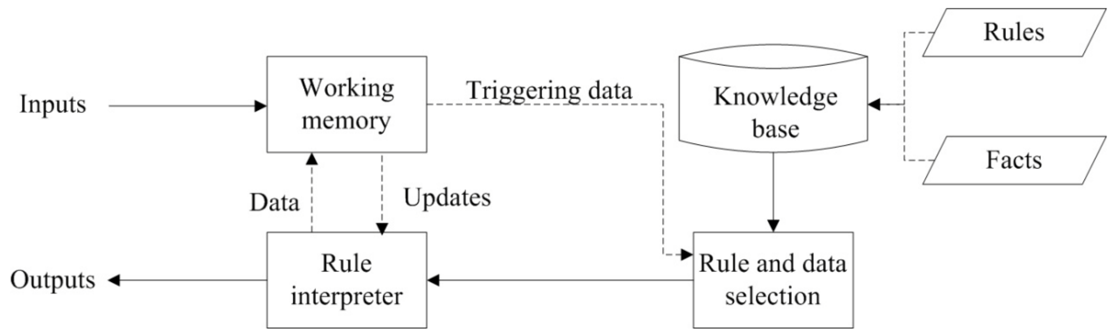

Fig. 2. 4 – The mechanism of RBR

The computing environment for rule interpretation consists of current facts and the inference engine itself, providing a context for interpreting the current state, understanding what the rules mean, and applying relevant rules appropriately (Hayes-Roth, 1985). Since RBR operates based on pre-defined rules and makes no reference to particular past cases (Gayer et al., 2007), it does not learn from experience. Therefore, RBR is suitable for knowledge-rich situations in which experience is not critical when making decisions (Chi & Kiang, 1993). According to Hayes-Roth (1985), the applications of RBR in QA include assessing tasks, proposing practices and enforcing requirements.

2.4.4 Artificial Neural Network

Artificial neural networks (ANNs) were defined by Kohonen (1988) as "massively parallel interconnected networks of simple (usually adaptive) elements and their hierarchical organizations which are intended to interact with objects of the real world in the same way as biological nervous systems do". Inspired by networks of biological neurons, ANN models contain layers of simple computing nodes that are richly interconnected by weighted connection lines, and the weights are adjusted when data are presented to the network through a "training" process. According to Dayhoff and DeLeo (2001), successful training can result in ANN that perform tasks such as predicting an output value, classifying an object, approximating a function, recognizing a pattern in multifactorial data, and completing a known pattern.

In the field of QA, the applications of ANN can be classified into two types, namely reactive QA and proactive QA (Zhang & Huang, 1995). Reactive QA is related to monitoring and diagnosis, thus ANN can play in important role in reactive QA when high processing and classification capabilities are required. ANNs have been applied to detect and classify different defects, such as surface blemishes on light-emitting diode chips (Lin, 2009), stitching defects (Wong et al., 2009) and garment defects (Yuen et al., 2009).

On the other hand, ANN can also be applied for proactive QA. Aguilera et al. (2001) applied ANN to assess and predict the water quality. Niska et al. (2004) evolved an ANN model for forecasting air quality. Jung and Yum (2011) developed an ANN-based approach for determining the optimal setting of design parameters.

However, the quality of solutions determined by the ANN is affected by the number of layers, the number of neurons on each layer, the transfer function of each neuron, and the size of the training set (Li, 1994). Therefore, users of ANNs must conduct experiments or sensitivity analyses in order to identify the best possible configuration of the network. In addition, a solution to a non-linear problem reached by the ANN may not be the global optimum, and there is no way to verify that an ANN is correct unless every possible input is tried (Li, 1994). Therefore, it is suggested that the ANN should be run for a long period of time to ensure that the ANN systems are error-free before they are used in real situations. In line with this view, since the garment industry is very time-sensitive and dynamic, ANN may not be efficient enough to solve the QA problems.

2.4.5 Association Rule Mining

Association rule mining is useful in finding the correlations between items (Altuntas & Selim, 2012) and expressing them in terms of association rules. An association rule is represented in the form of "X →Y", where X and Y are defined as sets of attributes or items representing the "If" part and the "Then" part of the rule respectively. The Apriori Algorithm proposed by Agrawal and Srikant (1994) is considered a classical algorithm, effective for generating association rules between items in large databases (Chung & Tseng, 2012; Lim et al., 2012). Two values, namely support and confidence, can be used to describe an association rule as follows:

$$\text{Support}(X \Rightarrow Y) = P(X \cup Y) \tag{2.2}$$

$$\text{Confidence }(X \Rightarrow Y) = P(Y|X) \tag{2.3}$$

The support for a rule is the percentage of transactions in the databases containing both X and Y while the confidence for the rule is the percentage of transactions in the database containing X that also contain Y (Martínez-de-Pisón et al., 2012). According to Yang et al. (2011), association rule mining may generate a large number of rules. Some of them could be contradictory or irrelevant, thus only a reduced number of significant rules are valid for efficient decision making (Moreno et al., 2008). A rule is considered as significant if its support and confidence are greater than the user's-defined threshold values (Demiriz et al., 2011). Both threshold values for support and confidence which are defined by users will thus affect the quality of association rules (Lim et al., 2012). Consequently, in any association rule mining model, it is important to ensure that user-specified minimum support and confidence are appropriate to generate significant rules.

To perform QA, various types of knowledge such as knowledge of the defect problems are required (Deslandres & Pierreval, 1997). Association rule mining is a popular tool to find the correlation between different defects or anomalies. It has been applied for root cause analysis of anomalies to improve service and repair in the automotive domain (Chougule et al., 2011), the discovery of defect patterns for defect prediction (Chang et al., 2009; Lee, Choy, Ho, Chin et al., 2013), and the discovery of the relationship between predefined events in multiple time series, so as to explain failures in the hot-dip galvanizing of steel lines (Martínez-de-Pisón et al., 2012). The findings in these works are consistent with the view of Ur-Rahman and Harding (2012) who pointed out that product quality can be improved through the discovery of hidden knowledge. Nevertheless, a major drawback in using association rule mining is that the attributes concerned are limited to Boolean attributes (Alatas et al., 2008). Considering that there are many other situations where data are numeric, it is not always practical to use association rule mining to solve problems.

Furthermore, there are many forms of uncertainties in industrial decision environments, such as imprecise process times, unpredictable demands and uncertain capacities (Aliev et al., 2007; Mula et al., 2007). Taking the fuzziness of data into consideration is of great importance for improving the usefulness of association rule mining in the context of QA.

2.4.6 Fuzzy Logic

Fuzzy logic is an effective AI technique for managing imprecise attributes by offering a mathematical model in which vagueness is based on the introduction of a degree of truth ranging from 0 to 1 (Ma et al., 2006; Ordoobadi, 2009; Novák, 2012). It mimics human decision making by performing approximate reasoning with linguistic terms so to as generate solutions (Liu & Lai, 2009; Wong & Lai, 2011).

Judgment in the human mind is usually expressed in linguistic terms or in fuzzy ones which have no clear boundaries and cannot be precisely associated with a real number (Büyüközkan & Feyzioğlu, 2004). In fuzzy logic, these linguistic terms are represented by fuzzy sets which are employed to develop causal relationships between input and output variables (Tahera et al., 2008). Each of the fuzzy sets is associated with a membership function which allows the variables to carry a degree of membership in a fuzzy set within a range between 0 and 1 (Azadeganm et al., 2011; Otero & Otero, 2012). There are three main components in a fuzzy system (Lau et al., 2008): (i) Fuzzification, (ii), Inference engine, and (iii) Defuzzification.

Fuzzification is responsible for converting crisp input values into fuzzy sets. These fuzzy sets are then input into an inference engine for converting the input fuzzy sets into output fuzzy sets on a basis of a collection of fuzzy rules. Each fuzzy rule, in the form of if–then–else rules (Son & Kim, 2012), implies a fuzzy relationship between an antecedent and a consequence (Otero & Otero, 2012). Defuzzification is finally carried out to convert these output fuzzy sets into crisp values, as only exact numerical values are needed in actual control operations.

In manufacturing, uncertainties or vagueness can arise from market demand, capacity availability, process times, and costs (Aliev et al., 2007; Mula et al., 2007). Therefore, decision making in manufacturing always requires the consideration of various uncertainties (Petrovic & Duenas, 2006; Azadeganm et al., 2011), making fuzzy logic a good candidate to deal with the uncertain and vague manufacturing variables (Guiffrida & Nagi, 1998; Wong & Lai, 2011). Many researchers have applied fuzzy logic to solve manufacturing problems in which linguistic terms are more effective in decision making. Díaz et al. (2004) incorporated fuzzy approaches to manage the production priority in manufacturing metal rolls. Petrovic and Duenas (2006) presented a fuzzy logic based system for production scheduling in the presence of uncertain disruptions. Suhail and Khan (2009) adopted fuzzy logic to determine the amount of machinery resources with the aim of achieving low work-in-process inventory and no stockouts.

In the area of QA, fuzzy logic has been applied in a number of industries. For example, Pfeufer (1997) used fuzzy logic to formulate a fault-diagnostic scheme for QA of automotive actuators. Besides, strategies using fuzzy logic for control operations and decision making have encountered great interest to enhance the quality of food and beverage during the last few years (Birle et al., 2013). Statistically, research shows that, especially in the field of quality assessment and analysis, fuzzy logic for decision support of experts plays an important role (Miguel, 2002; Perrot et al., 2006; Lao et al., 2011). In addition, fuzzy logic is commonly adopted for fabric quality assessment in the textile and garment industry (Zeng & Koehl, 2003; Lau et al., 2006; Chen et al., 2009). In their work, subjective assessment of fabric properties such as surface smoothness and roughness are described in linguistic terms. It is observed that fuzzy logic is capable in providing decision support in QA when there are no clear-cut boundaries to associate most parameter values to one single linguistic term. With the use of fuzzy logic, the fuzziness of data can thus be taken into consideration.

2.4.7 Genetic Algorithms

In recent decades, some outstanding algorithms, such as the genetic algorithm (GA), have surfaced to solve optimization problems. GA generates new solutions by applying crossover and mutation to current solutions and approaching statistically more optimal points in the search space (Haupt & Haupt, 2004). It is based on the principles of genetics and natural selection, and a possible solution for a given problem in GA is called an individual or a chromosome. The crossover operator generates two offsprings (new candidate solutions) by recombining the information from two parents, followed by the mutation operator to perform a random alteration of some values in a chromosome (Juang, 2004).

There are existing research studies applying GA for improving the quality of products or services. The focus of these works is mainly on the optimization of parameters. For instance, GA has been applied in searching for the optimal protection relay response time extremes for software QA (Alander et al., 1998). It has also been applied to determine the optimal combination of kinetic rate parameters and constants that results in a best fit for water quality modeling (Pelletier et al., 2006). However, in the existing works using GA for solving quality problems, the length of the chromosomes is fixed. As a consequence, the best achievable fitness is inherently limited by the chromosome length and it is difficult to define an optimal chromosome length, especially for optimization problems (Kim & De Weck, 2005).

To overcome this limitation, a number of variable-length GAs have been proposed to increase the diversity of the chromosome lengths. A typical variable-length GA has additional mutation operators that vary the length of the chromosomes and is thus able to perform crossover on chromosomes of differing length (Hutt & Warwick, 2007). It has been commonly applied to some design problems where the chromosomes can have a variable number of components and the problem is incremental in nature (Qiu et al., 2009).

The earliest example of a GA with variable length was the messy GA proposed by Goldberg et al. (1989). It replaced crossover with cut and splice operators to produce variable-length chromosomes. Furthermore, Han et al. (2002) designed an adaptive length chromosome hyper-GA with two new mutation operators, namely removing-worst mutation and inserting-good mutation. The former one removes the worst group of genes in the selected chromosome while the latter one inserts the best group of genes from a randomly selected chromosome to a random point of the desire chromosome. As genes are removed or inserted, the length of the chromosomes in each generation changes. In addition, one of the novel GAs proposed by researchers in recently years was the Jumping Gene GA (JGGA) (Man et al., 2004). It emulates the genetic phenomenon of horizontal transmission in which genes can be transposed from one position to another, either within the same or in a different chromosome (Nawaz Ripon et al., 2007; Chan et al., 2008). In the JGGA, although the diversity of solutions was improved, the chromosome length remained fixed throughout each generation.

Despite the fact that variable-length GAs more appropriately match the biological genetic representation (Burke et al., 1998), variable-length GAs have not been applied in QA in the garment industry.

2.4.8 Hybrid Approaches

It has been observed that there is an increasing trend in the use of intelligent systems incorporating more than one technique from the areas of DM and AI into systems for solving quality problems. Tsai et al. (2005) and Hassouna and Tahvildari (2010) applied CBR to predict defects and used clustering algorithms to group similar cases into different clusters. Ho et al. (2005) designed a quality enhancement system incorporating CBR, fuzzy logic and ANN to identify potential quality problems and direct them to the appropriate agent for problem-solving. Lau, Tang et al. (2009) integrated fuzzy logic and GA to determine optimal process parameter settings with the aim of achieving minimum defects.

Furthermore, hybrid approaches have been adopted to solve quality problems in a number of diverse industries. Tsai (2012) employed a two-stage clustering algorithm to portray soldering quality levels in the electronics assembly industry, followed by a decision tree algorithm to induce a set of association rules for classifying the quality levels. In addition, fuzzy association rule mining is a popular approach to develop intelligent systems for QA. It integrates fuzzy set concepts and DM to generate association rules from quantitative data (Hong et al., 2003). The fuzzy association rules obtained represent knowledge in fuzzy linguistic terms which are easily understandable by human beings and can provide direct knowledge support for quality prediction.

Previous research has applied fuzzy association rule mining to help manufacturers understand the relationship between parameter settings and the finished quality (Lau, Ho et al., 2009; Lee, Ho et al., 2014). The results showed that the approach is capable of capturing process parameters and quality features of products to support knowledge discovery for QA. In the abovementioned work, the data considered were expressed in linguistic terms, such as “medium” and “high”, in the rules. These rules are useful in the development of a fuzzy rule base for the application of fuzzy logic. If they are of good quality, the results of the fuzzy logic can be greatly enhanced (Tahera et al., 2008). In most hybrid approaches, however, the chromosome length is fixed when traditional GAs are used to optimize fuzzy rules (Wang et al., 2000; Ho et al., 2008; Lau, Tang, et al., 2009). As a consequence, if a large number of parameters need to be optimized, then the search space a GA must traverse in order to find the optimum can be immense (Hutt & Warwick, 2007).

Despite the effectiveness of fuzzy association rule mining in supporting QA at the parameter level, variable-length GAs have not been hybridized with it for QA in the manufacturing industry. Consequently, the knowledge discovered for QA is limited by the fixed-length of the chromosomes.

2.5 Mobile Technologies Supporting Automatic Data Collection

Since DM involves the collection of a huge set of data before analysis, there are various tools to enhance the speed and accuracy of the data capturing processes. In this section, two commonly used mobile technologies supporting automatic data collection are presented. They are the barcode and Radio Frequency Identification (RFID) technologies. Though they are both identification and data collection technologies, they also differ significantly in many areas (Qian et al., 2012). Details of each technology are presented in the following sections.

2.5.1 Barcode Technologies

Barcodes technologies have been widely used in many commercial applicatons for automatic identification in data collection. They are line-of-sight technologies, requiring a scanner to "see" the barcode in order to read it (Attaran, 2007). In the following sections, linear barcode and 2D barcode technologies are introduced.

2.5.1.1 Linear Barcode Technologies

A linear barcode is made up of a series of wide and narrow parallel bars and spaces arranged according to a set of rules that determines how data is to be represented (Islam & Shuva, 2010). Different bar and space patterns are used to express different symbols. Code 39 is one of the most commonly used linear barcodes. It is defined in American National Standards Institute standard MH10.8M-1983. Each character included in the Code 39 consists of 9 elements: 5 bars and 4 spaces. Code 39 is the only type of barcode in common use that does not require a checksum, thus making it attractive for applications where it is inconvenient or unfeasible to perform calculations each time a barcode is printed (Youssef & Salem, 2007).

Most barcode scanners consist of three different parts including an illumination system, a sensor and a decoder. A barcode scanner begins by illuminating the black and white elements of a barcode with red light. The sensor then detects the reflected light from the illumination system and generates an analog signal representing the intensity of the reflection. The decoder interprets the signal, validates the barcode using the check digit, and coverts it into text.

A linear barcode typically contain any type of text information. In contrast, a 2D barcode is more complex and can include more information in the code such as price, quantity, web address or image. Furthermore, a linear barcode scanner cannot read a 2D barcode, thus requiring the use of an image scanner for reading the information embedded in a 2D barcode.

2.5.1.2 2D Barcode Technologies

Compared to linear barcodes, 2D barcodes can achieve much higher capacity (Ozcelik & Acarturk, 2011) by encoding data in both horizontal and vertical directions (Chen et al., 2013). The major characteristics of 2D barcode technologies are the high capacity to represent data content, and the arrangement of a specific geometric diagram in a relatively small matrix area that can record significant quantities of data.

Two typical types of 2D barcodes include the 2D stacked codes and the 2D matrix codes. The 2D stacked code was developed on the basis of the linear barcode. It is composed by thinning down the linear barcode and stacking it in layers to create multi-row symbols (Lin et al., 2014). Representative types of the 2D stacked code include Code 16K, Code 49 and Code PDF417. In addition, the 2D matrix code is composed by the distribution of black–white picture elements, such as square, dot or other types, in a square area in a relative matrix position. Examples of 2D matrix codes include the QR Code and Data Matrix (Kato & Tan, 2011).

The benefits of using the barcode technology are high speed and high accuracy. According to Youssef and Salem (2007), entering barcode data is at least 100 times faster and more accurate than traditional manual keyboard entry, which translates into a dramatic increase in efficiency and productivity for any operation. However some environmental conditions, such as temperature, dirt or hazardous contamination, can adversely affect the effectiveness of barcode scanning on a label (Ramanathan et al., 2014). It is considered that RFID is a significant improvement over the conventional barcode, which needs to be read by scanners in “line-of-sight” fashion and can be stripped away if the paper product labels become ripped or damaged (Angeles, 2005).

2.5.2 Radio Frequency Identification Technologies

Radio Frequency Identification (RFID) technology is an automatic identification and data capture technology composed of three elements, namely RFID tags, RIFD readers and RFID middleware (McFarlane et al. 2003; Sarac et al., 2010). In recent years, a growing body of literature has discussed the application of RFID for automatic data collection. Lao et al. (2011) adopted RFID to capture data for determining the required operation procedures for QA in the food industry. In their studies, the decision process time for QA operations was shortened significantly.

Ngai et al. (2012) implemented an RFID-based manufacturing management system in a garment factory where RFID tags were associated with a bundle of cut-raw materials while RFID readers were installed next to each sewing machine to keep track of the production process. Zhong et al. (2013) presented an RFID-enabled real-time manufacturing execution system which deployed RFID devices on the shop-floor to track and trace manufacturing components and collect real-time production data for planning, scheduling, execution and control. In their system, RFID eliminated the manual and paper-based data collection and ungraded the shop-floor data to a level that was real time, complete and accurate. On the other hand, with the use of RFID technology, a manufacturing planning and control system was proposed by Wang and Lin (2009), capable of performing three main functions, which are (i) the timely generation of an accountable production and operation schedule, (ii) active monitoring, control and execution of shop floor operations, and (iii) Real-time evaluation of production performance.

Although RFID technology can have a positive impact on manufacturing by improving productivity, increasing flexibility in production planning and control, enabling products to be customized, improving change-over management, improving tracking and utilization of reusable assets, higher visibility and accuracy of real-time data, strengthening customer relationships and, most importantly, facilitating effective resource allocation (Qiu, 2007; Moon & Ngai, 2008; Kwok & Wu, 2009; Meyer et al., 2009; Huang et al., 2011; Lin et al., 2012), it has not yet been widely adopted in manufacturing processes (Ngai et al., 2012; Zhou & Piramuthu, 2012).

With its unique data capturing characteristics, RFID supports real-time decision-making (Chatziantoniou et al., 2011). It can be foreseen that RFID will be able to increase the efficiency of the data collection process in DM for decision-making.

2.6 Summary

After reviewing the QA literature relevant to the garment industry and various mobile technologies, it is observed that conventional inspection-oriented QA applications in the garment industry are not sophisticated enough to investigate the quality problems at the parameter level. It is also found that the use of fuzzy association rule mining, optimized by GA, is a possible way to develop intelligent systems for enhancing QA in the garment industry. Meanwhile, considering the time-sensitivity of the garment industry, it is important to speed up the data collection process. Therefore, RFID technologies are also selected for data capturing in the proposed system.

Chapter 3 A Fuzzy Rule-based Recursive Mining System (FRRMS)

3.1 Introduction

In this chapter, the design of the Fuzzy Rule-based Recursive Mining System (FRRMS) is presented for supporting QA in the garment industry. It integrates and hybridizes different DM and AI techniques including fuzzy association rule mining, GA, and fuzzy logic, to determine appropriate process parameter settings for production so as to improve the product quality. RFID technologies are also employed for real-time data capturing.

A recursive algorithm is an algorithm in which a series of procedures is carried out repeatedly, as an infinite loop, by returning parts of its output to the initial steps of the procedures as new input. The algorithm embedded in the FRRMS is regarded as a recursive one because the process parameters, learnt from a series of mining and optimization procedures, can be adopted in the production and their relationships with the resultant product quality features are investigated through the algorithm all over again. As a result, new knowledge between process parameters and the quality features can be continually discovered and improved, supporting a more reliable and effective QA scheme for the garment industry.

In this chapter, an overview of the architecture of the FRRMS is firstly presented, followed by an explanation of each module involved in the FRRMS.

3.2 Architecture of the FRRMS

The architecture of the FRRMS is shown in Fig. 3.1. It consists of three modules, which are the (i) Fuzzy Association Rule Mining Module (FARMM), (ii) Slippery Genetic Algorithm-based Optimization Module (sGAOM), and (iii) Decision Support Module (DSM).

In the FARMM, there is a centralized database storing the process parameters and the resultant product quality features captured by the RFID devices. Fuzzy association rule mining is then performed to discover the relationships among the process parameters and the quality features in terms of fuzzy association rules. Obtained rules are stored in a fuzzy rule-based repository and are referred to in the sGAOM and DSM.

In the sGAOM, a novel algorithm, namely, a slippery genetic algorithm in fuzzy association rule mining (sGA-FARM), is employed to optimize the fuzzy rules. Unlike conventional GAs, the sGA-FARM allows the rules to be encoded in variable-length chromosomes. As a consequence, the diversity of solutions is not limited by the fixed chromosome length. The optimized rules replace the old rules and are stored in the fuzzy rule-based repository as decision rules for supporting QA activities.

Finally, based on the decision rules in the repository, the DSM applies fuzzy logic to determine the product quality features when a set of process parameters are inputted to the system. By comparing the resultant product quality through the input of different process parameters, production operators are able to determine the appropriate process parameters to be used in production for achieving better product quality. The learnt process parameters, after being adopted in the production lines, form part of the new input of the initial step of the mining algorithm in the FARMM. Hence, the FRRMS operates recursively and the process parameters can be continually refined for QA purposes. Details of each module are presented in the following sections and the notations used in the FRRMS are listed in Table 3.1.

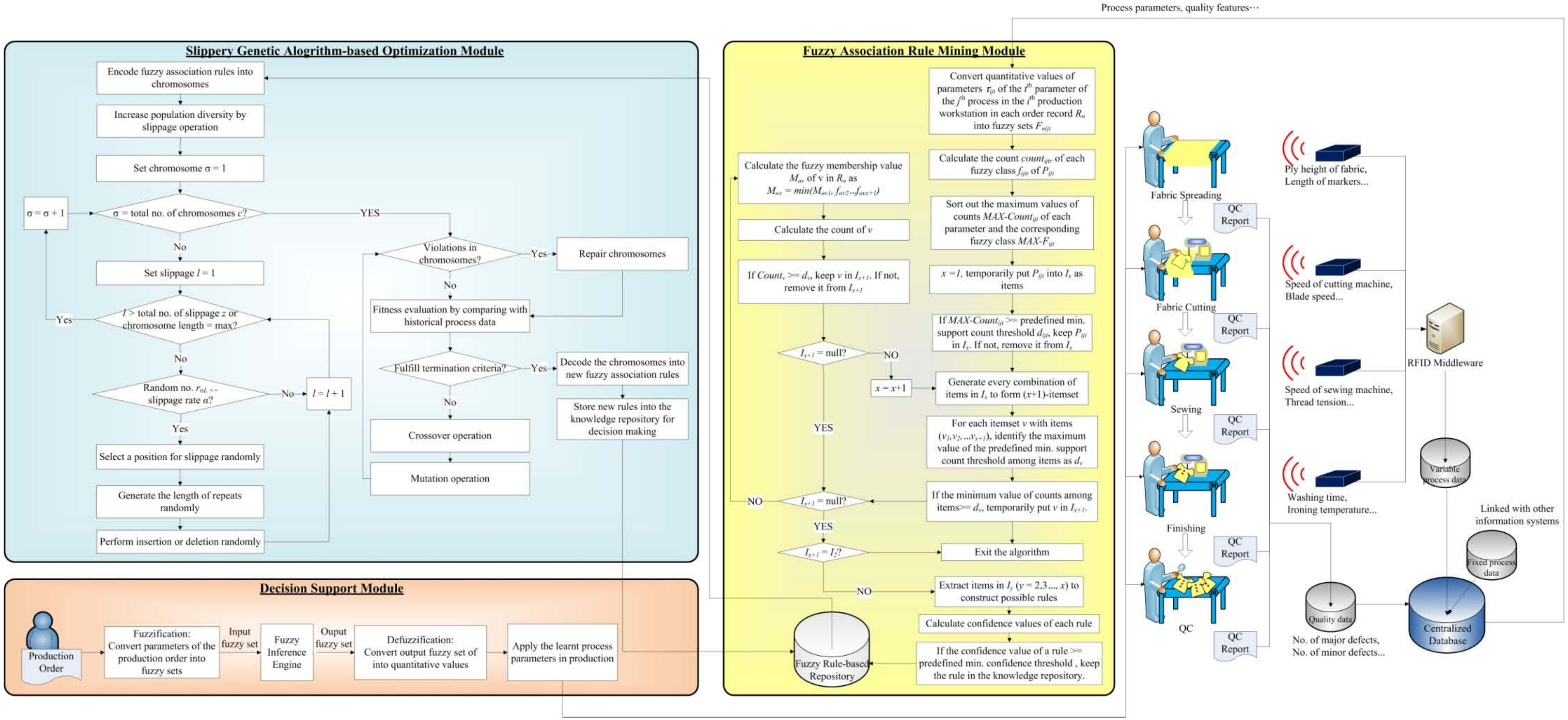

Fig. 3. 1 – The architecture of the FRRMS

Table 3. 1 – Notations used in the FRRMS

Symbol	Description
n	The number of historical order records
$N=\{1,2,\ldots,n\}$	The set of index of historical order records
R_θ	The θ^{th} order record, $\forall\theta \in N$
s	The number of production workstations in an order record
$S=\{1,2,\ldots,s\}$	The set of index of production workstations in an order record
W_i	The i^{th} production workstation, $\forall i \in S$
e_i	The number of processes in i^{th} production workstation, $\forall i \in S$
$E_i=\{1,2,\ldots e_i\}$	The set of index of processes in i^{th} production workstation
δ_{ij}	The j^{th} process of i^{th} production workstation, $\forall i \in S, \forall j \in M_a$
k_{ij}	The number of process parameters in j^{th} process of i^{th} production workstation
$K_{ij}=\{1,2,\ldots k_{ij}\}$	The set of index of process parameters in j^{th} process of i^{th} production workstation
P_{ijt}	The t^{th} process parameters of j^{th} process of i^{th} production workstation
τ_{ijt}	The quantitative value of t^{th} process parameters of P_{ij} of W_i, $\forall t \in K_{ij}$
$F_{\theta ijt}$	The fuzzy set converted from τ_{ijt} in R_θ
a_{ijt}	The number of fuzzy classes of P_{ijt}
$A_{ijt}=\{1,2,\ldots,a_{ijt}\}$	The set of index of fuzzy classes of P_{ijt}
f_{ijtr}	The r^{th} fuzzy classes of P_{ijt}, $\forall r \in A_{ijt}$
$M_{\theta ijtr}$	The fuzzy membership values of P_{ijt} in R_θ in fuzzy class f_{ijtr}
$Count_{ijtr}$	The summation of $M_{\theta ijtr}$, representing the count of f_{ijtr}
$MAX\text{-}Count_{ijt}$	The maximum value among $Count_{ijtr}$ of P_{ijt}
$MAX\text{-}F_{ijt}$	The fuzzy classes of P_{ijt} with $MAX\text{-}Count_{ijt}$
I_x	The set of itemsets with x items
d_{ijt}	The predefined minimum support count threshold of P_{ijt}
Ω	The predefined minimum confidence threshold of rules
c	The number of chromosomes in the population
$C=\{1,2,\ldots,c\}$	The set of index of chromosomes in the population
H_σ	The σ^{th} chromosome, $\forall\sigma \in C$
z	The number of slippage operation
$Z=\{1,2,\ldots,z\}$	The set of index of slippage operation
l	The l^{th} slippage operation, $\forall l \in Z$
α	The slippage rate
β	The crossover rate
γ	The mutation rate

3.3 Fuzzy Association Rule Mining Module (FARMM)

The FARMM is responsible for identifying the hidden patterns between process parameters and the finished quality of products so as to generate a set of fuzzy association rules. In each fuzzy association rule, parameters are described in terms of fuzzy terms instead of quantitative values.

The FARMM starts with the use of RFID technologies for collecting and managing data in a centralized database. There are three types of data collected, which are (i) fixed process data, (ii) variable process data, and (iii) quality data.

Fixed process data includes customer and product requirements such as the production volume, number of trims involved per product, and the delivery time. These data have been predefined by customers or determined during pre-production operations. Therefore, they are initially stored in some existing information systems. To allow the collection of fixed process data, the centralized database is linked with other information systems such as Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM). These data are initially written into the RFID tags.

Variable process data are the data which can be adjusted for achieving better product quality. Examples of variable process data include different parameter settings of machines used in various production workstations. As these data are always adjustable by operators during production, creating either positive or negative impacts on the finished quality of products, RFID devices are employed to collect the data on a real-time basis. A RFID middleware is used to transform the received RFID signals into meaningful information before sending the data to the centralized database.

Quality data are the data related to the quality of both semi-finished and finished products. They are collected from the QC reports generated from each production workstation before they are stored in the centralized database.

Since the data stored in the centralized database are from diverse sources, Extensible Markup Language (XML) is used as the standardized format to allow data exchange. After the essential data are captured, the fuzzy association rule mining algorithm can be used.

The algorithm of the FARMM integrates fuzzy set concepts and DM techniques to generate useful association rules from quantitative data. In this module, quality engineers extract production order records from the database as each record contains the quantitative values of the production process setting and finished product quality. Fuzzy membership functions, minimum support count and confidence threshold values have to be predefined by domain experts and are used in the mining process. The quantitative parameters in the order records are converted into fuzzy sets based on the predefined membership functions. After that, the fuzzy sets are kept for use in a series of mining processes, such as the calculation of support counts and the generation of itemsets. The details of the fuzzy association rule mining algorithm are described below.

Step 1: For each production order R_θ, convert the quantitative value τ_{ijt} of the t^{th} parameter of the j^{th} process in the i^{th} production workstation into fuzzy set $F_{\theta ijt}$ based on the predefined membership functions. Represent $F_{\theta ijt}$ as ($M_{\theta ijt1} / f_{ijt1} + M_{\theta ijt2} / f_{ijt2}$ +…+ $M_{\theta ijta} / f_{ijta}$).

Step 2: Calculate the count $Count_{ijtr}$ of each fuzzy class f_{ijtr} of parameter P_{ijt} as

$$Count_{ijtr} = \sum_{\forall \theta \in N} M_{\theta ijtr}$$

Step 3: Select the maximum values of the count $MAX\text{-}Count_{ijt}$ among the fuzzy classes of each parameter and identify the corresponding fuzzy class $MAX\text{-}F_{ijt}$ to represent the fuzzy characteristic of P_{ijt} in the later mining process.

Step 4: Set x=1, and temporarily put the parameters into I_x as items. If the $MAX\text{-}Count_{ijt}$ of P_{ijt} is larger than or equal to the predefined minimum support count threshold d_{ijt}, keep P_{ijt} as an item in I_x. Otherwise, remove it from I_x.

Step 5: Generate every combination of items in I_x to form (x+1)-itemsets. For each itemset v with items $\{v_1,v_2,\ldots,v_{x+1}\}$, identify the maximum value of the predefined minimum support count threshold among the items as d_v. If the minimum value of the counts among the items is equal to or larger than d_v, temporarily put v in I_{x+1}.

Step 6: If $I_{x+1} \neq$ null, go to the next step. If I_{x+1} = null and x=1, exit the algorithm. If I_{x+1} = null and x>1, go to Step 11.

Step 7: The fuzzy membership value of the itemset is the minimum value of the fuzzy membership values among all the items in the itemset. Therefore, the fuzzy membership value $M_{\theta v}$ of v in R_θ is calculated as

$$M_{\theta v} = min\ (M_{\theta v_1}, M_{\theta v_2} \cdots, M_{\theta v_{x+1}}).$$

Step 8: Calculate the count of v as

$$Count_v = \sum_{\forall \theta \in N} \mathrm{M}_{\theta v}$$

Step 9: If $Count_v$ is larger than or equal to d_v, keep v in I_{x+1}. Otherwise, remove it from I_{x+1}.

Step 10: If $I_{x+1} \neq$ null, set $x= x+1$ and repeat Steps 5-10. If I_{x+1} = null and x=1, exit the algorithm. If I_{x+1} = null and x>1, go to Step 11.

Step 11: Extract items from I_y for $y \geq 2$ to construct possible rules. Calculate the confidence value of each rule.

Step 12: If the confidence value of a rule is larger than or equal to the predefined minimum confidence threshold Ω, the rule is regarded as a useful fuzzy association rule.

Useful fuzzy association rules obtained in this module are "IF-THEN" rules indicating relationships between process setting and the finished product quality. Since the product quality are the desired output parameters, rules with the quality features appearing in the "THEN" part of the rules are extracted as decision rule candidates and stored in the rule-based repository. After the rules are stored, they can be transferred to the sGAOM where sGA-FARM is applied for optimization. The DSM can also provide decision support for production operators in their attempt to determine appropriate process settings based on the rules stored in the repository.

3.4 Slippery Genetic Algorithm-based Optimization Module (sGAOM)

In the sGAOM, a novel nature-inspired algorithm, namely the slippery genetic algorithm in fuzzy association rule mining (sGA-FARM), is introduced. It imitates and transcribes biological slippage into a new computational GA, to solve optimization problems. The biological slippage is able to provide new and advantageous solutions which are sensitive to the environment. By the same analogy, a computational slippage operation can be designed for evolutionary algorithms to enhance the search for novel as well as superior solutions. In this section, the background of biological slippage is firstly presented, followed by an introduction to the sGA-FARM.

3.4.1 Background of Biological Slippage

There are four bases which can be found in a DNA molecule. They are adenine (A), cytosine (C), guanine (G) and thymine (T). In a DNA molecule, A is paired with T while G is paired with C. Because of such a specific pairing mechanism, a DNA molecule has two strands which are complementary to each other (Elrod & Stansfield, 2010), as shown in Fig. 3.2, and the sequence of one strand determines that of another. However, it was discovered that a strand often slips and is misaligned with the other strand when there are repeating patterns of the bases in the DNA (Petruska et al., 1998; Huntley & Golding, 2006). This phenomenon is called slippage and is commonly observed in DNA replication (Macey et al., 1997).

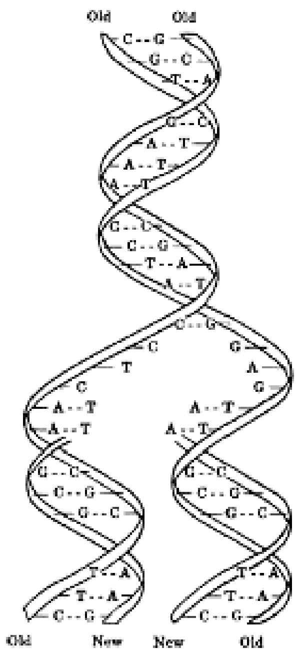

Fig. 3. 2 – DNA (Extracted from Elrod & Stansfield, 2010)

During DNA replication, new strands are synthesized using the old strands as a template. When slippage occurs, a single strand of DNA slips and curls back on itself (Caporale, 2003a). The slipped part becomes self-complementary and a hairpin is formed, leading to changes in DNA sequences (Nishizawa & Nishizawa, 2002). If the hairpin is formed on the newly synthesized strand, insertion mutation results, as shown in Fig. 3.3, increasing the length of repeats in the next generation (Caporale, 2003b). On the other hand, if the hairpin is formed on the template strand, deletion mutation results, as shown in Fig. 3.4, shortening the length of repeats in the next generation (Caporale, 2003b).

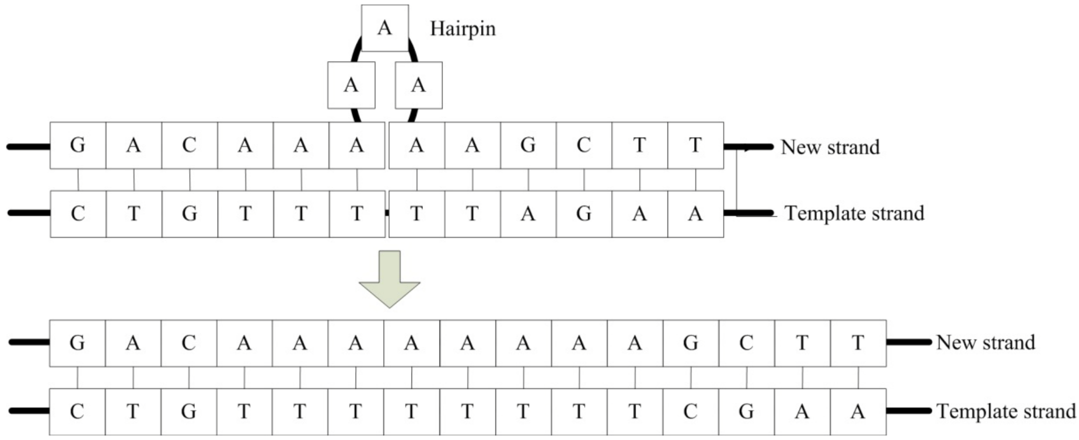

Fig. 3. 3 – Slippage mutation – insertion

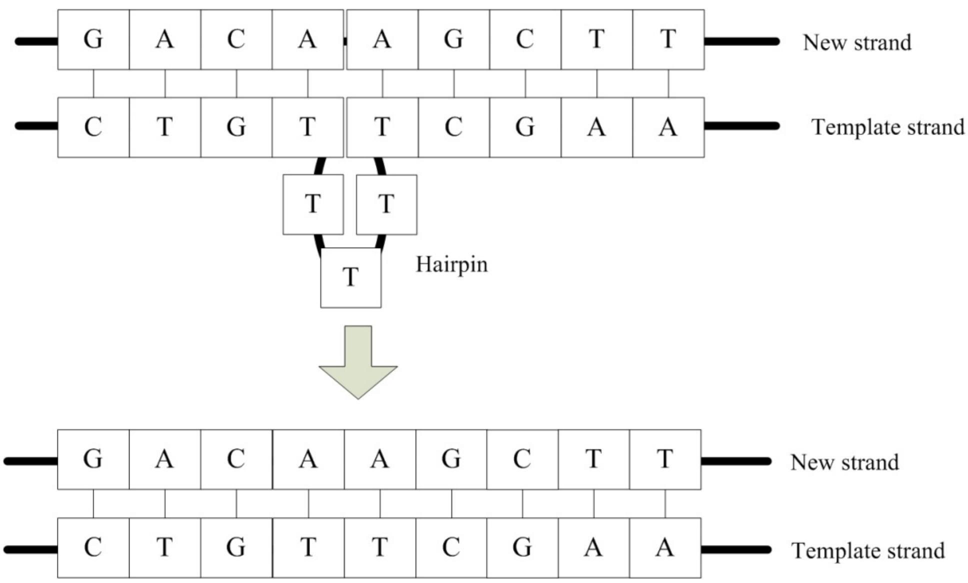

Fig. 3. 4 – Slippage mutation – deletion

Due to strategic slippage operations, organisms can continue to generate diversity, allowing them to find the right approach to adapt to changing environments (Moxon et al., 1994; Kashi et al., 1997; Trifonov, 1999; Verstrepen et al., 2005). For instance, fruit flies that cannot maintain their body temperature can still survive in extreme climates because fruit fly variants have different lengths of TGs for managing their biological clock at different temperatures (Caporale, 2003a). *Haemophilus influenza*, a bacterium surviving in the human nose and throat, keeps changing its coat by slipping at locations with repetitive gene sequences so that it can find a coat which does not trigger an immune response (Caporale, 2003b). Considering the large amount of repetitive gene sequences, slippage is one of the most widespread and powerful means of providing genetic variation for evolution (Kashi & King, 2006). Inspired by biological slippage, a new evolutionary computing algorithm, sGA-FARM, is proposed to improve the diversity of solutions.

3.4.2 A Slippery Genetic Algorithm in Fuzzy Association Rule Mining (sGA-FARM)

In the sGAOM, slippage concepts are adopted as an enhancement to a conventional GA framework. The proposed sGA-FARM is an algorithm in which slippage takes place to increase diversity in the population by varying the chromosome length. The flow of the sGA-FARM is shown in Fig. 3.5. It starts with a set of fuzzy association rules, obtained in the FARMM, which are encoded into chromosomes. Only parameters which appear in the rules are represented as genes and included in the chromosomes. As a result, the diversity of the initial population of the sGA-FARM is inherently limited. Slippage thus takes place to increase the population diversity. With the slippage operation, different parameters can have a chance to be inserted into or removed from the chromosomes. Because of the randomness, violations in chromosome encoding may occur and thus repair of these chromosomes is required. A fitness function is then adopted to evaluate each chromosome. Based on the fitness of the chromosomes, some chromosomes are selected for crossover and mutation. After the chromosomes are repaired, if needed, fitness evaluation is again performed. Before the termination criteria are reached, crossover and mutation are repeated to generate different solutions. When the termination criteria are fulfilled, the chromosomes are decoded into new fuzzy association rules and stored in the knowledge repository for future decision making.

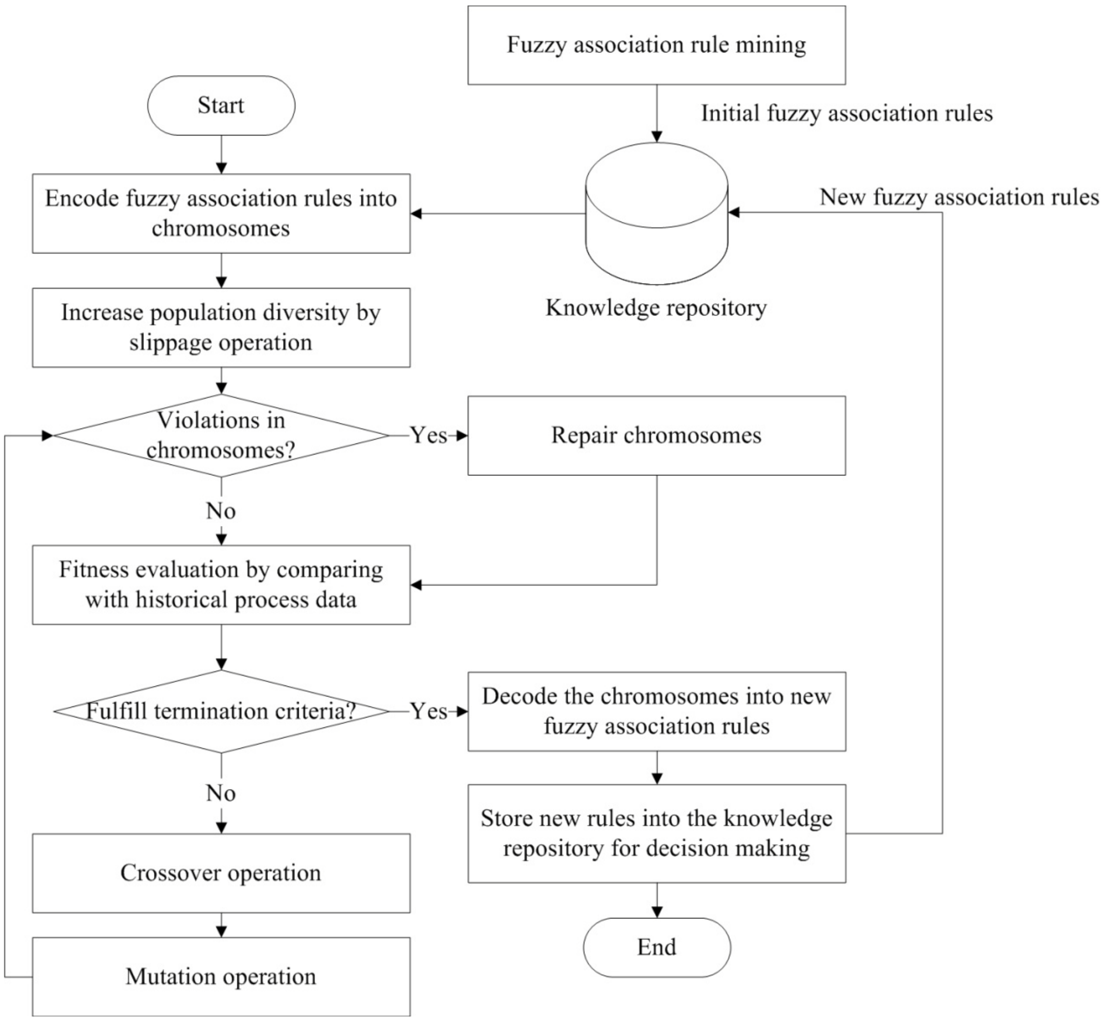

Fig. 3. 5 – Flow of the sGA-FARM

3.4.2.1 Chromosome Encoding

In the FRRMS, each chromosome is a solution for discovering the nearly optimal fuzzy rules so as to enhance the finished quality of the products. The basic idea of the chromosome encoding scheme comes from Ho et al. (2008). There are two regions in each chromosome: (i) the production workstation and process correlation region, and (ii) the parameter region.

(i) Production workstation and process correlation region

In the production workstation and process correlation region, the value of each gene is either 0 or 1. A gene with a value of 1 implies that the corresponding production workstation, process or parameter appears in the fuzzy association rule. For example, if process parameter 1 in process 1 in production workstation 1 appears in the rule, then the values of the three corresponding genes, W_1, δ_{11} and P_{111}, will be 1. On the other hand, if production workstation 2 does not appear in the rule, the value of gene W_2 will be 0 and that of other genes correlated with production workstation 2, such as δ_{2j} and P_{2jt} (for j=1,2,…., e_2 and t=1,2,…,k_{2j}), will also be 0.

(ii) Parameter region

In the parameter region, the values of the genes reflect the associated fuzzy classes of the corresponding parameters that appear in the fuzzy association rule. For ease of clarification, hereafter, the symbol Q is used to distinguish the quantitative value of a quality feature from that of the process parameter τ_{ijt}. The values of genes in the parameter region represent the belonging fuzzy classes converted from the quantitative values of process parameters or quality features according to the defined membership functions. Assuming that there are r fuzzy classes of parameter τ_{111}, the value of gene τ_{111} will range between 0 and r. If τ_{111} is associated with the r^{th} fuzzy class, the gene will contain r. Similarly, if Q_1 is associated with the g^{th} fuzzy classes, the gene will contain g. For parameters that are absent in the rules, the values of the corresponding genes are encoded as 0.

An example of a chromosome encoding a fuzzy association rule is shown in Fig. 3.6. As stated previously, the quality features are the desired output parameters in the rules. Hence, the condition part of a fuzzy association rule considers the process parameters while the consequent part considers the quality features.

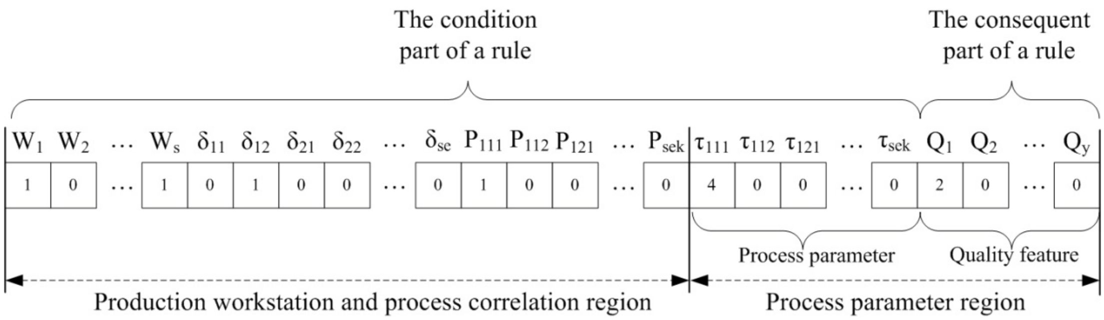

Fig. 3. 6 – Chromosome encoding a fuzzy association rule

3.4.2.2 Population Initialization

The rules obtained from the FARRM are used to form the initial population of the sGA-FARM. However, only those parameters with frequent associations can be mined and appear in the rules. As a result, parameters which rarely appear but are significant to the overall production can be neglected. In this sense, the knowledge obtained solely by FARMM is not sufficiently sophisticated to solve problems in actual production environments. In view of this, the slippage operation is introduced so that those initially neglected parameters have a chance to be inserted into the chromosomes, whilst some parameters existing in the initial rules can also have a chance to be removed from the chromosomes. To illustrate the slippage ideas, two types of genes, namely housekeeping genes and slippery genes, are introduced. Their correlation is shown in Fig. 3.7. In the sGA-FARM, the genes representing fuzzy association rules obtained, based on FARMM, are called housekeeping genes. According to the mined rules, different housekeeping genes are linked together to form chromosomes in the initial population of the sGA-FARM. Meanwhile, other parameters which are excluded from the fuzzy association rules are referred to as slippery genes. They are able to slip into the chromosome through the insertion operation. On the other hand, the housekeeping genes can also be removed through the deletion operation. Details of the slippage operation are discussed below.

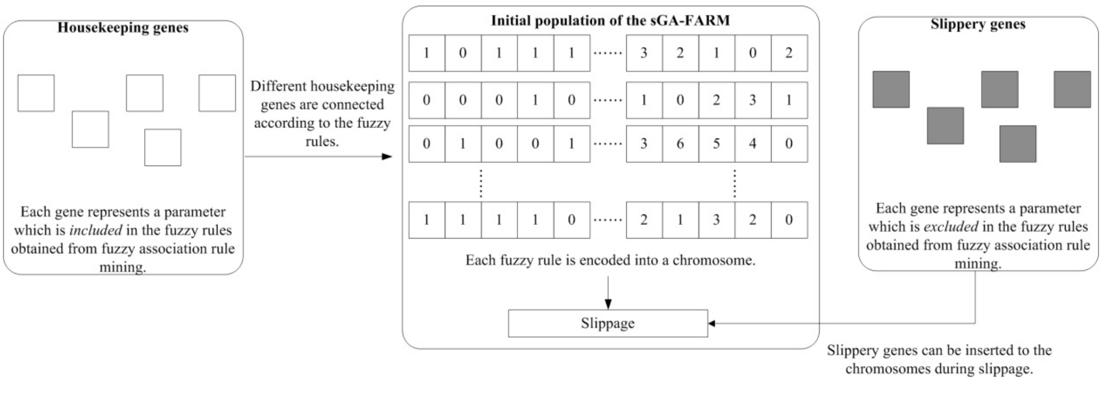

Fig. 3. 7 – Housekeeping genes and slippery genes

3.4.2.3 Slippage Operation

In the sGA-FARM, slippage operation is adopted to provide extra diversity among the chromosomes, other than crossover and mutation operations. By imitating the biological slippage behavior, the sGA-FARM allows insertion and deletion to vary the number of genes in a chromosome. The flow of the proposed slippage operation is shown in Fig. 3.8. Each chromosome has a chance to undergo a slippage operation if the random number being generated is smaller than or equal to the predefined slippage rate. When slippage is undertaken, a position for slippage is selected randomly. As slippage takes place in the chromosomes constituted from the housekeeping genes, the slippage position must be larger than 0 but not exceed the number of housekeeping genes. For instance, if the slippage position being generated is 3, then slippage will take place at the third housekeeping gene. In addition, the length of repeats is generated randomly and it represents the number of genes to be inserted into or removed from the original chromosome, starting from the selected position. Therefore, the length of repeats must be larger than 0 but not exceed the number of slippery genes. The maximum length of a chromosome is the total sum of the number of housekeeping genes and slippery genes. During slippage, whether insertion or deletion should be performed in the chromosome, is chosen randomly.

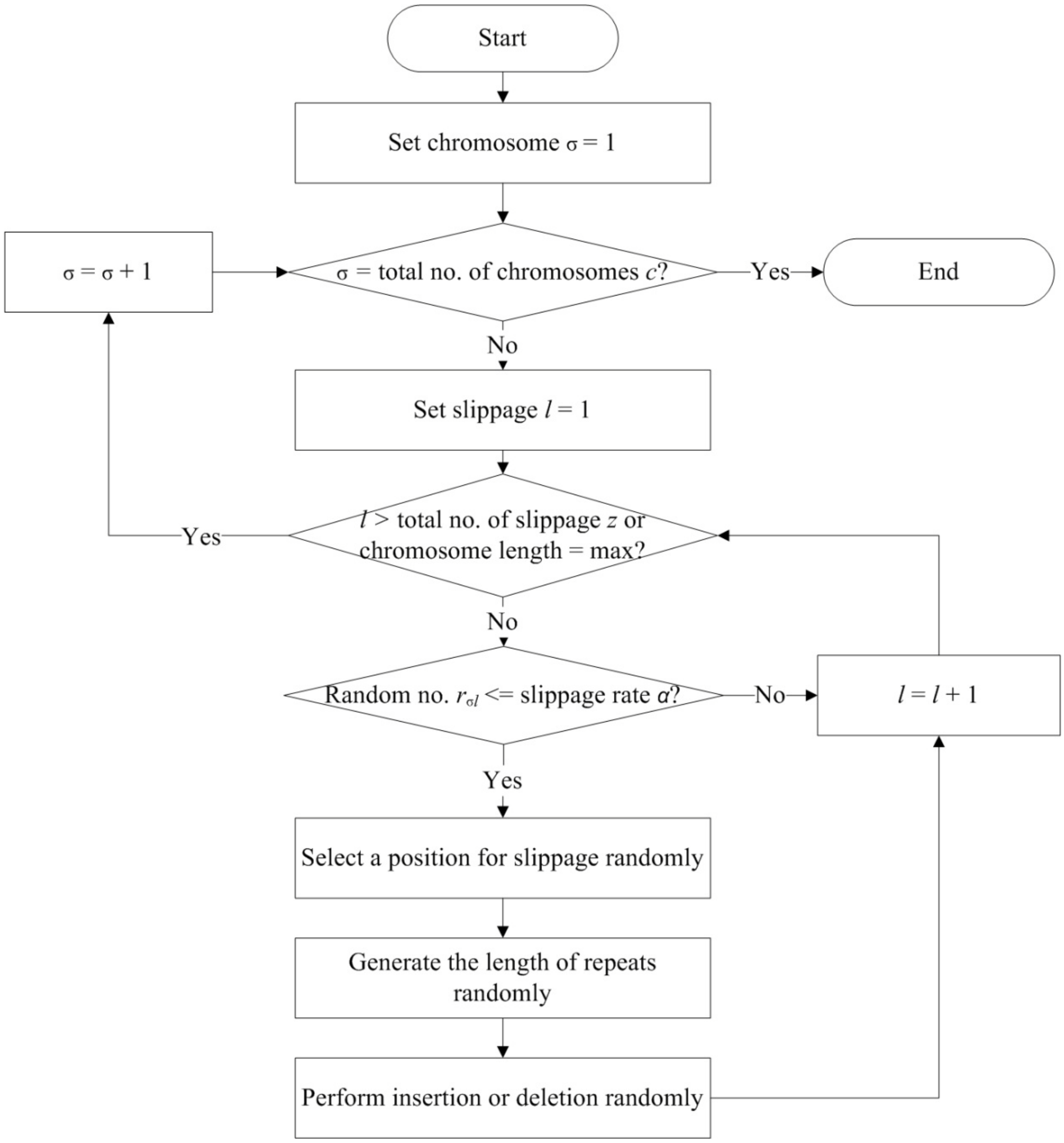

Fig. 3. 8 – Flow of slippage operation

(i) Insertion

When insertion is chosen, the length of the elongation of the chromosomes is dependent on the length of the slipped part generated. The values contained in the inserted genes are identical to those in the gene at the slippage position. If the length of the slipped part is n and the value of the gene at the slippage position is 1, the length of the chromosome will be increased by *n* units of genes and the extra genes will all carry the value of 1. An example of the insertion operation is shown in Fig. 3.9. The slippage position is 6 and the 6th gene contains the value of 1. If the length of repeats is 2, the length of the chromosome will then be increased by 2 units of genes and the extra genes will all carry the value of 1.

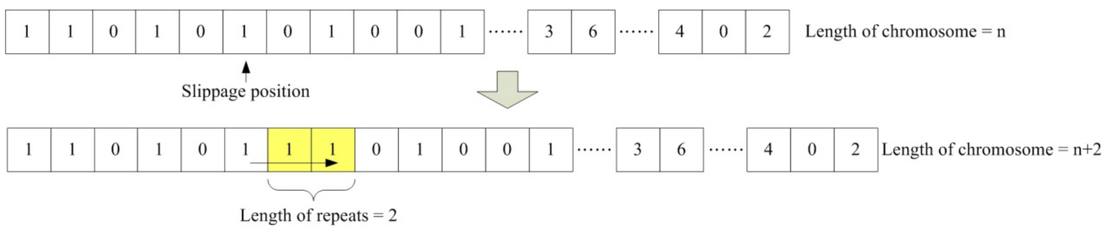

Fig. 3. 9 – Example of insertion

In addition, the change in the number of genes in a chromosome implies that the number of parameters considered in a fuzzy rule changes. Therefore, there is a need to update the parameters represented by each gene. In the sGA-FARM, the chromosome encoding fuzzy association rules are read from left to right. The first parameter considered in production is placed on the left while the last parameter is placed on the right. As the chromosomes are sequence-sensitive, the names of the genes have to be updated according to the parameter sequence. Considering that the selected gene slips to the right hand side of the chromosome, only those slippery genes which can be placed on the right hand side of the selected gene will be considered for insertion. An example is given in Fig. 3.10, assuming that W_4, δ_{12}, δ_{22}, δ_{32}, δ_{33}, $P_{132}…\tau_{134}…Q_4$ are the slippery genes and the slippage position generated is located at δ_{21} with the length of repeats of 2. Since δ_{22} and δ_{32} are the first two slippery genes which can be placed on the right hand side of δ_{21} in the chromosome, they will be selected and inserted at an appropriate location based on the parameter sequence. For instance, δ_{22} must be placed right after $\delta_{21,}$ resulting a sequence of "δ_{21}, δ_{22}". Similarly, δ_{32} must be placed right after $\delta_{31,}$ resulting a sequence of "δ_{31}, δ_{32}".

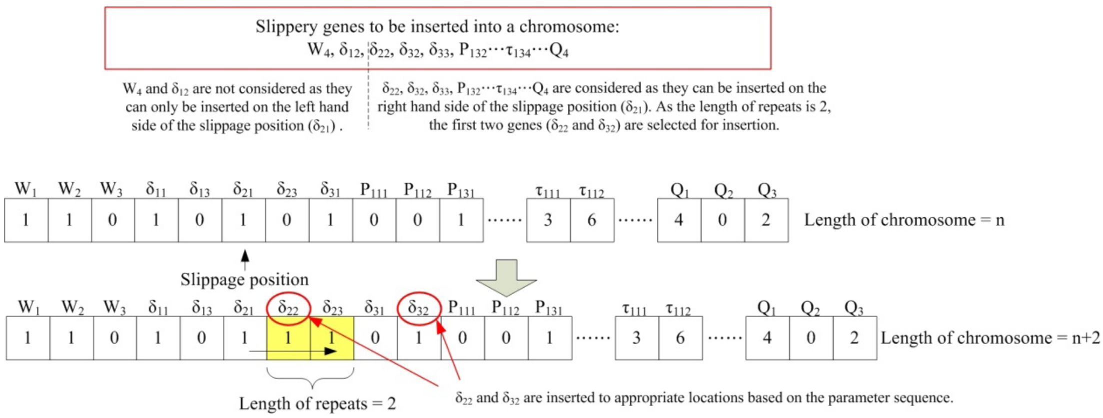

Fig. 3. 10 – A chromosome with updated gene names after insertion

(ii) Deletion

Deletion leads to a decrease in the length of the chromosomes. Compared with insertion, it is a less complicated process as it does not have to consider the types of genes and the gene names. According to the length of the slipped part generated, a certain number of consecutive genes will be removed from the chromosomes. If the length of the slipped part λ is generated, λ genes will be removed, starting from the slippage position. An example is shown in Fig. 3.11 with $\lambda = 3$. Three consecutive genes are removed from the chromosome and the sequence of the remaining genes is unchanged.

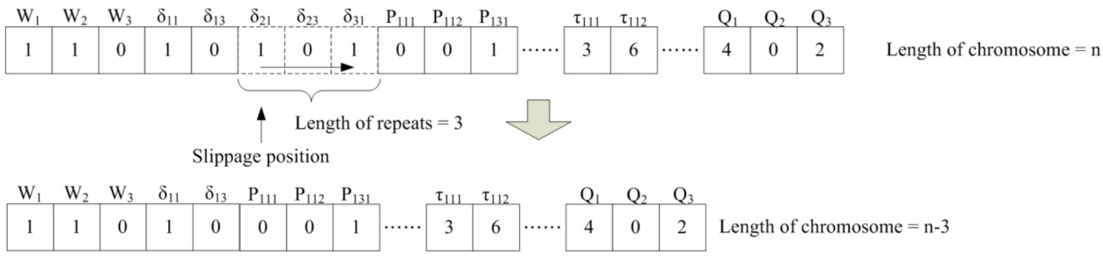

Fig. 3. 11 – Example of deletion

If the predefined number of the slippage is larger than 1, a chromosome can experience slippage more than once. Since there is no restriction on the choice of insertion and deletion, it is possible that each chromosome undergoes both insertion and deletion, generating a completely different set of fuzzy rules.

3.4.2.4 Chromosome Repairing

The aim of chromosome repairing is to fix any chromosomes which violate the chromosome encoding scheme. There are four types of violations.

The first type of violation refers to when there are inconsistencies between the two regions of a chromosome. If the genes in the production workstation and process correlation region contain 1, the related genes in the parameter region should contain a non-zero number to maintain consistency. Otherwise, forward repairing is performed by randomly assigning the related genes in the parameter region to a non-zero number. On the other hand, if the genes in the parameter region contain values larger than 1, the related genes in the production workstation and process correlation region should contain 1. Otherwise, backward repairing is carried out by changing the values of the corresponding genes in the production workstation and process correlation region into 1, to maintain consistency.

The second type of violation occurs when some expected genes are missing in the chromosomes. For example, it is expected that τ_{111} exists in the chromosomes when W_1, δ_{11} and P_{111} exist. Otherwise, there are no fuzzy classes representing P_{111}, violating the structure of a fuzzy rule. To deal with this type of violation, the values of the genes which are correlated with the missing genes will be changed to 0. With reference to the aforementioned example, genes W_1, δ_{11} and P_{111} have to carry a value of 0 when τ_{111} is absent in the chromosome.

The third type of violation occurs when the values of the genes in the production workstation and process correlation region are neither 0 nor 1. In such a case, a binary number is randomly assigned to the genes concerned during chromosome repairing.

The fourth type of violation exists when the values of the genes in the parameter region of a chromosome exceed the number of fuzzy classes of the corresponding parameters. To repair the chromosome, the values of the genes concerned are changed to their maximum values, i.e. the last fuzzy class of the corresponding parameters.

Chromosome repairing is completed when there are no more violations in each chromosome.

3.4.2.5 Fitness Function Evaluation

A fitness function is designed to evaluate the fitness of each chromosome in the population. In the FRRMS, a fit chromosome should be able to predict the finished quality with high accuracy. Therefore, the fitness function is used to minimize the differences between the predicted quality features and the actual quality features. The predicted quality features can be obtained by using fuzzy logic in which defuzzification is carried out to convert them into quantitative values based on the obtained rules. Consequently, the proposed fitness function is represented as:

$$\text{Minimize fitness} = \frac{1}{\mathrm{n}} \sum_{i \in N} \sum_{j \in Y} w_j \left(q_{ij} - q_{ij}{}'\right)^2$$

where n is the number of testing samples, N is the set of index of testing samples, Y is the set of the index of finished quality features, q_{ij} is the predicted quality features achieved by defuzzification, q_{ij}' is the actual quality features, and w_j is the weighting assigned to each quality feature.

3.4.2.6 Crossover and Mutation Operations

A crossover rate β, ranging between 0 to 1, is defined by users. To decide which pair(s) of chromosomes should be chosen for performing crossover, there are c random numbers ranging between 0 and 1 generated, each of which represents the crossover probability index of a chromosome. If the crossover probability index of a chromosome is smaller than β, crossover occurs in the chromosome. In the FRRMS, the uniform crossover method is adopted. A mask containing μ random binary numbers is generated where μ is the number of genes in the shortest chromosomes in the parent pool. Each binary number in the mask corresponds to one gene of the chromosomes, parent A and parent B. If the binary number corresponding to a gene is 1, the particular genes of parents A and B are exchanged. If not, the genes remain unchanged.

Similar to the crossover rate, a mutation rate γ, ranging between 0 to 1, is defined by users, and a random number within 0 and 1 is then generated for each gene. If the random number is smaller than γ, mutation occurs at the corresponding gene. In the production workstation and process correlation region, bit-flip mutation is used to convert the value of the gene from 0 to 1, or vice versa. On the other hand, in the mutation in the parameter region, a fixed value amount is added to or subtracted from the selected gene. The fixed value amount is generated randomly in each iteration of the sGA-FARM.

After crossover and mutation, chromosome repairing is performed again to ensure that every chromosome obeys the encoding scheme.

3.4.2.7 Chromosome Decoding

Chromosome decoding is carried out to convert the chromosomes into fuzzy association rules when the termination criteria of the sGA-FARM are satisfied. It can be viewed as a conversion process for chromosome encoding. Since the obtained rules represent knowledge in fuzzy linguistic terms after chromosome decoding, they are easily understandable by human beings. They are adopted as the decision rules for QA and are referred to in the DSM.

3.5 Decision Support Module (DSM)

The DSM is used to estimate the resultant product features when a set of process parameters are given. When process parameters are inputted into the module, relevant rules stored in the fuzzy rule-based repository are triggered. Based on the knowledge stated in the rules, the quality features are predicted which serves as valuable information for QA and thus the production operators are able to determine the appropriate process parameters to be used for assuring better product quality features.

The DSM is composed of an inference engine using fuzzy logic to determine quantitative values of the output parameters, which are defined as the quality features in the FRRMS. The mechanism of the inference engine is constructed on a basis of a collection of fuzzy association rules stored in the rule-based repository. These rules are expected to be of good quality as they are mined from the FARMM and optimized in the sGAOM.

Without the use of the FRRMS, production operators do not know whether their selection of the process settings are appropriate or threatening to the finished product quality. On the other hand, with the use of the FRRMS, production operators can input different process settings to the system for estimating the resultant product features. The DSM starts with a fuzzification process in which the inputted process parameters are converted into fuzzy sets based on the predefined membership functions. The input fuzzy sets are then entered in the inference engine to generate output fuzzy sets by matching relevant rules. Finally, a defuzzification process is needed to convert the output fuzzy sets into quantitative values of the quality features.

With the knowledge supported by the system, production operators can compare the resultant quality features with different inputs. As a result, they are provided with feedback on their parameter settings and the learnt process parameters can be adopted for production. The learnt process parameters form part of the new inputs of the initial step of the mining algorithm in the FRRMS. New knowledge in terms of fuzzy association rules can be recursively discovered in the FARMM and optimized in the sGAOM. As a consequence, process parameters used for garment production can be continually refined, assuring better product quality.

3.6 Summary

This chapter describes the system architecture of the FRRMS which is composed of three modules: FARMM, sGAOM and DSM. The ultimate goal of the FRRMS is to support QA in the garment industry based on the hidden patterns among process parameters and quality features in terms of fuzzy association rules. In addition, the mechanism of the novel sGA-FARM computational algorithm is presented to eliminate the limitations caused by fixed-length chromosomes in conventional GAs in rule optimization. To utilize the system in the garment industry, implementation procedures have to be followed, details of which are presented in Chapter 4.

Chapter 4 Implementation Procedures of the System

4.1 Introduction

This chapter details the implementation of the FRRMS in the garment industry. It provides a systematic approach on how to develop the intelligent system for achieving QA based on the infrastructure design of the FRRMS and the novel sGA-FARM algorithm. With reference to the architecture of the FRRMS described in Chapter 3, the three modules involved in the FRRMS, namely the FARMM, sGAOM and DSM, have to be formulated during the implementation. In general, there are four phases involved in the implementation procedures as shown in Fig. 4.1: (i) Understanding of a garment manufacturing company, (ii) Structural formulation of the FARRM, (iii) Structural formulation of the sGAOM and DSM, and (iv) System evaluation. Details of each phase are discussed in the following sections.

4.2 Phase 1 – Understanding of a Garment Manufacturing Company

In Phase 1, identifying the current situation and problems is critical to the success of the subsequent phases of the implementation. This helps understand the exact motivation and the desired outcome of the system implementation undertaken in the case company. There are three steps involved in this phase, which are (i)

Company process investigation, (ii) Identification of problems, and (iii) Preparation of a pilot run of the system.

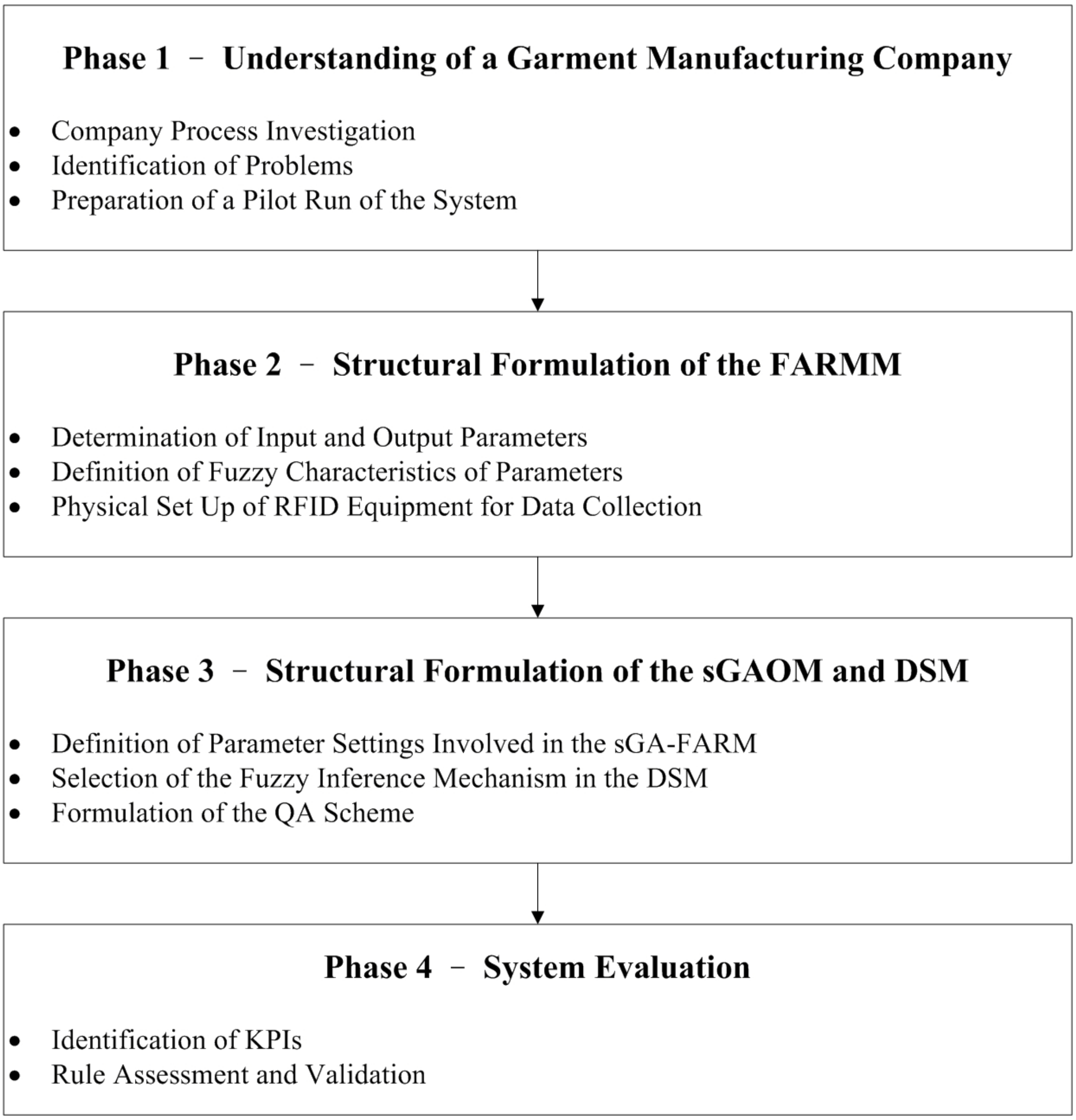

Fig. 4. 1 – Implementation procedures of the FRRMS

4.2.1 Company Process Investigation

The first step is to investigate processes within the company. In this step, different areas of activities are studied according to the company's focus and requirements. Although different companies in the garment industry can perform similar workflows in order to produce a final garment, there are still differences in their actual practice depending on the habits of individual staff as well as the company layout and the available resources. Therefore, apart from understanding the company processes by workflow studies, it is also critical to have interviews with the front-line workers, such as the production operators, in order to investigate the actual practice in the company. Considering that the garment industry is a labor-intensive industry, it is believed that workers' self-discipline and housekeeping affects the overall performance of the company processes.

4.2.2 Identification of Problems

Identification of problems within the company is necessary because it influences the selection of tools for building an intelligent system and defining the scope of the project. Based on the workflow studies and the information obtained in the interviews in the previous step, potential problems hindering the company from achieving effective QA are identified in this step. For instance, some types of quality problems could be due to the poor workmanship of the production operators, while some could be due to the adoption of inappropriate process parameters during production. It is worth noting that not every problem identified can be solved by the implementation of the FRRMS. Thus, it is important to reach a consensus on the desired outcome of the system implementation, for example, eliminating particular quality problems with the use of the FRRMS.

4.2.3 Preparation of a Pilot Run of the System

In this step, the project managers and production operators have to determine the requirements of a pilot run of the system. For instance, they have to decide on the number of production lines to be used for the pilot run based on the scope of the project. In addition, details of the existing information system work have to be studied. The system developers need to ensure that historical data can be extracted by data analysis. Furthermore, the company has to inform the staff members in the related departments about the arrangements during the pilot run of the system.

4.3 Phase 2 – Structural Formulation of the FARMM

Phase 2 involves the structural formulation of the FARMM of the FRRMS. In order to define appropriate parameters to be analyzed by the FRRMS, knowledge acquisition is needed by conducting interviews with domain experts. Since, in most garment manufacturing companies, production operators are responsible for determine process parameters to be used in the production lines, they are the domain experts who are expected to be capable of providing relevant knowledge. Their knowledge is refined and verified at the management level before being stored in the system. In this phase, there are three steps involved: (i) Determination of input and output parameters, (ii) Definition of fuzzy characteristics of parameters, and (iii) Data collection.

4.3.1 Determination of Input and Output Parameters

In this step, both input and output parameters of the FRRMS have to be defined by the production operators. The input parameters refer to the parameters appearing in the IF part of the rules generated by the system. In the FRRMS, they are the production process parameters which, according to conventional practice, are heavily determined by human experience. On the other hand, the output parameters are the parameters appearing in the THEN part of the rules. They are defined as the quality features of the garment products. In this sense, the rules generated can inform the users about the estimated product quality based on a given set of parameter settings used in the production. All the parameters defined in this step must be able to be described qualitatively by fuzzy terms such as “short” and “long” for the use of fuzzy set theories.

4.3.2 Definition of Fuzzy Characteristics of Parameters

Considering that the FARMM uses qualitative descriptions to provide quantitative values, it is essential to determine some conventional terms for describing the parameters. In this step, all parameters selected in the previous step are associated with fuzzy linguistic terms. There is no restriction on the number of linguistic terms for each parameter. However, the linguistic terms determined in this step must be easily interpreted by the production operators.

For each parameter, the production operators have to define a range of values in which there are no clear-cut boundaries to associate most values to one single linguistic term. Within this range, membership functions are positioned in such a way that the input values can be associated with more than one complementary membership function. In fact, membership functions play an essential role in achieving a successful design for every fuzzy-based system. Unlike classical set theory that classifies the elements of the set into crisp sets, a fuzzy set has an ability to classify elements into a continuous set using the concept of degree of membership (Tahera et al., 2008). The membership function not only gives 0 or 1 but can also give values between 0 and 1. Furthermore, the choice of membership function is based on subjective decision criteria and the initial values rely heavily on trial and error methods (Bosma et al., 2012). When the production operators are asked to describe the fuzzy character of each linguistics term by means of membership functions, only triangular and trapezoidal membership functions are provided for their selection. This is because people lacking AI knowledge, like most production operators, will find it easier to understand triangular and trapezoidal membership functions, compared to other smooth functions such as Gaussian functions. In addition, since the predicted quality features are obtained by rounding up the defuzzified outputs, very precise membership function positioning is not essential for the FRRMS. As a result, though the choice of membership function becomes limited, the accuracy of the FRRMS will not be significantly affected.

Furthermore, according to the fuzzy association rule mining algorithm, threshold support counts of the parameters have to be determined so that useful rules can be mined. If the thresholds are set too low, many trivial or inexplicable rules could be mined, providing no insight to practitioners. Conversely, if the thresholds are set too high, it could be difficult to obtain any rules. Hence, the final choice of the thresholds relies heavily on a trial and error approach until some useful fuzzy association rules can be generated. Considering that both membership functions and the threshold support count of each parameter are based on subjective decision criteria and rely heavily on a series of trial and error procedures, regular evaluation of the chosen values is suggested to guarantee the quality of the decisions obtained.

4.3.3 Physical Set Up of RFID Equipment for Data Collection

After identification of the parameters, data collection is required to consolidate all the essential data and input them into the system. In this step, RFID equipment is evaluated and selected according the actual operation needs and the reading performance of the equipment. The function of the RFID is to capture process parameters and quality features from the production line on a real-time basis.

After the data are captured, data errors are minimized by verifying the accuracy, correcting spelling errors, and filling in any missing or incomplete entries. The data are then loaded into a centralized database. Considering that data from different sources can be in different formats, these formats are converted to XML for standardization, which can prevent problems from occurring in data retrieval and data updating. In order to improve data integrity in the company, the centralized database is an aggregation of data marts. Individual data marts are created for storing data within each department or workstation. Each data mart has the same structure as the database, but its stored data are organized according to the corresponding department or workstation.

4.4 Phase 3 – Structural Formulation of the sGAOM and DSM

In Phase 3, the sGAOM and the DSM are constructed. Like the traditional GA approaches, the sGA-FARM embedded in the sGAOM involves parameters which have to be defined before the execution of the algorithm. For example, apart from the crossover and mutation rates, the slippage rate has to be defined in this phase. In addition, fuzzy logic has to be adopted in the DSM to generate the quantitative values of the predicted quality features after defuzzification, the results of which are useful for the formulation of effective QA strategies. Three steps are involved in this phase: (i) Definition of parameter settings involved in the sGA-FARM, (ii) Selection of the fuzzy inference mechanism in the DSM, and (iii) Formulation of the QA scheme.

4.4.1 Definition of Parameter Settings involved in the sGA-FARM

In order to construct the sGAOM, the first issue is to define the parameter settings, such as the slippage rate, the crossover rate, the mutation rate and the population size, involved in the sGA-FARM. The definition of parameter settings in the sGA-FARM is case sensitive and it is thus unwise to adopt values directly from other related work. To ensure their suitability, a trial-and-error approach is used to determine the appropriate crossover, mutation and slippage rates. In fact, the rates used in the algorithm can be allowed to vary. It is natural to try to modify the values of these parameters during the execution of the sGA-FARM. For instance, the crossover rate can be started at an initially high level and then progressively reduced with each generation or in response to particular performance measures. On the other hand, decreasing the mutation rates over the course of evolution is often helpful with respect to the convergence reliability and speed of GAs. In the case studies, different settings are adopted to illustrate the differences in fitness performance. Based on the feedback information obtained from different settings, fixed settings are used in applications within the case company.

4.4.2 Selection of the Fuzzy Inference Mechanism in the DSM

The DSM is composed of a reasoning engine that uses fuzzy logic for suggesting quantitative QA solutions based on the rules mined in the FRRMS. For the structural formulation of the DSM, various software programs, such as the Fuzzy Logic Toolbox in MATLAB, are available for the implementation of the fuzzy logic inference mechanism. In general, Mamdani fuzzy models are popular in low-level direct control (Karray & deSilva, 2004) and a min-operator is considered as a natural choice for inference when the rules are fuzzy “AND” rules (Bellman & Giertz, 1973;

Zimmermann, 1991). In addition, the degree to which the combined rules are fulfilled is mostly calculated by taking the union of the rule output using the maximum operator (Bosma et al., 2012). In view of this, Mamdani with min-max operators are selected for the DSM. Before input parameters are fed into the DSM, the predefined membership functions and fuzzy rules are referred to in the fuzzy inference process. For defuzzification, the center of area method, one of the most popular defuzzification methods, is chosen due to its simplicity and ease of use. The method can calculate the center of area (Y) of the consequent fuzzy region by:

$$Y = \frac{\sum_{j=1}^{N} w_j \overline{C_J A_J}}{\sum_{j=1}^{N} w_j \overline{A}_J}$$

where w, C and A denote the weight, center of gravity and area of the individual fuzzy region of rule j respectively. By calculating Y, the fuzzy output is converted into numerical values with reference to the output membership function. In the DSM, the output numerical values are the estimated quality features of the products based on the rules mined. Users are able to feed different input process parameters into the DSM in order to know the resultant quality features and to sort out the most appropriate process parameters for production.

4.4.3 Formulation of the Quality Assurance Scheme

The ultimate goal of using the FRRMS is to formulate effective QA schemes in a garment manufacturing company based on the knowledge mined from historical data. The knowledge is in the form of fuzzy association rules, which indicates the "IF-THEN" relationships between production process parameters and the resultant quality features of the products. For instance, based on a rule stating that " IF the ply height of the fabric is *high* AND the speed of the cutting machine is *high*, THEN the average number of major defects per garment is *large*.", production operators can learn that they should avoid such settings in order to lower the number of major defects.

In addition, to further assist the production operators in determining the exact process parameters, such as the ply height of the fabrics and the speed of the cutting machine, to be used in production, they are allowed to test different quantitative values of the parameters in the system. Subject to the values inputted to the system, they are given the estimated quality features such as the average number of major defects per garment. When the number of decision rules stored in the system increases, the estimated quality features are more accurate. As a consequence, production operators can make well informed decisions when they determine the process parameters with product quality taken into consideration. In this sense, a parameter-oriented QA scheme can be formulated.

4.5 Phase 4 – System Evaluation

Phase 4 is the system evaluation, which is the last phase of the implementation procedures of the FRRMS. In this phase, a set of key performance indicators (KPIs) has to be selected, measured and then compared to assess the effectiveness of the FRRMS. In particular, the knowledge stored in the FRRMS in terms of fuzzy rules are assessed and validated. In general, the two main steps involved in this phase are: (i) Identification of KPIs, and (ii) Rule assessment and validation.

4.5.1 Identification of Key Performance Indicators

To evaluate the FRRMS, KPIs have to be identified. It is suggested that the selection of KPIs is performed at the management level as this may be related to business objectives and future company policies. For instance, rework cost and production time are commonly used KPIs for the scope of such studies. Furthermore, the measurement method of each KPI has to be considered during the identification of KPIs. Depending on the nature of the KPIs, the measurement method could be system-based or manual-based. If it is the former, the Information Technology Department has to ensure that the KPIs collected from the system are accurate and up-to-date. If it is the latter, providing training for corresponding staff members is suggested so that they understand why and how to measure the desired KPIs accurately. The KPIs measured before system implementation and those after system implementation have to be compared. The comparison results serve as useful information for the company to assess the fuzzy association rules. For each KPI, management has to obtain a consensus on the desired improvement after system implementation and the KPIs before system implementation are referred to as a benchmark. Some remedial polices should also be planned so as to tackle any possible problems if KPIs show system implementation has not met expectation.

4.5.2 Rule Assessment and Validation

To confirm the truthfulness of the outputs generated by the FRRMS, rule assessment and validation are carried out. Pieces of important information for the management to assess the rules include the comparison results of KPIs. If the improvement cannot reach the desired level over a specific period of time, an examination of the rules is needed. Individual fine-tuning is done according to judgment by management personnel. If there are rules which are always seen to be redundant, they can be removed. A reduction in the number of rules can help increase system efficiency and ease rule complexity in the future. It is suggested that rule assessment and validation should be performed on a regular basis so that the fuzzy association rules can be challenged and improved. As a result, a company can obtain a set of decision rules which are of good quality.

4.6 Summary

In this chapter, the implementation procedures of the FRRMS are presented. By following the four phases involved in the implementation, the garment industry can adopt the proposed system in formulating QA strategies. In order to validate the functions of the FRRMS, case studies conducted in a garment manufacturing company are presented in Chapter 5.

Chapter 5 Case Studies

5.1 Introduction

In order to validate the feasibility of adopting the FRRMS in supporting QA strategies in the garment industry, case studies are conducted in a garment manufacturing company. In this chapter, two case studies are presented. In case study 1, two of the modules of the FRRMS, the FARMM and DSM, are implemented. The sGAOM is excluded in case study 1 in order to investigate whether the knowledge discovered by the system, without optimizing the fuzzy association rules in the sGAOM, is sufficiently useful for supporting QA activities. Based on the results obtained in case study 1, several problems are observed, highlighting the needs of rule optimization. Therefore, in case study 2, the sGAOM is included in the implementation so as to apply the sGA-FARM for optimizing the rules. Based on the optimized rules, more effective QA strategies are formulated and the results are measured in terms of KPIs.

The results obtained from the two case studies are compared in Chapter 6. It is believed that the differences found in the comparison of results are mainly due to the introduction of sGAOM in the system for optimization purposes. By so doing, the effectiveness of the novel sGA-FARM proposed can also be evaluated.

5.2 Case Study 1 – The Use of Fuzzy Association Rule Mining for Quality Assurance

In case study 1, the use of the fuzzy association rule mining for QA is illustrated. This is contributed by the deployment of the FARMM and the DSM of the system. In this section, the background of the case company is firstly presented, followed by the existing problems identified in the company. Following that, the deployment of both the FARRM and the DSM is described.

5.2.1 Background of the Company

With 8 subsidiaries and 7 joint ventures in China, Tungtex (Holdings) Company Limited (THC) is one of the largest garment manufacturing companies in Hong Kong. Founded in 1977, it is headquartered in Hong Kong and has been listed in the Hong Kong Stock Exchange since 1988. Its manufacturing facilities are spread all over Asia, in such countries as Hong Kong, China, Malaysia, Thailand, the Philippines, and Vietnam. It produces over 15 million garments, mostly ladies' apparel, annually. It also has expertise in making silk garments as well as producing different types of fabric such as linen, cotton, wool and synthetic fibres. However, the profitability of THC has been affected due to the transformation of the garment industry. In the past, retailers were the main customers of garment manufacturers, however, they are now increasingly becoming the competitors of garment manufacturers. Companies in the garment industry are thus facing more intense competition. Meanwhile, due to the trend of fast fashion, companies not only have to guarantee the quality of finished garments, but also deliver the garments as quickly as possible. These industrial changes have made the business environment in which THC operates a tougher one. In addition, owing to China's entry to the WTO, RMB appreciation and the increasing awareness of labor rights in China, there is a further opening up of the China markets. Manufacturing plants in China are thus aiming for increasing their operation efficiency so as to remain competitive in the industry. Facing the challenges in the market, THC decided to have a pilot run of the system in one of its manufacturing plants located in Shenzhen, China, in an attempt to improve of their product quality and production efficiency.

The existing production workflow in the THC is shown in Fig. 5.1. After merchandisers receive a production order, they will pass the order to the production department which consists of five workstations: (i) spreading, (ii) cutting, (iii) sewing, (iv) finishing, and (v) inspection. Some of these operations are shown in Fig. 5.2, 5.3 and 5.4. At the same time, merchandisers and the Material Department will order the fabrics and trimmings for production. The fabrics and trimmings will be sent to the Production Department when they are received from the suppliers. In order to monitor the progress of the production process, there is a barcode label on the production order which is scanned when the order is passed to a workstation. This is to indicate that the production order has been passed to a particular workstation for production. When merchandisers find that the production progress is unsatisfactory, they will request the production shop floor to increase the production efficiency. Production operators will determine if the process parameters can be improved or if extra sewing lines are required in order to meet the production target.

5.2.2 Existing Problems Faced by the Company

With the existing production workflow, the company is facing the following problems:

(i) The visibility of production operations is low

The company relies on the traditional manual and partial bar coding system when managing production operations. Operators scan the barcode on the production order when it arrives at a new workstation. However, the barcode is not associated with a particular product, so the visibility of the production operations is low.

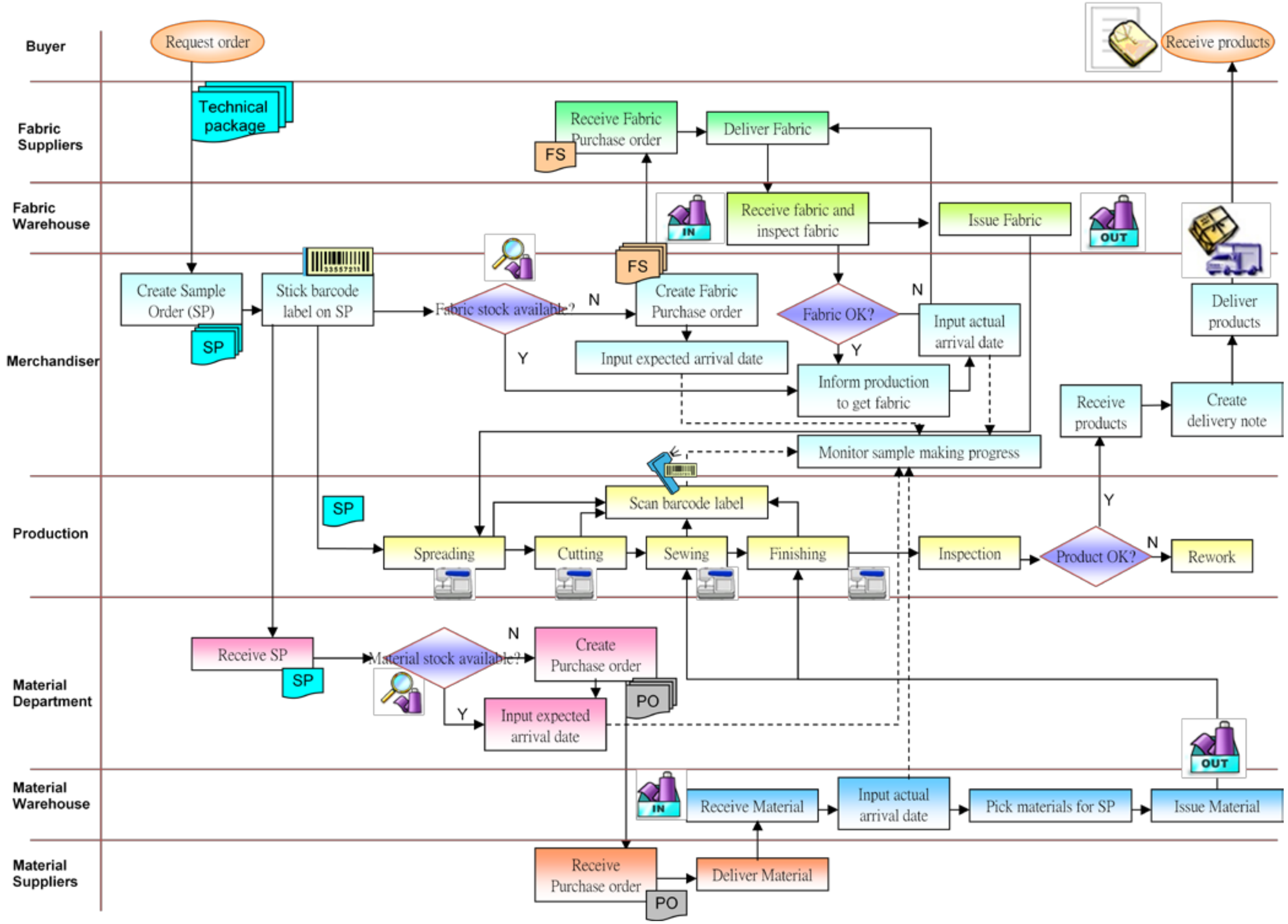

Fig. 5. 1 – Existing workflow in the case company

Fig. 5. 2 – Fabric spreading operation

Fig. 5. 3 – Fabric cutting operation

Fig. 5. 4 – Sewing operation

(ii) QA relies on human inspection

The quality of semi-finished and finished products is determined after inspection by human beings. When there are unacceptable defects, inspectors will send the products to the corresponding workstations to be reworked. There are no standardized procedures for conducting causal analysis for QA.

(iii) Lack of knowledge support for determination of process parameters

To estimate the process parameters to be used during production, production operators in the THC evaluate the requirements of the garments from the garment samples and the production documents, such as the size specification forms and the technical packages provided by the customers. Decisions are heavily reliant on the experience of particular individuals and are made without referring to actual production situations. Without a systematic approach for capturing the tacit knowledge in process parameter determination, less experienced staff may not be able to make appropriate decisions and the company eventually loses the relevant knowledge.

5.2.3 Deployment of the FARMM

In order to implement the FRRMS in the THC, the domain experts are invited to identify both the input and output parameters of the system. The production operators are regarded as the domain experts in this research because they are the ones who are the most familiar with the practical operations involved in garment production and are the ones who determine the process parameters to be used during production. Prior to the deployment of the FARMM, the fuzzy characteristics of the parameters have to be determined. In the THC, RFID technologies are employed to facilitate the data collection process on a real-time basis. Data captured are then used to generate decision rules by fuzzy association rule mining

5.2.3.1 Determination of the Fuzzy Characteristics of Parameters

Each identified parameter has to be associated with a set of linguistic terms, and the fuzzy characteristics of each linguistic term are represented by membership functions. In order to determine the positioning of the membership functions, the production operators firstly define the discourse of the parameters with reference to historical data. They have to define a range of values in which there are no clear-cut boundaries in order to associate most values to one single linguistic term. Within this range, membership functions are positioned in such a way that the input values can be associated with more than one complementary membership function. Operators are invited to associate each linguistic term with a membership function such as trapezoidal, triangular, and Gaussian. According to their opinions, triangular membership functions are the most useful for the case in hand, followed by trapezoidal functions. For each triangular and trapezoidal membership function, three points and four points have to be defined for positioning respectively, by trial and error. Some examples of the membership functions of the parameters are shown in Fig. 5.5.

For instance, the linguistic terms describing the parameter “Number of trims for attachment per garment” are “Very small”, “Small”, “Normal”, “Large”, and “Very large”. According to the historical records stored in the centralized database, the maximum number of trims for attachment per garment handled by the company is 18 pieces. Therefore, the x-axis of the membership functions of this parameter is set in a range between 0 and 18 pieces. After that, based on their experience, production operators get a consensus that the number of trims for attachment between 3 and 15 pieces per garment cannot be easily described by using one linguistic term, Therefore, if the input values are within this range, it is possible for them to be associated with more than one membership function.

As an initial starting point, triangular membership functions are used for simplicity. The membership functions for “Small”, “Normal” and “Large” are positioned in such a way that the range of the graph from 3 to 15 pieces can be evenly covered. As a result, the middle point of the x-axis, i.e. 9 pieces, is associated with “Normal”, with a membership of 1. Following that, 6 and 12 are associated with

“Small” and “Large” both with memberships of 1. To improve the accuracy of the results, it is suggested that the three points of the triangular membership functions be determined by trial and error. However, as previously mentioned, precise membership function positioning is not essential in the FRRMS. Therefore, the company agrees with the positioning if it is found that the aggregated surface area of the membership functions covers the x-axis of the graph. On the other hand, it is agreed that the number of trims for attachment per garment is regarded as “Very small” if it is not greater than 3 pieces. According to the opinions of the operators, the handling process for attaching a very small number of trims onto a garment is the same regardless of the actual number of trims. Therefore, it is expected that the membership values of “Very small” should always equal to 1 when the number is less than or equal to 3. As a consequence, a trapezoidal membership function for “Very small” is positioned as shown in Fig. 5.5. Similarly, the parameter is described as “Very large” if it is greater than 15 pieces and the handling process for attaching a very large number of trims onto a garment is also found, irrespective of the actual number. Thus, a trapezoidal membership function for “Very large” is positioned in such a way that the membership values of “Very large” should always be 1 when the number of trims is larger than or equal to 15 pieces. Operators repeat the above procedures for the remaining parameters. After all fuzzy characteristics of parameters are defined, data collection from the production shop floor can be started.

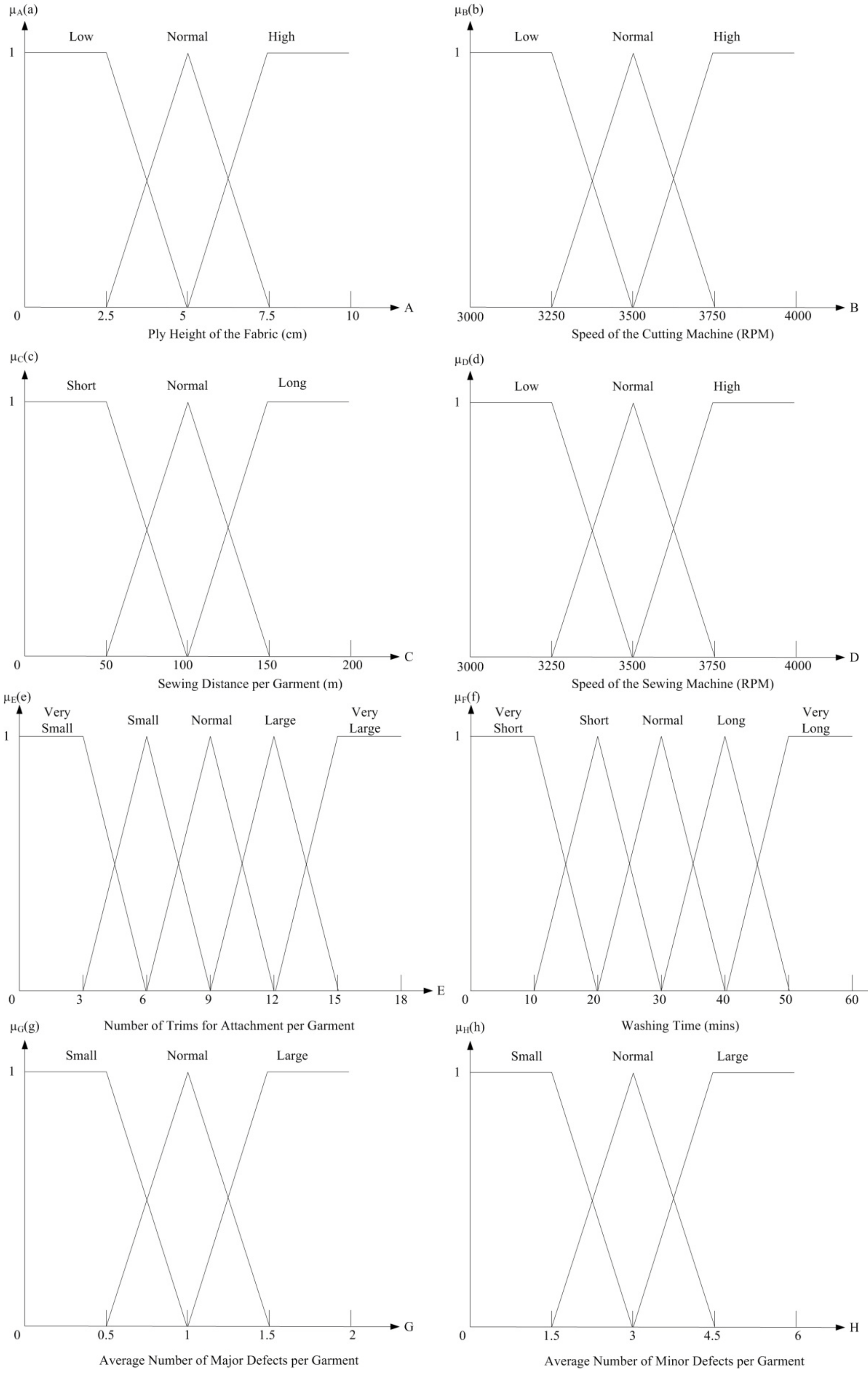

Fig. 5. 5 – Examples of membership functions of parameters

5.2.3.2 Real-time Capture of Parameters with the Use of RFID Technologies

To improve the efficiency of the data collection process, THC has decided to employ RFID technologies to collect the essential parameters from the production shop floor on a real-time basis. The flow chart of the data capturing operations with the use of RFID technologies is shown in Fig. 5.6. There are two types of RFID cards storing RFID data, namely material cards and staff cards. Fixed process parameters such as sewing distance per garment and the number of trims for attachment per garment are collected from existing internal databases in the case company. They are initially written onto the material cards which are associated with the raw materials for the fulfillment of the production orders. Variable process parameters such as the ply height of the fabrics and speed of the cutting machines are determined by individual operators during production. They are inputted by the operators during production, via the RFID devices.

When an operation starts, operators are required to place both their staff card and the material card in the reading slots of the readers. They enter the variable process data they used in production by using the keypads connected to the RFID readers. The data are then transmitted to the database for recording the process parameters used. The variable process data can only be inputted to the system when the RFID readers receive both signals from the material card and staff card. This accurately associates the variable data with the corresponding production operations and the identity of the operators.

When an operation is finished, operators take out the material card and pass the materials together with the material card to the inspector for quality inspection. Inspectors put the staff card and material card into the readers which have keypads for inspectors to input and transmit the quality data to the database. The quality data are used to describe the finished product quality features, for example, in terms of critical defects, major defects and minor defects. A critical defect is a defect which has a high possibility of creating a hazardous or unsafe impact on users or which is contravening legal regulations. A major defect is a defect which is severe enough to detract from the saleability of the garment. It can be caused by poor workmanship such as open seams, raw edges and skipped stitching. A minor defect is a defect which is not in a highly visible location and does not detract from the comfort of the garment. Examples of minor defects include small holes or tears which are partially or completely hidden by trims or only slightly visible when the garment is worn. In general, however, three minor defects are equivalent to one major defect. If no rework is required, inspectors pass the materials to the next workstation.

Since having wiring on the manufacturing shop floor is dangerous due to the large number of machines and equipment in the garment factory, the RFID devices are wirelessly networked so that RFID data are sent to the RFID middleware for transfer to the system where DM takes place. As the data are captured by the RFID devices on a real-time basis, the production status is tracked. With reference to the RFID information, production operators and quality engineers can determine whether the current process parameter setting can improve the finished product quality without lowering the production efficiency. Their feedback is sent to the relevant operators so that the operators can recursively improve their process setting and record them into the database.

5.2.3.3 Generation of Fuzzy Association Rules with Case Data

A case scenario is given in this section to illustrate the feasibility of using the FARMM to generate fuzzy association rules with the case data. Process parameters and finished quality selected for illustration are listed in Table 5.1. Six production orders, as shown in Table 5.2, are extracted from the FRRMS for demonstrating the mechanism of the FARMM.

Initially, the threshold support count of each parameter is defined, as shown in Table 5.3. There are 12 steps involved in the FARMM.

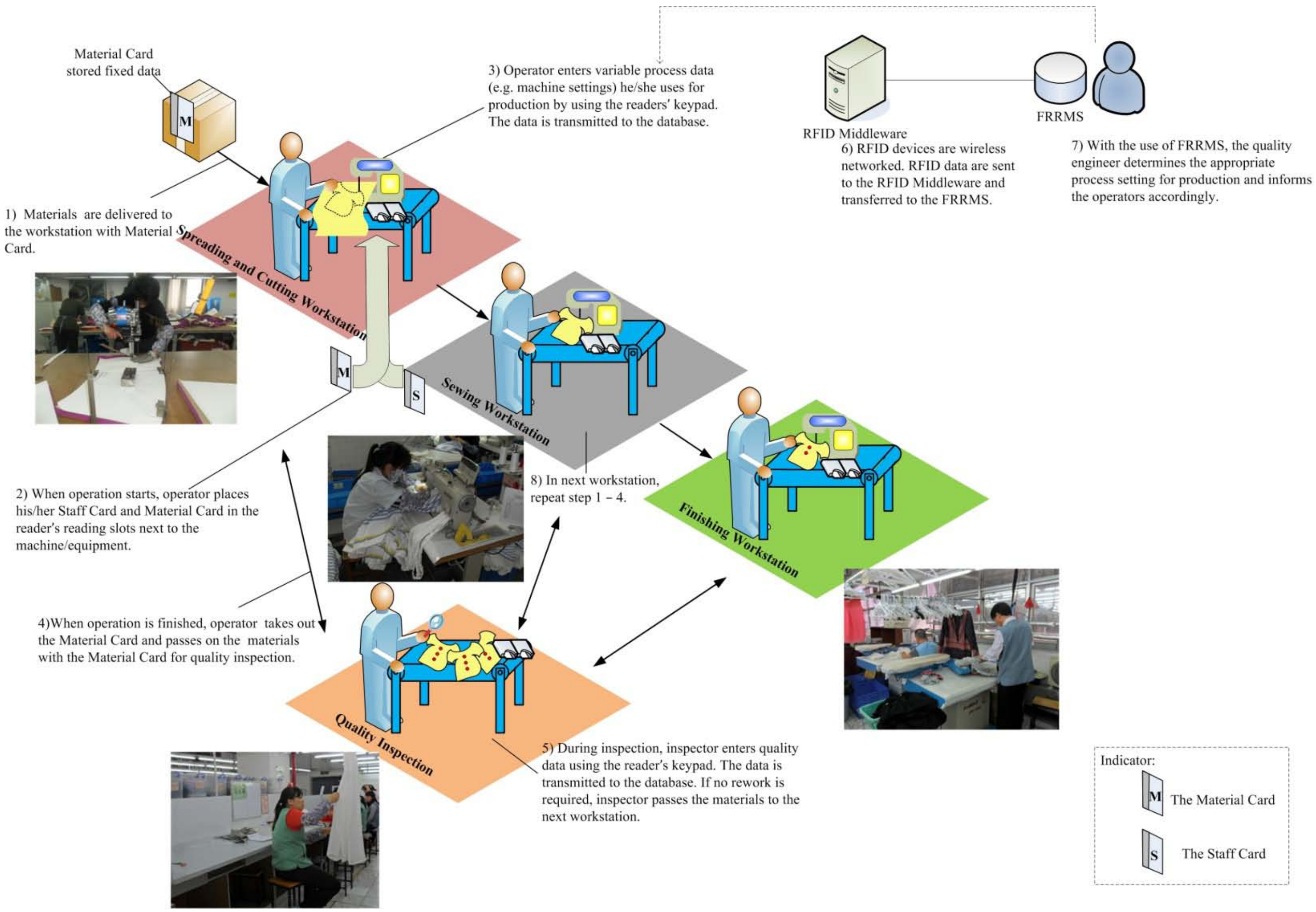

Fig. 5. 6 – Flow chart of data capturing operations with the use of RFID technologies

Table 5. 1 – Parameters used for illustration

	Parameter	Symbol
Process parameters (Input)	Ply height of the fabric	A
	Speed of the cutting machine	B
	Sewing distance per garment	C
	Speed of the sewing machine	D
	Number of trims for attachment per garment	E
	Washing time	F
Finished product quality (Output)	Average number of major defects per garment	G
	Average number of minor defects per garment	H

Table 5. 2 – Six samples of production orders

	Spreading and Cutting Station(S_1)		Sewing Station(S_2)		Finishing Station(S_3)		Finished Quality(Q)	
Order ID	A	B	C	D	E	F	G	H
1	3.8	3100	134	3300	10	25	0.8	4
2	7.3	3400	86	3500	7	10	0.3	2.3
3	9	3600	121	3100	6	35	0.5	1.9
4	3.2	3800	130	3800	8	36	1.3	3.7
5	3.6	3725	97	3300	8	27	2.8	0.5
6	4.1	3200	180	3650	5	48	1	2.4

Table 5. 3 – Threshold support count of each parameter

Parameter	A	B	C	D	E	F	G	H
Minimum support count	0.2	0.9	1.3	1.1	1.4	0.6	0.8	1.1

Step 1: Convert all the quantitative values of both the input and output parameters into fuzzy sets based on the predefined membership functions. For instance, the first parameter in the first order, 3.8, lies in both "Low" and "Normal" fuzzy classes according to its fuzzy membership function, as shown in Fig. 5.7. It is converted into a fuzzy set which is represented as (0.48/Low +0.52/Normal). Such fuzzy set conversion is applied to all parameters involved in the orders and the result is shown in Table 5.4. The converted structure of parameters with fuzzy classes is represented as "station.parameter.fuzzy_class".

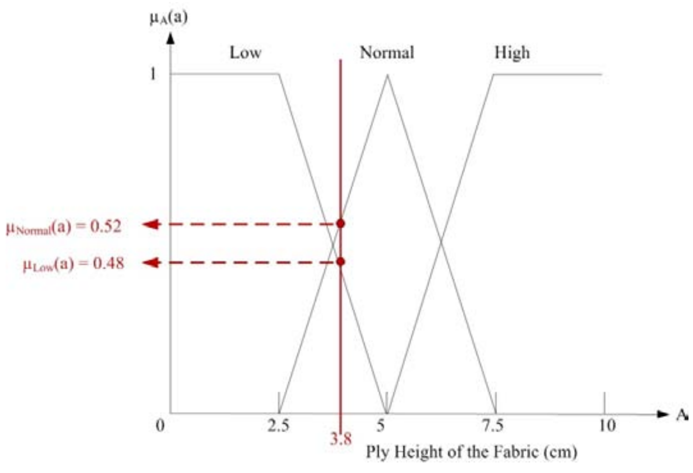

Fig. 5.7 Fuzzy set conversion of parameter "A"

Table 5. 4 – Converted fuzzy sets

Order ID	Quantitative values of parameters using fuzzy sets
1	$(\frac{0.48}{\mathrm{S_1.A.Low}}+\frac{0.52}{\mathrm{S_1.A.Normal}})(\frac{1}{\mathrm{S_1.B.Low}})(\frac{0.32}{\mathrm{S_2.C.Normal}}+\frac{0.68}{\mathrm{S_2.C.Long}})(\frac{0.8}{\mathrm{S_2.D.Low}}+\frac{0.2}{\mathrm{S_2.D.Normal}})(\frac{0.67}{\mathrm{S_3.E.Normal}}+\frac{0.33}{\mathrm{S_3.E.Large}})(\frac{0.5}{\mathrm{S_3.F.Short}}+\frac{0.5}{\mathrm{S_2.F.Normal}})(\frac{0.4}{\mathrm{Q.G.Small}}+\frac{0.6}{\mathrm{Q.G.Normal}})$ $(\frac{0.33}{\mathrm{Q.H.Normal}}+\frac{0.67}{\mathrm{Q.H.Large}})$
2	$(\frac{0.08}{\mathrm{S_1.A.Normal}}+\frac{092}{\mathrm{S_1.A.High}})(\frac{0.4}{\mathrm{S_1.B.Low}}+\frac{0.6}{\mathrm{S_1.B.Normal}})$ $(\frac{0.28}{\mathrm{S_2.C.Short}}+\frac{0.72}{\mathrm{S_2.C.Normal}})(\frac{1}{\mathrm{S_2.D.Normal}})(\frac{0.67}{\mathrm{S_3.E.Small}}+\frac{0.33}{\mathrm{S_3.E.Normal}})(\frac{1}{\mathrm{S_3.F.VeryShort}})(\frac{1}{\mathrm{Q.G.Small}})(\frac{0.47}{\mathrm{Q.H.Small}}+\frac{0.53}{\mathrm{Q.H.Normal}})$
3	$(\frac{1}{\mathrm{S_1.A.High}})(\frac{0.6}{\mathrm{S_1.B.Normal}}+\frac{0.4}{\mathrm{S_1.B.High}})$ $(\frac{0.58}{\mathrm{S_2.C.Normal}}+\frac{0.42}{\mathrm{S_2.C.Long}})(\frac{1}{\mathrm{S_2.D.Low}})(\frac{1}{\mathrm{S_3.E.Small}})(\frac{0.5}{\mathrm{S_3.F.Normal}}+\frac{0.5}{\mathrm{S_2.F.Long}})(\frac{1}{\mathrm{Q.G.Small}})(\frac{0.73}{\mathrm{Q.H.Small}}+\frac{0.27}{\mathrm{Q.H.Normal}})$
4	$(\frac{0.72}{\mathrm{S_1.A.Low}}+\frac{0.28}{\mathrm{S_1.A.Normal}})(\frac{1}{\mathrm{S_1.B.High}})(\frac{0.4}{\mathrm{S_2.C.Normal}}+\frac{0.6}{\mathrm{S_2.C.Long}})(\frac{1}{\mathrm{S_2.D.High}})(\frac{0.33}{\mathrm{S_3.E.Small}}+\frac{0.67}{\mathrm{S_3.E.Normal}})(\frac{0.4}{\mathrm{S_3.F.Normal}}+\frac{0.6}{\mathrm{S_2.F.Long}})(\frac{0.4}{\mathrm{Q.G.Normal}}+\frac{0.6}{\mathrm{Q.G.Large}})($ $\frac{0.53}{\mathrm{Q.H.Normal}}+\frac{0.47}{\mathrm{Q.H.Large}})$
5	$(\frac{0.56}{\mathrm{S_1.A.Low}}+\frac{0.44}{\mathrm{S_1.A.Normal}})(\frac{0.1}{\mathrm{S_1.B.Normal}}+\frac{0.9}{\mathrm{S_1.B.High}})$ $(\frac{0.06}{\mathrm{S_2.C.Short}}+\frac{0.94}{\mathrm{S_2.C.Normal}})(\frac{0.8}{\mathrm{S_2.D.Low}}+\frac{0.2}{\mathrm{S_2.D.Normal}})(\frac{0.33}{\mathrm{S_3.E.Small}}+\frac{0.67}{\mathrm{S_3.E.Normal}})(\frac{0.3}{\mathrm{S_3.F.Short}}+\frac{0.7}{\mathrm{S_2.F.Normal}})(\frac{1}{\mathrm{Q.G.Large}})(\frac{1}{\mathrm{Q.H.Small}})$
6	$(\frac{0.36}{\mathrm{S_1.A.Low}}+\frac{0.64}{\mathrm{S_1.A.Normal}})(\frac{1}{\mathrm{S_1.B.Low}})$ $(\frac{1}{\mathrm{S_2.C.Long}})(\frac{0.4}{\mathrm{S_2.D.Normal}}+\frac{0.6}{\mathrm{S_2.D.High}})(\frac{0.33}{\mathrm{S_3.E.VerySmall}}+\frac{0.67}{\mathrm{S_3.E.Small}})(\frac{0.2}{\mathrm{S_3.F.Long}}+\frac{0.8}{\mathrm{S_2.F.VeryLong}})(\frac{1}{\mathrm{Q.G.Normal}})(\frac{0.4}{\mathrm{Q.H.Small}}+\frac{0.6}{\mathrm{Q.H.Normal}})$

Step 2: Add up the number of occurrences (counts) of each fuzzy class of the parameters. For example, the number of counts of the “Low” fuzzy class of parameter A is calculated from the six orders by adding the fuzzy counts of S1.A.Low for each order, and is calculated as (0.48+0+0+0.72+0.56+0.36) = 2.12. The counts of the fuzzy classes of the remaining parameters follow the same steps. The results are shown in Table 5.5.

Step 3: Sort out the maximum number of counts of each parameter and the corresponding fuzzy class. The counts of the three classes of parameter A, “Low”, “Normal” and “High” are 2.12, 1.96 and 1.92 respectively. Therefore, the class “Low” is selected for parameter A. The maximum counts and the corresponding classes of all the parameters are calculated and shown in Table 5.6.

Step 4: Temporarily put the parameters in 1-itemset as items. Compare the maximum number of counts of the parameters in the 1-itemset with the threshold support counts of the corresponding parameter. If the maximum count is smaller than the threshold support count, the parameter is removed from the 1-itemset. In this case example, all the maximum counts are larger than the threshold support counts. Therefore, no parameters are removed from the 1-itemset.

Table 5. 5 – The fuzzy counts of the 1-itemset

Parameter item	Counts	Parameter item	Counts
S_1.A.Low	2.12	S_3.E.Normal	2.34
S_1.A.Normal	1.96	S_3.E.Large	0.33
S_1.A.High	1.92	S_3.E.VeryLarge	0
S_1.B.Low	2.4	S_3.F.VeryShort	1
S_1.B.Normal	1.3	S_3.F.Short	0.8
S_1.B.High	2.3	S_3.F.Normal	2.1
S_2.C.Short	0.34	S_3.F.Long	1.3
S_2.C.Normal	2.96	S_3.F.VeryLong	0.8
S_2.C.Long	2.7	Q.G.Small	2.4
S_2.D.Low	2.6	Q.G.Normal	2
S_2.D.Normal	1.8	Q.G.Large	1.6
S_2.D.High	1.6	Q.H.Small	2.6
S_3.E.VerySmall	0.33	Q.H.Normal	2.26
S_3.E.Small	3	Q.H.Large	1.14

Table 5. 6 – The maximum counts and corresponding fuzzy classes of the 1- itemset

Parameter item	Counts	Parameter item	Counts
S_1.A.Low	2.12	S_3.E.Small	3
S_1.B.Low	2.4	S_3.F.Normal	2.1
S_2.C.Normal	2.96	Q.G.Small	2.4
S_2.D.Low	2.6	Q.H.Small	2.6

Step 5: Generate every combination of items to form a 2-itemset. The combination is put in the 2-itemset only when the minimum number of counts of the two parameters is larger than or equal to the maximum of their predefined threshold support counts. Take {S_1.A.Low, S_1.B.Low} as an example. The counts of S_1.A.Low and S_1.B.Low are 2.12 and 2.4 respectively, and thus the minimum value is 2.12. The threshold support counts of S_1.A.Low and S_1.B.Low are 0.2 and 0.9 respectively, and thus the maximum value is 0.9. Since the minimum number of counts of these two parameters (2.12) is larger than the maximum of their predefined threshold support counts (0.9), {S_1.A.Low, S_1.B.Low} is put in the 2-itemset. The same calculation is applied to the other combinations. Parameters in the 2-itemset with the

maximum values of the corresponding threshold support counts are listed in Table 5.7.

Step 6: Since the 2-itemset does not have a null value, the algorithm can be continued.

Step 7-8: Calculate the fuzzy counts of the itemsets in the 2-itemset by summing up the minimum number of counts for each item in the orders. Take {S_1.A.Low, S_1.B.Low} as an example again. In Order 1, the counts of S_1.A.Low and S_1.B.Low are 0.48 and 1 respectively, so the minimum value is 0.48. On the other hand, since {S_1.A.Low, S_1.B.Low} does not occur in Order 2, the count is equal to 0. The calculation of Order 3 to Order 6 is the same. By summing up the minimum values of the six orders, the fuzzy count of {S_1.A.Low, S_1.B.Low} is calculated as 0.48+0+0+0+0+0.36 = 0.84. The other 2-itemsets follow the same way of calculating the counts and the result is listed in Table 5.8.

Step 9: Similar to Step 4, compare the count of the parameters in the 2-itemset with the minimum value of the threshold support counts of the corresponding parameters. If the count (listed in Table 5.8) is smaller than the threshold support count (listed in Table 5.7), the parameter is removed from the 2-itemset. Since the count of {S_1.A.Low, S_1.B.Low} is 0.84 which is smaller than the minimum value of threshold support counts (0.9), {S_1.A.Low, S_1.B.Low} is removed from the 2-itemset. On the other hand, the count of {S_1.A.Low, S_3.F.Normal} is 1.44 and the minimum value of threshold support counts is 0.6, {S_1.A.Low, S_3.F.Normal} is thus kept in the 2-itemset. The reviewed 2-itemset is shown in Table 5.9.

Step 10: Since the reviewed I_x does not have a null value, steps 5-10 are repeated to generate a higher level of itemset until there are no available combinations to be formed. The 3-itemset obtained is shown in Table 5.10. In this case example, only one itemset {S_2.C.Normal, S_2.D.Low, S_3.F.Normal, Q.H.Small} can be put in the 4-itemset. However, its count (1.2) is smaller than the threshold support count (1.3), so it is removed from the 4-itemset. As a result, there are no 4-itemsets and the calculation stops.

Table 5. 7 – Parameters in the 2-itemset

Parameter itemset	Max. of d_{ijt}	Parameter itemset	Max. of d_{ijt}
{S_1.A.Low, S_1.B.Low}	0.9	{S_2.C.Normal, S_3.E.Small}	1.4
{S_1.A.Low, S_2.C.Normal}	1.3	{S_2.C.Normal, S_3.F.Normal}	1.3
{S_1.A.Low, S_2.D.Low}	1.1	{S_2.C.Normal, Q.G.Small}	1.3
{S_1.A.Low, S_3.E.Small}	1.4	{S_2.C.Normal, Q.H.Small}	1.3
{S_1.A.Low, S_3.F.Normal}	0.6	{S_2.D.Low, S_3.E.Small}	1.4
{S_1.A.Low, Q.G.Small}	0.8	{S_2.D.Low, S_3.F.Normal}	1.1.
{S_1.A.Low, Q.H.Small}	1.1	{S_2.D.Low, Q.G.Small}	1.1
{S_1.B.Low, S_2.C.Normal}	1.3	{S_2.D.Low, Q.H.Small}	1.1
{S_1.B.Low, S_2.D.Low}	1.1	{S_3.E.Small, S_3.F.Normal}	1.4
{S_1.B.Low, S_3.E.Small}	1.4	{S_3.E.Small, Q.G.Small}	1.4
{S_1.B.Low, S_3.F.Normal}	0.9	{S_3.E.Small, Q.H.Small}	1.4
{S_1.B.Low, Q.G.Small}	0.9	{S_3.F.Normal, Q.G.Small}	0.8
{S_1.B.Low, Q.H.Small}	1.1	{S_3.F.Normal, Q.H.Small}	1.1
{S_2.C.Normal, S_2.D.Low}	1.3	{Q.G.Small, Q.H.Small}	1.1

Table 5. 8 – The fuzzy counts of the 2-itemset

Parameter itemset	Count	Parameter itemset	Count
{S_1.A.Low, S_1.B.Low}	0.84	{S_2.C.Normal, S_3.E.Small}	1.91
{S_1.A.Low, S_2.C.Normal}	0.96	{S_2.C.Normal, S_3.F.Normal}	2
{S_1.A.Low, S_2.D.Low}	1.04	{S_2.C.Normal, Q.G.Small}	1.62
{S_1.A.Low, S_3.E.Small}	1.02	{S_2.C.Normal, Q.H.Small}	2.24
{S_1.A.Low, S_3.F.Normal}	1.44	{S_2.D.Low, S_3.E.Small}	1.33
{S_1.A.Low, Q.G.Small}	0.4	{S_2.D.Low, S_3.F.Normal}	1.7
{S_1.A.Low, Q.H.Small}	0.92	{S_2.D.Low, Q.G.Small}	1.4
{S_1.B.Low, S_2.C.Normal}	0.72	{S_2.D.Low, Q.H.Small}	1.53
{S_1.B.Low, S_2.D.Low}	0.8	{S_3.E.Small, S_3.F.Normal}	1.16
{S_1.B.Low, S_3.E.Small}	1.07	{ S_3.E.Small, Q.G.Small}	1.67
{S_1.B.Low, S_3.F.Normal}	0.5	{ S_3.E.Small, Q.H.Small}	1.53
{S_1.B.Low, Q.G.Small}	0.8	{S_3.F.Normal, Q.G.Small}	0.9
{S_1.B.Low, Q.H.Small}	0.8	{S_3.F.Normal, Q.H.Small}	1.2
{S_2.C.Normal, S_2.D.Low}	1.7	{Q.G.Small, Q.H.Small}	1.2

Table 5. 9 – Reviewed 2-itemset

Parameter itemset	Count	Parameter itemset	Count
{S_1.A.Low, S_3.F.Normal}	1.44	{S_2.D.Low, Q.G.Small}	1.4
{S_2.C.Normal, S_2.D.Low}	1.7	{S_2.D.Low, Q.H.Small}	1.53
{S_2.C.Normal, S_3.E.Small}	1.91	{S_3.E.Small, Q.G.Small}	1.67
{S_2.C.Normal, S_3.F.Normal}	2	{S_3.E.Small, Q.H.Small}	1.53
{S_2.C.Normal, Q.G.Small}	1.62	{S_3.F.Normal, Q.G.Small}	0.9
{S_2.C.Normal, Q.H.Small}	2.24	{S_3.F.Normal, Q.H.Small}	1.2
{S_2.D.Low, S_3.F.Normal}	1.7	{Q.G.Small, Q.H.Small}	1.2

Table 5. 10 – 3-itemset

Parameter itemset	Counts
{S_2.C.Normal, S_2.D.Low, S_3.F.Normal}	1.52
{S_2.C.Normal, S_2.D.Low, Q.H.Small}	1.38
{S_2.D.Low, S_3.F.Normal, Q.H.Small}	1.2

Step 11: Items in the y-itemset with y>=2 are extracted to construct possible fuzzy association rules and the confidence value of each rule is calculated. Take {S_2.C.Normal, S_2.D.Low, S_3.F.Normal} as an example. One of the possible

rules that can be constructed is "IF {S_2.C.Normal, S_2.D.Low}, then {S_3.F.Normal}.", and the confidence value of the rule is calculated as

$$\frac{(S_2.\text{C.Normal} \cap S_2.\text{D.Low} \cap S_3.\text{F.Normal})}{(S_2.\text{C.Normal} \cap S_2.\text{D.Low})} = \frac{1.52}{1.7} = 0.894$$

All the possible fuzzy association rules are listed in Table 5.11.

Step 12: Compare the confidence values of each rule with the predefined threshold confidence value, which is set to be 0.75 in this case. Only rules with confidence values greater than 0.75 are kept as useful association rules, as shown in Table 5.12. The recursive process mining algorithm ends and a set of useful fuzzy association rules is obtained.

To assist users, especially those lacking DM knowledge, to understand the meaning of the rules, the decision rules are decoded into the form of a statement. Table 5.13 shows some samples of the decision rules in statement form.

Table 5. 11 – All possible fuzzy association rules with confidence values

Rule	Confidence value		Rule	Confidence value	
If {S_1.A.Low} then {S_3.F.Normal}	1.44/2.12 =	0.679	If {Q.G.Small} then {S_3.F.Normal}	0.9/2.4 =	0.375
If {S_3.F.Normal} then {S_1.A.Low}	1.44/2.1 =	0.686	If {S_3.F.Normal} then {Q.H.Small}	1.2/2.1 =	0.571
If {S_2.C.Normal} then {S_2.D.Low}	1.7/2.96 =	0.574	If {Q.H.Small} then {S_3.F.Normal}	1.2/2.6 =	0.462
If {S_2.D.Low} then {S_2.C.Normal}	1.7/2.6 =	0.654	If {Q.G.Small} then {Q.H.Small}	1.2/2.4 =	0.5
If {S_2.C.Normal} then {S_3.E.Small}	1.91/2.96 =	0.645	If {Q.H.Small} then {Q.G.Small}	1.2/2.6 =	0.462
If {S_3.E.Small} then{S_2.C.Normal}	1.91/3 =	0.634	If {S_2.C.Normal, S_2.D.Low} then { S_3.F.Normal}	1.52/1.7 =	0.894
If {S_2.C.Normal} then {S_3.F.Normal}	2/2.96 =	0.676	If {S_2.C.Normal, S_3.F.Normal} then {S_2.D.Low}	1.52/2 =	0.760
If {S_3.F.Normal} then {S_2.C.Normal}	2/2.1 =	0.952	If {S_2.D.Low, S_3.F.Normal} then {S_2.C.Normal}	1.52/1.7 =	0.894
If {S_2.C.Normal} then {Q.G.Small}	1.62/2.96 =	0.547	If {S_2.C.Normal} then {S_2.D.Low, S_3.F.Normal}	1.52/2.96 =	0.514
If {Q.G.Small} then {S_2.C.Normal}	1.62/2.4 =	0.675	If {S_2.D.Low} then {S_2.C.Normal, S_3.F.Normal}	1.52/2.6 =	0.585
If {S_2.C.Normal} then {Q.H.Small}	2.24/2.96 =	0.757	If {S_3.F.Normal} then {S_2.C.Normal, S_2.D.Low}	1.52/2.1 =	0.724
If {Q.H.Small} then {S_2.C.Normal}	2.24/2.6 =	0.862	If {S_2.C.Normal, S_2.D.Low} then {Q.H.Small}	1.38/1.7 =	0.812

If {S_2.D.Low} then {S_3.F.Normal}	1.7/2.6 =	0.654	If {S_2.C.Normal, Q.H.Small} then {S_2.D.Low}	1.38/2.24 =	0.616
If {S_3.F.Normal} then {S_2.D.Low}	1.7/2.1 =	0.810	If {S_2.D.Low, Q.H.Small} then {S_2.C.Normal}	1.38/1.53 =	0.902
If {S_2.D.Low} then {Q.G.Small}	1.4/2.6 =	0.538	If {S_2.C.Normal} then {S_2.D.Low, Q.H.Small}	1.38/2.96 =	0.466
If {Q.G.Small} then {S_2.D.Low}	1.4/2.4 =	0.583	If {S_2.D.Low} then {S_2.C.Normal, Q.H.Small}	1.38/2.6 =	0.531
If {S_2.D.Low} then {Q.H.Small}	1.53/2.6 =	0.588	If {Q.H.Small} then {S_2.C.Normal, S_2.D.Low}	1.38/2.6 =	0.531
If {Q.H.Small} then {S_2.D.Low}	1.53/2.6 =	0.588	If {S_2.D.Low, S_3.F.Normal} then {Q.H.Small}	1.2/1.7 =	0.706
If {S_3.E.Small} then {Q.G.Small}	1.67/3 =	0.557	If {S_2.D.Low, Q.H.Small} then {S_3.F.Normal}	1.2/1.53 =	0.784
If {Q.G.Small} then {S_3.E.Small}	1.67/2.4 =	0.696	If {S_3.F.Normal, Q.H.Small} then {S_2.D.Low}	1.2/1.2 =	1.000
If {S_3.E.Small} then {Q.H.Small}	1.53/3 =	0.510	If {S_2.D.Low} then {S_3.F.Normal, Q.H.Small}	1.2/2.6 =	0.462
If {Q.H.Small} then {S_3.E.Small}	1.53/2.6 =	0.588	If {S_3.F.Normal} then {S_2.D.Low, Q.H.Small}	1.2/2.1 =	0.571
If {S_3.F.Normal} then {Q.G.Small}	0.9/2.1 =	0.429	If {Q.H.Small} then {S_2.D.Low, S_3.F.Normal}	1.2/2.6 =	0.462

Table 5. 12 – Fuzzy association rules with confidence values $\geq$ 0.75

Rule	Confidence value
If {S_3.F.Normal} then {S_2.C.Normal}	2/2.1 =0.952
If {S_2.C.Normal} then {Q.H.Small}	2.24/2.96 =0.757
If {Q.H.Small} then {S_2.C.Normal}	2.24/2.6 =0.862
If {S_3.F.Normal} then {S_2.D.Low}	1.7/2.1 =0.810
If {S_2.C.Normal, S_2.D.Low} then {S_3.F.Normal}	1.52/1.7 =0.894
If {S_2.C.Normal, S_3.F.Normal} then {S_2.D.Low}	1.52/2 =0.760
If {S_2.D.Low, S_3.F.Normal} then {S_2.C.Normal}	1.52/1.7 =0.894
If {S_2.C.Normal, S_2.D.Low} then {Q.H.Small}	1.38/1.7 =0.812
If {S_2.D.Low, Q.H.Small} then {S_2.C.Normal}	1.38/1.53 =0.902
If {S_2.D.Low, Q.H.Small} then {S_3.F.Normal}	1.2/1.53 =0.784
If {S_3.F.Normal, Q.H.Small} then {S_2.D.Low}	1.2/1.2 =1.000

Table 5. 13 – Samples of decision rules in statement form

Rule 1	
IF	Production time before delivery is short AND
	The sewing distance is long AND
	The number of trims for attachment per garment is large AND
	The speed of the sewing machine is high AND
	The speed of the finishing machine is high
THEN	
	The average number of minor defects per garment is small.
Rule 2	
IF	Production volume is normal AND
	The ply height of the fabrics is low AND
	The number of cutting pieces per garment is small AND
	The length of the marker is long AND
	The speed of the cutting machine is normal
THEN	
	The average number of major defects per garment is normal.

5.2.4 Deployment of the DSM

After the deployment of the FARMM, a set of fuzzy association rules is obtained. These rules discover the hidden relationships between the process parameters and the quality features of the products. However, in order to further assist the production operators in determining the exact quantitative values of the process parameters for improving the product quality, the DSM is necessary to estimate the resultant product features when a set of process parameters is given. Based on the estimated resultant product features, the production operators are able to determine the appropriate process parameters for achieving the desired product quality. In addition, to evaluate whether the output of the DSM improves the quality of decisions, a set of KPIs is measured.

5.2.4.1 Estimation of Quality Features for Process Settings Determination

In the FRRMS, the Fuzzy Logic Toolbox in MATLAB is employed to execute the fuzzy inference mechanism in the DSM. The membership functions of parameters defined and the fuzzy association rules obtained are inputted to the Fuzzy Logic Toolbox. Whenever the production operators input the quantitative values of the input parameters, which are defined as the production process parameters, the

Fuzzy Logic Toolbox reads the membership functions and maps each input parameter to the corresponding fuzzy set. For instance, the input parameter "Production volume" may be mapped to fuzzy sets such as "Large" and "Very large", which are then used to trigger relevant fuzzy association rules. Based on the triggered rules, the fuzzy sets of output parameters, which are defined as the quality features in the FRRMS, are determined and the actual values of each output parameter can also be determined.

In fact, for each triggered rule, the output fuzzy sets construct an individual fuzzy region based on the membership functions and a consequent fuzzy region is obtained by combining the individual fuzzy regions of all the triggered rules. Fig 5.7 shows an example of how a consequent fuzzy region of one of the output parameters is obtained.

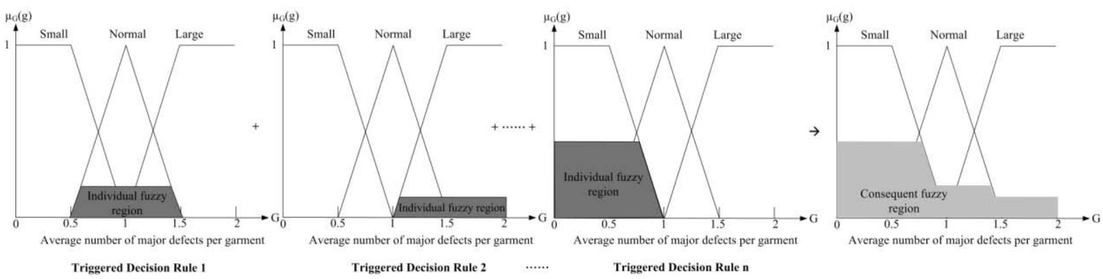

Fig. 5. 7 – A consequent fuzzy region of an output parameter

In addition, users are allowed to study the rule viewer and the surface plot generated by the Fuzzy logic Toolbox. The rule viewer, as shown in Fig. 5.8, shows the fuzzy regions of the input and output parameters in each rule. It allows users to view how each rule impacts on the final output values. Furthermore, Fig. 5.9 shows an example of an output surface plot given by two input parameters, based on the rules. These plots help users to view the effectiveness of the set of rules and identify rules which are responsible for any discontinuity on the output surface.

Fig. 5. 8 – Rule viewer generated by the Fuzzy Logic Toolbox of MATLAB

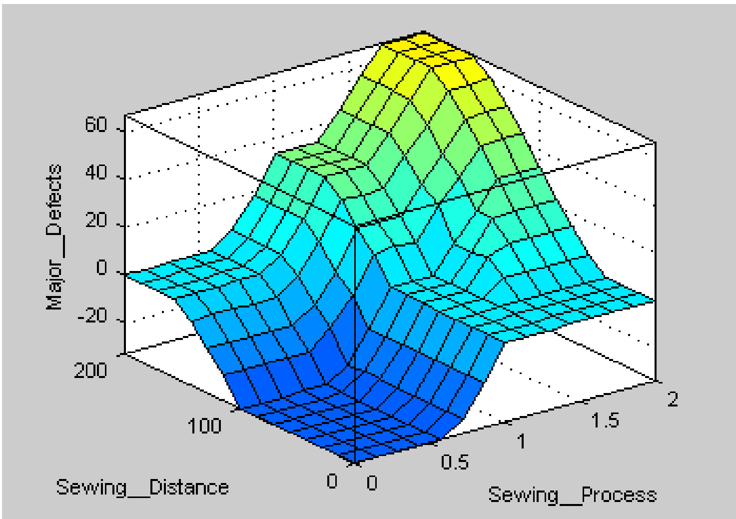

Fig. 5. 9 – An output surface plot given by two input parameters

5.2.4.2 Measurement of KPIs

In this case study, there are five KPIs selected, which are (i) production time, (ii) rework cost, (iii) the number of critical defects, (iv) the number of major defects, and (v) the number of minor defects. According to the historical data, the average values of each KPI over the past year before system implementation are calculated and serve as the benchmarks when evaluating the system improvement. After the implementation of the system, the KPIs are measured every three months. During a six-month pilot run of the system in the THC, the benchmarks and the KPIs averaged over three months and six months after the implementation are compared. Consequently, the evolution of the KPI improvement over time can be monitored.

5.3 Case Study 2 – Optimization of Fuzzy Association Rules by the sGA-FARM for Quality Assurance

In case study 2, the sGA-FARM is introduced to optimize the fuzzy association rules obtained in case study 1. The sGAOM is deployed for performing the function of rule optimization, after which the rules are stored in the DSM for supporting QA. By comparing the results with those of case study 1, the effectiveness of optimizing the fuzzy association rules by the sGA-FARM can be verified. In this section, the problems faced by the company after conducting case study 1 are firstly identified, after which the deployment of both the sGAOM and the DSM are described.

5.3.1 Problems Faced by the Company after Conducting Case Study 1

In case study 1, the decision rules for QA are not optimal. Therefore, the knowledge discovered by the system is not sophisticated enough to support effective QA. There are three problems observed in the company:

(i) Limited combinations of parameters appearing in the rules

Since the decision rules are generated by the FARMM, the knowledge discovered was mainly based on the occurrence of frequent patterns. Parameters having rare associations are usually not considered, nor included, in the rules. As a consequence, the combinations of parameters appearing in the rules are limited. However, considering the involvement of numerous process parameters in actual garment production, this could be a drawback in formulating effective QA schemes as many other possible combinations of parameters are being ignored. Hence, the knowledge discovered by the system can still be further improved.

(ii) Variance between expected and actual quality features

Though the DSM in case study 1 is responsible for estimating the resultant product quality features based on the rules, it is found that variance exists between the expected and actual quality features after the implementation of the system in case study 1. In this sense, the adoption of the learnt process parameters, based on the outputs of the system, cannot guarantee that the resultant quality features of the products are the desired ones. In fact, one of the possible reasons for the variance between the expected and actual quality features is that the knowledge represented by the obtained rules is not responsive enough to the actual situation. In particular, the rules obtained are not optimal or nearly optimal. In line with this view, there is a need to optimize the decision rules obtained in case study 1 so as to lower the variance between the expected and actual quality features.

5.3.2 Deployment of the sGAOM

The major difference between case study 1 and case study 2 is that the sGAOM is deployed in case study 2. In the deployment of the sGAOM, the parameter settings involved in the sGA-FARM algorithm have to be defined and the rules are encoded into chromosomes. The fitness function of each chromosome has to be evaluated before a set of optimal fuzzy association rules can be obtained.

5.3.2.1 Selection of Parameter Settings involved in the sGA-FARM

In this case study, the uniform crossover method, with two different crossover rates: 0.7 and 0.9, is selected. In addition, three slippage rates (0.01, 0.02 and 0.05), and two mutation rates (0.01 and 0.02) are used to control the rate of diversification. Different combinations of the settings are used to compare their effects on the generated solutions. The parameters, which can generate solutions, are averaged from 50 independent runs, with the best fitness values in up to 4000 iterations selected for implementation. In this case study, the suggested crossover, mutation and slippage rates are 0.7, 0.02 and 0.05, respectively.

5.3.2.2 Evaluation of the Fitness Function of Chromosomes

The evaluation of the fitness of the chromosomes in the FRRMS requires the use of the centre of area method for defuzzification and the assignment of weighting factors to each quality feature. More serious quality problems are assigned with larger weights. Suppose there is a chromosome stating that "IF the ply height of the fabric is large and the cutting speed is high, THEN the average number of critical defects per garment is high, the average number of major defects per garment is normal, and the average number of minor defects per garment is small". In order to evaluate the fitness function of this chromosome, a searching process begins to look for any historical production orders which fulfill the IF part of the chromosome, i.e. having the quantitative values of the ply height of the fabric and cutting speed belong to fuzzy classes of "large" and "high" respectively. For instance, there is one order fulfilling the IF part of the chromosome and, according to the order, the actual average numbers of critical defects, major defects and minor defects are 0.72, 1.01 and 1.25 per garment respectively.

In order to test how effective the chromosome is in estimating the quality features, the quantitative values of the ply height of the fabrics and the cutting speed used in the order are referred to. Based on the knowledge stated in the chromosome, the predicted average numbers of critical defects, major defects and minor defects are 0.51, 0.89 and 1.43 per garment respectively. Suppose the weights assigned to the numbers of critical defects, major defects and minor defects are 0.5, 0.3 and 0.2 respectively, then, in this case example, the fitness value of the chromosome = $0.5x(0.51-0.72)^2 + 0.3x(0.89-1.01)^2 + 0.2x(1.43-1.25)^2 = 0.03285$.

In the sGAOM, chromosomes with minimum fitness values are regarded as better solutions, capable of predicting the product quality more accurately. Thus, more appropriate parameter settings can be determined based on these solutions.

5.3.2.3 Fuzzy Association Rule Optimization

Through the use of the sGA-FARM, different parameters can be inserted into or removed from the chromosomes. Table 5.14 lists three fuzzy association rules with the greatest confidence values after the use of the sGA-FARM. Some parameters, such as thread tension, were initially ignored in the FARMM but are now re-considered during rule optimization and appear in the rules. They are considered in the chromosome because of the insertion operation, one of the slipped mutations in the sGA-FARM. On the other hand, there are also some parameters removed from the chromosomes because of the deletion operation. As a result, different combinations of parameters can be considered in a rule, increasing the diversity of the solutions. On the other hand, it is expected that rules with greater confidence values are more responsive to the actual production environment. The knowledge discovered by them is more significant and can help the decision makers realize the strong relationships between the process parameters and the product quality.

Table 5. 14 – Examples of fuzzy association rules obtained after the use of sGA

Rule		Confidence
Rule 1		0.91
IF	The speed of the cutting machine is *high* AND	
	The thread tension is *high*,	
THEN	The number of broken stitches is *high*.	
Rule 2		0.87
IF	The ply height of fabric is *low* AND	
	The speed of the cutting machine is *low* AND	
	The length of the marker is *short*	
THEN	THEN the number of major defects is *low*.	
Rule 2		0.85
IF	The sewing distance per garment is *high* AND	
	The skill level of sewing operator is *low* AND	
	The operator efficiency is *normal*	
THEN	THEN the number of major defects is *normal*.	

5.3.3 Deployment of the DSM

Similar to that in case study 1, the DSM in case study 2 is illustrated with the use of the Fuzzy Logic Toolbox in MATLAB. After the rules are optimized in the sGAOM, it is expected that the combinations of parameters appearing in certain rules are changed. In this step, users are required to revise the rules before the fuzzy inference process is undertaken to generate the estimated quality features based on the optimized rules. To achieve this, the decision rules for QA stored in the Fuzzy Logic Toolbox can be adjusted by changing the fuzzy terms of the parameters in each rule as shown in Fig. 5.10. It is expected that improved QA strategies can be formulated when the rules are well adjusted and improved to more optimal ones. In order to verify the effectiveness of the knowledge supported by the FRRMS with the function of rule optimization, the KPIs are measured again and compared with those in case study 1.

Fig. 5.11 shows the user interface of the FRRMS. Users are allowed to view the membership functions and the minimum support count thresholds of the parameters. Furthermore, they can define the minimum confidence threshold of the rules for the fuzzy association rule mining process. On the other hand, to optimize the rules, users have to input the slippery rate, crossover rate, mutation rate and the number of iterations. After that, the mined fuzzy association rules will be displayed to users.

To improve the rule mining results, users are allowed to edit the membership functions and the minimum support count thresholds of the parameters. Fig. 5.12 shows the interface for editing the membership functions of the parameters. Besides, to help users to determine the appropriate process parameters, the DSM in the FRRMS, as shown in Fig. 5.13, estimates the resultant quality features when a set of input process parameters is given. After users input their process parameters, the predicted output quality features based on the rules mined will be displayed to the users for decision making purposes.

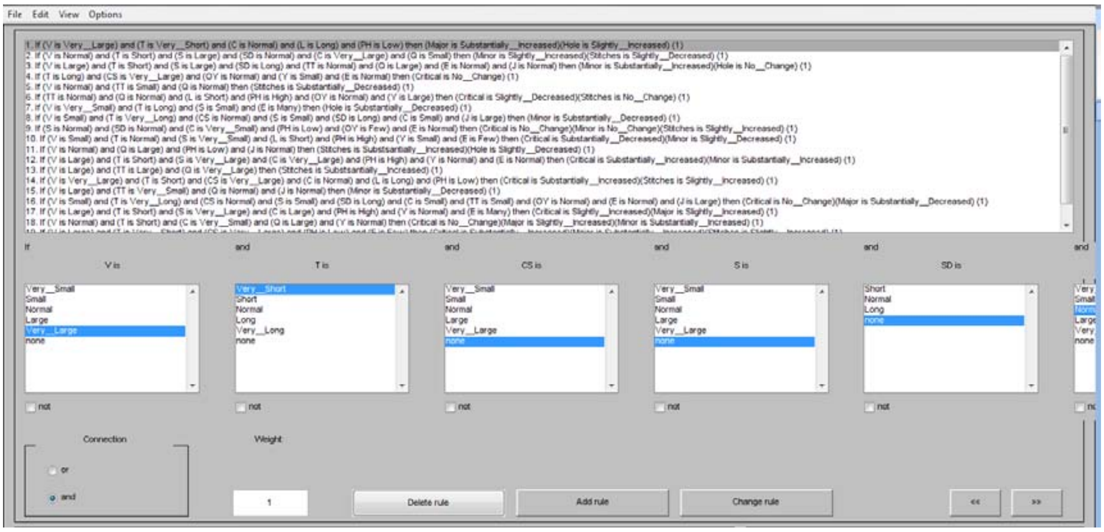

Fig. 5. 10 – Adjustment of fuzzy association rules in the Fuzzy Logic Toolbox of MATLAB

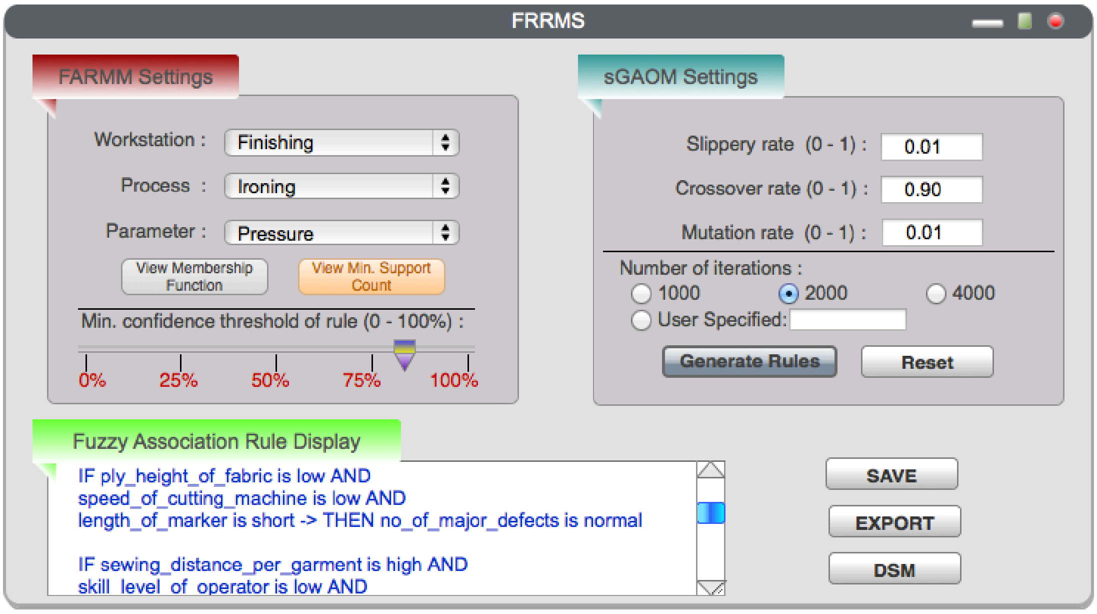

Fig. 5. 11 – User interface of the FRRMS

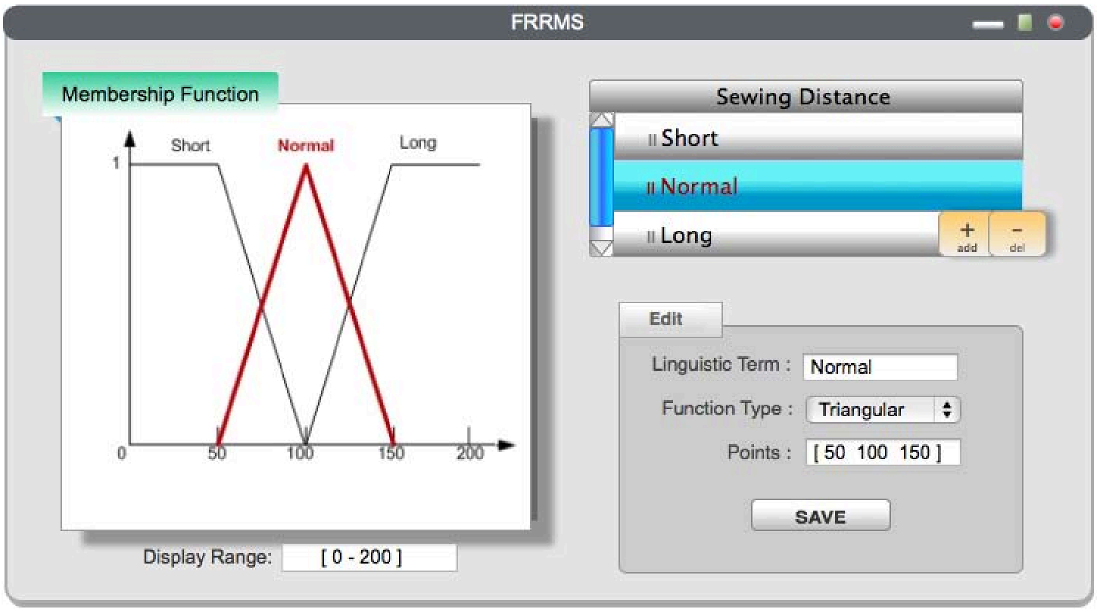

Fig. 5. 12 – Interface for editing membership functions

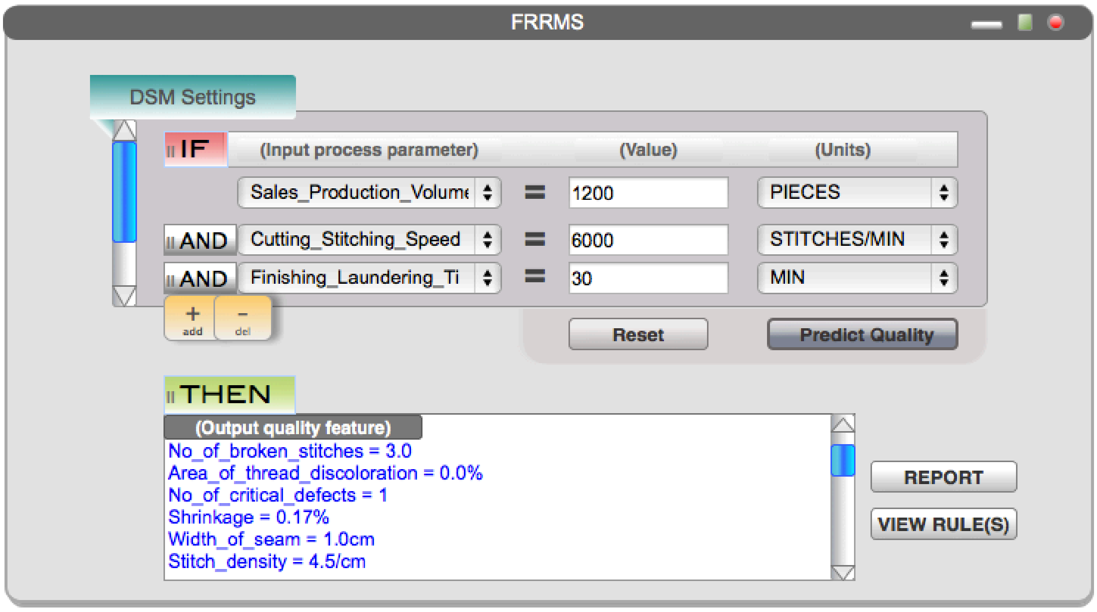

Fig. 5. 13 – Interface for quality feature prediction of the FRRMS

In fact, the key issues in the system implementation are the determinations of fuzzy membership functions, minimum support counts of parameters and the parameter setting involved in the sGA-FARM. Bottlenecks could exist as these determinations are confirmed by means of trial-and-error approaches. Another bottleneck could be found during the rule assessment process. In order to verify the quality of the rules, a set of KPIs has to be measured. As a consequence, it takes time for the company to implement the rules during production before the KPIs can be measured.

5.4 Summary

In this chapter, two case studies of implementing the FRRMS in a garment manufacturing company are described. The roles of the three modules, i.e. FARMM, sGAOM, and DSM, are presented. In case study 1, only the FARMM and DSM are implemented. The rules obtained for QA are not optimized. On the other hand, in case study 2, the sGAOM is included to optimize the rules obtained. Therefore, the focus of case study 1 is solely on the use of fuzzy association rule mining for QA while the focus of case study 2 is on the optimization of the rules. The results obtained in the two case studies and the discussion of the FRRMS in supporting QA in the garment industry are presented in Chapter 6.

Chapter 6 Results and Discussion

6.1 Introduction

In this research, the FRRMS is developed to support the decision making process involved in the determination of the process parameters for assuring better product quality in garment production. This requires an understanding of the relationships between the process parameters and the resultant product quality. To achieve this, the FRRMS hybridizes fuzzy logic, association rule mining, and GAs to discover important knowledge for QA. A new GA framework, sGA-FARM, is also designed to allow the optimization of knowledge which is expressed in terms of fuzzy association rules. By so doing, different combinations of parameters can be considered when looking for the optimal solutions in the search space. Case studies are conducted to implement the FRRMS in a garment manufacturing company. This chapter presents the results and discussion of this research in three areas: (i) General discussion of the FRRMS, (ii) Experimental results and discussion of the case studies, and (iii) Implications for QA in the garment industry.

6.2 General Discussion of the FRRMS

The FRRMS is composed of three modules: (i) FARMM, (ii) sGAOM, and (iii)

DSM. Each module is responsible for a specific function of the FRRMS and is interrelated with each other in order to support effective QA in the garment industry. In this section, discussion of each module is presented. It is believed that each module involved in the FRRMS has some critical features in facilitating better QA for garment production.

6.2.1 Discussion of the FARMM

Since the FARRM hybridizes fuzzy set concepts and association rule mining, the FARMM is discussed in two aspects: (i) comparison of the FARMM with fuzzy logic based approaches, and (ii) comparison of the FARRM with association rule mining-based approaches. The aim of these comparisons is to investigate whether hybridizing these two techniques in FARMM outperforms the use of either one of the techniques in supporting QA. The results of the comparisons are summarized in Table 6.1.

6.2.1.1 Comparison of the FARMM with Fuzzy Logic-based Approaches

In addition to fuzzy association rule mining, fuzzy logic has also been applied to quality improvement. This is achieved by determining the optimal settings of the involved parameters based on a set of decision rules. For instance, Lao et al. (2011) used fuzzy logic to determine optimal storage conditions to maintain food quality while Shabgard et al. (2013) applied fuzzy logic to predict the quality of output with different input parameters, so that users were able to select appropriate input parameters. It was observed that the final decisions determined by fuzzy logic heavily rely on the quality of the decision rules. Nevertheless, such fuzzy logic based approaches lack a systematic approach to monitor the quality of rules stored in the rule base. As a result, great effort has to be made in constructing the collection of fuzzy decision rules, or the decisions supported by fuzzy logic can be poor in quality. To overcome this problem, decision rules in the FRRMS are obtained by fuzzy association rule mining in the FARMM. Subject to predefined membership functions and threshold support counts of the parameters, the quality of the decision rules can be controlled. Thus, the incorporation of fuzzy logic and fuzzy association rule mining in the FARMM ensures better decision quality than traditional fuzzy logic approaches.

6.2.1.2 Comparing the FARMM with Association Rule Mining-based Approaches

Association rule mining is commonly chosen as a knowledge discovery technique for quality management. However, applying association rule mining only is not adequate in providing a comprehensive quality analysis. Kamsu-Foguem et al. (2013) and Lee, Choy, Ho, Chin at al. (2013) applied association rule mining to extract knowledge from a set of quality related data. In their work, the extracted association rules without fuzzy set theory only analyzed quality problems at the binary level, for instance, whether a particular event will occur. Such knowledge extracted by association rule mining is only useful in sequential discovery for defect prediction or causal analysis. Without analyzing the quality problems at the parameter level, practitioners will not receive sufficient knowledge support to determine appropriate process parameters for quality improvement. Therefore, the FRRMS, which introduces fuzzy set theory into association rules in the FARMM, outperforms existing association rule mining based approaches as the process parameters can be taken into consideration while solving product quality problems. In the FARMM, the settings of the process parameters are represented as fuzzy terms when they appear in a fuzzy association rule. Practitioners can understand the relationship between the parameter setting and the resultant product quality. Thereby, a more in-depth quality analysis can be achieved with the use of the FARMM.

Table 6. 1 – Comparison of FARMM with fuzzy logic-based approaches and association rule mining-based approaches

		Fuzzy Logic-based Approaches		Association Rule Mining-based Approaches	
	FARMM	Fuzzy approach to select machining parameters (Shabgard et al., 2013)	Real-time inbound decision support system for food management (Lao et al., 2011)	Mining association rules for quality improvement of production processes (Kamsu-Foguem et al., 2013)	Hybrid OLAP-association rule mining based quality management system (Lee, Choy, Ho, Chin et al., 2013)
Objective(s)	To discover relationships between process parameters and finished quality so as to identify appropriate process parameters	To determine machining parameters which can lead to better machining conditions with low costs	To determine optimal storage conditions to guarantee the quality of food	To analyze the manufacturing process and extract effective knowledge associated to dysfunctions causes	To extract garment defect patterns in terms of association rules which allow users to predict potential defects
Tool(s)	fuzzy association rule mining	Fuzzy logic	RFID, CBR, fuzzy logic	Association rule mining, deductive reasoning	Online analytical processing, association rule mining
Mining Level	Parameter level	Parameter level	Parameter level	Binary level	Binary level
Decision Support Level	Relatively high – decision rules are derived via mining algorithms and are used to determine parameters in quantitative values	Relatively low – relies on human experience to define and review a set of fuzzy decision rules regularly		Relatively low – does not provide insights on how process parameters could be set to reduce product defects	

6.2.2 Discussion of the sGAOM

In this research, several experiments have been carried out to assess the performance of the sGAOM. Firstly, optimal slippage rates are chosen under different parameter settings involved in the sGA-FARM. Secondly, the sGA-FARM is compared with other algorithms to evaluate its effectiveness from the perspective of optimization.

6.2.2.1 Slippage Rate Selection

In this experiment, three slippage rates (α): 0.01, 0.02, and 0.05, are tested to compare their effects on the generated solutions. The uniform crossover method with two different crossover rates (β): 0.7 and 0.9, are suggested while two different mutation rates (γ): 0.01 and 0.02, are used in this experiment. There are four different parameter settings in which the population size is either 100 or 200, with 1000 or 2000 iterations. In each setting, the best and average fitness values and the standard deviation (SD) are recorded and averaged from 50 independent runs. The results are shown in Table 6.2.

Table 6. 2 – Performance of the sGA-FARM with different parameter settings

Parameter settings	sGA-FARM parameters			α=0.01			α=0.02			α=0.05		
				Best	Average	SD	Best	Average	SD	Best	Average	SD
Parameter setting 1	population size=100 (1,000 iterations)	β=0.7	γ=0.01	0.05585	0.06887	0.00877	**0.04323**	0.06709	0.00842	0.04402	**0.05495**	**0.00788**
			γ=0.02	0.03950	0.05192	0.00324	0.04578	0.05762	**0.00214**	**0.03399**	**0.04922**	0.00593
		β=0.9	γ=0.01	0.05020	0.06984	0.00928	**0.03905**	**0.05875**	0.01032	0.05005	0.06933	**0.00874**
			γ=0.02	**0.05840**	**0.06476**	0.00670	0.06820	0.06940	**0.00588**	0.06356	0.06975	0.00682
Parameter setting 2	population size=100 (2,000 iterations)	β=0.7	γ=0.01	0.05892	0.06507	**0.00649**	**0.05005**	**0.05616**	0.00849	0.05173	0.06842	0.01022
			γ=0.02	0.03974	0.05076	0.00956	0.04365	0.05530	**0.00728**	**0.03205**	**0.04658**	0.00809
		β=0.9	γ=0.01	0.06237	0.06383	**0.00771**	**0.04215**	0.06606	0.00965	0.04323	**0.05839**	0.01189
			γ=0.02	0.04165	0.05523	**0.00623**	0.04459	0.06165	0.00841	**0.03949**	**0.05017**	0.01225
Parameter setting 3	population size=200 (1,000 iterations)	β=0.7	γ=0.01	0.04569	0.05158	0.00357	0.05953	0.06978	**0.00169**	**0.03260**	**0.04548**	0.00624
			γ=0.02	**0.03000**	0.05352	0.00429	0.04974	0.05057	**0.00394**	0.03384	**0.04375**	0.00674
		β=0.9	γ=0.01	**0.02214**	**0.04347**	**0.00313**	0.03878	0.04875	0.00970	0.02522	0.04712	0.00777
			γ=0.02	0.05372	0.06819	0.00995	0.03361	**0.04627**	**0.00616**	**0.02633**	0.04786	0.01272
Parameter setting 4	population size=200 (2,000 iterations)	β=0.7	γ=0.01	0.03273	**0.04434**	**0.00727**	0.02999	0.06376	0.01428	**0.02899**	0.05584	0.01808
			γ=0.02	0.02901	0.04205	0.00533	**0.02205**	0.03830	0.00397	0.00346	**0.03779**	**0.00306**
		β=0.9	γ=0.01	**0.03205**	0.04660	0.01402	0.04379	0.04765	0.01018	0.04165	**0.04628**	**0.00690**
			γ=0.02	0.03370	0.04390	**0.00652**	**0.03348**	**0.04067**	0.01032	0.03765	0.04846	0.01387

In parameter setting 1, it is found that fitness values with β=0.7 and γ =0.02 are relatively lower. Under this setting, the best fitness value is obtained at α=0.05. The average fitness values from 50 trials in parameter setting 1, with β=0.7 and γ =0.02, are plotted in Fig. 6.1. It can be seen that the sGA-FARM at α=0.02 and α=0.05 gives better results compared to that at α=0.01. However, it does not reveal any signs of convergence and thus highlights the need to increase the number of iterations in the experiment. In parameter setting 2, the number of iterations used is twice that of parameter setting 1. Lower fitness values are obtained at β=0.7 and γ =0.02 and the best value appears at α=0.05. The average fitness values in parameter setting 2 with β=0.7 and γ =0.02 are then plotted in Fig. 6.2. It is found that the sGA-FARM at α=0.02 and α=0.05 perform equally well in terms of the fitness values. However, the sGA-FARM at α=0.05 converges more rapidly. Therefore, α=0.05 is more favorable in parameter setting 2.

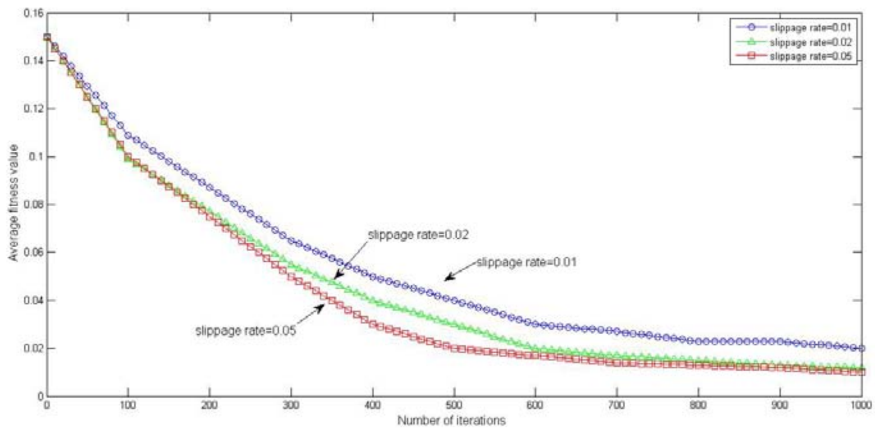

Fig. 6. 1 – Performance of the sGA-FARM (size=100, iteration=1000, β=0.7, γ =0.02)

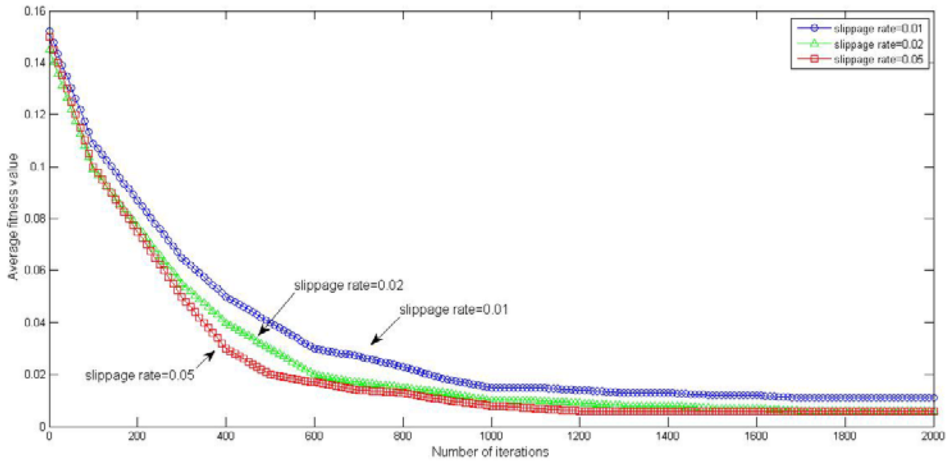

Fig. 6. 2 – Performance of the sGA-FARM (size=100, iteration=2000, β=0.7, γ =0.02)

In parameter settings 3 and 4, the population size is increased to 200. It is observed that fitness values are relatively better when the population size is increased. In parameter setting 3, the sGA-FARM at β=0.9 and γ =0.01 gives relatively lower fitness values and the best value is obtained at α=0.01. The average fitness values from the trials in parameter setting 3, with β=0.9 and γ =0.01, are plotted in Fig. 6.3. It is noted that the sGA-FARM can reach a fitness value of similar quality at different slippage rates. However, the sGA-FARM converges slightly faster at α=0.01. On the other hand, in parameter setting 4, the performance of the sGA-FARM is relatively better when β and γ are 0.7 and 0.02, respectively. In particular, the fitness value is the lowest at α=0.02. The average fitness values in parameter setting 4, with β=0.7 and γ =0.02, are plotted in Fig. 6.4. It is observed that the sGA-FARM at α=0.02 and that at α=0.05 nearly converge at the same time. However, according to the SD, the sGA-FARM is more stable at α=0.02. Thereby, α=0.02 is preferred in parameter setting 4.

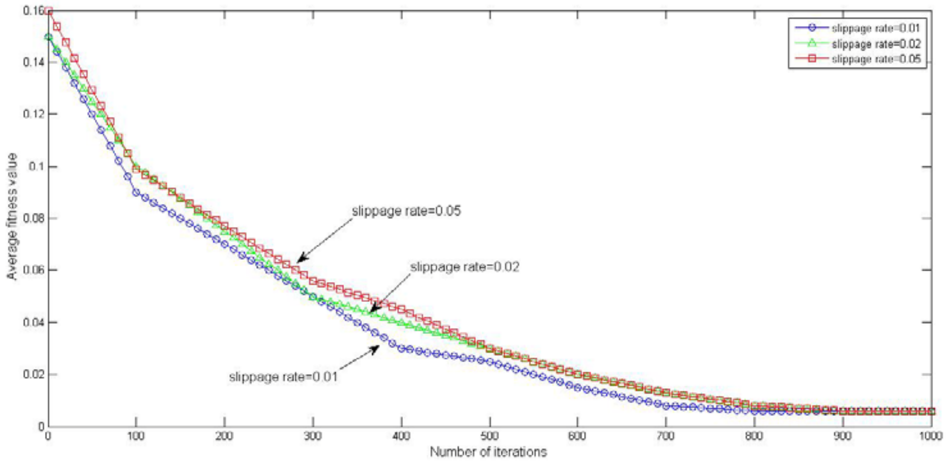

Fig. 6. 3 – Performance of the sGA-FARM (size=200, iteration=1000, β=0.9, γ =0.01)

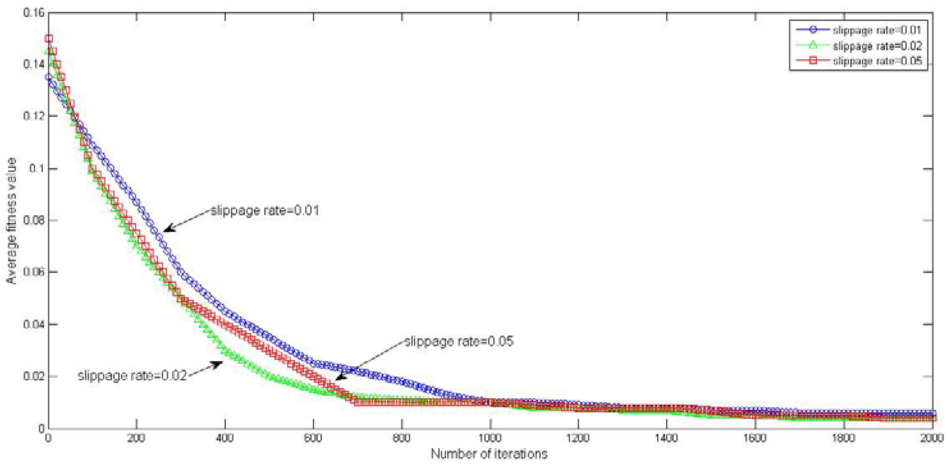

Fig. 6. 4 – Performance of the sGA-FARM (size=200, iteration=2000, β=0.7, γ =0.02)

Based on the experimental results, the optimal parameter settings in the sGA-FARM in each scenario are shown in Table 6.3. These settings are used in the comparison experiments presented in the next section.

Table 6. 3 – Optimal parameter settings in the sGA-FARM in each parameter setting

Parameter setting	Optimal parameter settings in the sGA-FARM
Parameter setting 1	size=100, iteration=1000, α=0.05, β=0.7,γ =0.02
Parameter setting 2	size=100, iteration=2000, α=0.05, β=0.7,γ =0.02
Parameter setting 3	size=200, iteration=1000, α=0.01, β=0.9,γ =0.01
Parameter setting 4	size=200, iteration=2000, α=0.02, β=0.7,γ =0.02

6.2.2.2 Comparison of the sGA-FARM with GA-FARM and SA-FARM

In this section, the sGA-FARM was compared with two other algorithms: the standard GA in FARM (GA-FARM), and simulated annealing in FARM (SA-FARM).

(i) GA-FARM: The proposed sGA-FARM is an extension of the GA-FARM presented in Ho et al. (2008). In the GA-FARM, each chromosome encodes a fuzzy association rule, containing the existence of each parameter and the associated fuzzy term of parameters, using binary and real numbers respectively. The length of all the chromosomes is fixed and is dependent on the number of parameters considered in the algorithm. The fitness function considers both the error measurement and the complexity of the process change. For comparison with the sGA-FARM, however, the fitness function of the GA-FARM is revised to the fitness function of the sGA-FARM.

(ii) SA-FARM: In this algorithm, simulated annealing (SA) is adopted to replace the role of the GA in the GA-FARM for optimization. SA was introduced by Kirkpatrick and Vecchi (1983) and is analogous to thermodynamics processes, specifically with the way that substances cool and crystallize (Brooks and Morgan, 1995). It belongs to a class of local search algorithms. In this thesis, fuzzy rules are treated as energy states in the SA-FARM and iterative improvement of the states is achieved because of random modification of the variable values.

Table 6.4 and Table 6.5 show the performance of the GA-FARM and SA-FARM, respectively, under different parameter settings. Only the best parameter values achieving the best performance in each of the four parameter settings are selected and adopted for the comparison with sGA-FARM. Table 6.6 summarizes the comparison results of the sGA-FARM, GA-FARM and SA-FARM in terms of best and average fitness values and the SD averaged from 50 independent trials.

Table 6. 4 – Performance of the GA-FARM under different parameter settings

Algorithm	Case	Parameter setting 1			Parameter setting 2			Parameter setting 3			Parameter setting 4		
		Best	Average	SD	Best	Average	SD	Best	Average	SD	Best	Average	SD
GA-FARM	β=0.9, γ=0.01	**0.03781**	0.05288	0.00374	**0.03101**	**0.04728**	0.00693	0.02965	**0.03561**	0.00578	0.03085	0.05467	**0.00339**
	β=0.9, γ=0.02	0.03910	**0.04624**	**0.00293**	0.04082	0.05526	**0.00421**	0.03190	0.03864	0.00791	0.03207	0.04993	0.00461
	β=0.7, γ=0.01	0.04012	0.05629	0.00490	0.03746	0.06093	0.00714	0.02843	0.05123	0.00617	**0.02543**	**0.04085**	0.00163
	β=0.7, γ=0.02	0.03928	0.05730	0.00681	0.03893	0.05082	0.00510	**0.02466**	0.03750	**0.00499**	0.02898	0.05221	0.00385

Table 6. 5 – Performance of the SA-FARM under different parameter settings

Algorithm	Case	Parameter setting 1			Parameter setting 2			Parameter setting 3			Parameter setting 4		
		Best	Average	SD	Best	Average	SD	Best	Average	SD	Best	Average	SD
SA-FARM	γ=0.01, cooling rate=0.1	0.04988	0.06625	0.00513	0.04177	0.05910	0.00557	0.03494	0.05893	**0.00248**	0.03316	0.05882	**0.00223**
	γ=0.02, cooling rate=0.1	0.04193	0.06131	**0.00399**	0.04035	0.05611	0.00512	0.02910	0.05702	0.00491	0.04069	0.06023	0.00492
	γ=0.01, cooling rate=0.01	**0.04061**	0.06020	0.00708	**0.03837**	**0.05252**	0.00421	**0.02860**	**0.03812**	0.00267	0.03142	**0.04708**	0.00584
	γ=0.02, cooling rate=0.01	0.04727	**0.05832**	0.00455	0.04202	0.05793	**0.00265**	0.03824	0.05916	0.00605	**0.03084**	0.04586	0.00272

Table 6. 6 – Comparison results of the sGA-FARM, GA-FARM and SA-FARM

Algorithm \ Case	Parameter setting 1			Parameter setting 2			Parameter setting 3			Parameter setting 4		
	Best	Average	SD	Best	Average	SD	Best	Average	SD	Best	Average	SD
sGA-FARM	**0.03399**	**0.04922**	0.00593	0.03205	**0.04658**	0.00809	**0.02214**	**0.03347**	0.00313	**0.02205**	**0.03830**	0.00197
GA-FARM	0.03781	0.05288	**0.00374**	**0.03101**	0.04728	0.00693	0.02466	0.03750	0.00499	0.02543	0.04085	**0.00163**
SA-FARM	0.04061	0.06020	0.00708	0.03837	0.05252	**0.00421**	0.02860	0.03812	**0.00267**	0.03084	0.04586	0.00272

After testing the different parameters in the GA-FARM, it is found that the GA-FARM in parameter setting 1 obtains the best solutions when β and γ are 0.9 and 0.01, respectively. Similarly, it is noted that the SA-FARM obtains the best solutions when γ and the cooling rate are both 0.01. The average fitness values obtained in the three approaches in parameter setting 1 are plotted in Fig. 6.5. It is observed that the SA-FARM is the most inferior among the three approaches and the sGA-FARM performs the best in terms of the best average fitness values. Similar to parameter setting 1, the GA-FARM in parameter setting 2 obtains the best solutions when β and γ are 0.9 and 0.01, while the SA-FARM obtains the best solutions when γ and the cooling rate are both 0.01. However, the performance of the algorithms in parameter setting 2 is improved after the iteration is increased from 1000 to 2000. The average fitness values obtained in the three approaches in parameter setting 2 are plotted in Fig. 6.6. It can be observed that the algorithms tend to converge after 1000 iterations and the best of the average fitness values obtained in the sGA-FARM and GA-FARM are comparable. However, the GA-FARM is considered slightly superior to the sGA-FARM as it converges more rapidly.

In parameter setting 3, the GA-FARM obtains the best solutions when β and γ are 0.7 and 0.02, respectively, whilst the SA-FARM obtains the best solutions when γ and the cooling rate are both 0.01. The average fitness values obtained in the three approaches in parameter setting 3 are plotted in Fig. 6.7. It is found that the average fitness value obtained in the sGA-FARM is significantly better that that obtained in the GA-FARM and SA-FARM. In addition, no convergence is observed in both GA-FARM and SA-FARM, so parameter setting 4 is thus necessary to compare the performance of algorithms when the iteration is increased from 1000 to 2000. Compared to parameter setting 3, parameter setting 4 allows the GA-FARM and SA-FARM to reach convergence at around 1700 iterations. In this sense, when only a short time is allowed for executing the algorithms, the sGA-FARM is more preferred. The average fitness values obtained in the three approaches in parameter setting 4 are plotted in Fig. 6.8. Although the best average fitness values obtained by the three algorithms are comparable, the sGA-FARM converges more rapidly in less than 1000 iterations. Based on the results, it is worth noting that the sGA-FARM is a better choice when the population size is increased.

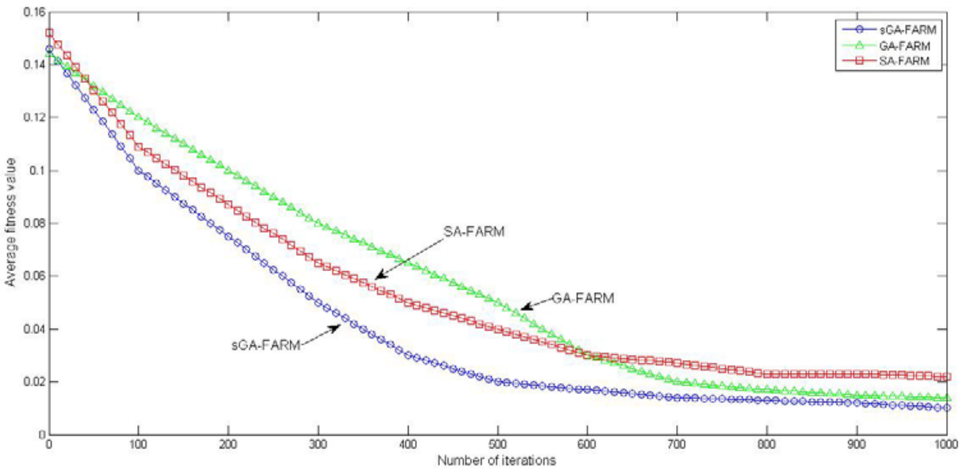

Fig. 6. 5 – Comparison of the three approaches in parameter setting 1

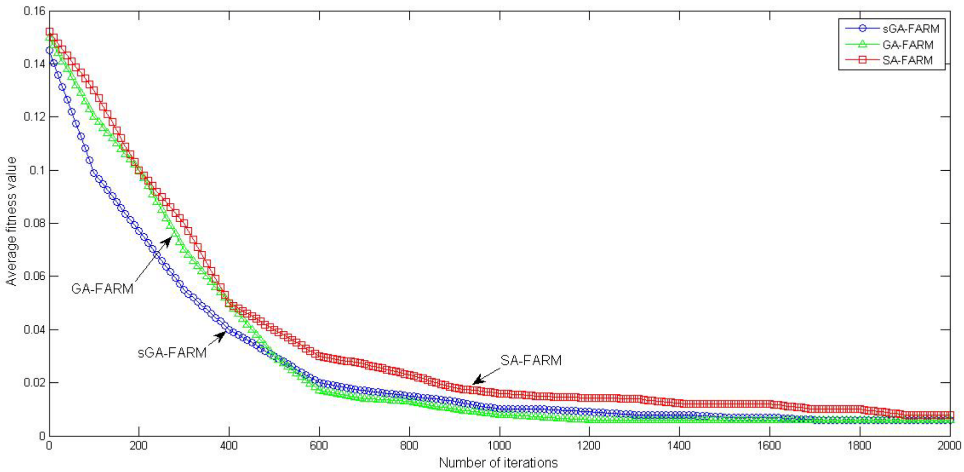

Fig. 6. 6 – Comparison of the three approaches in parameter setting 2

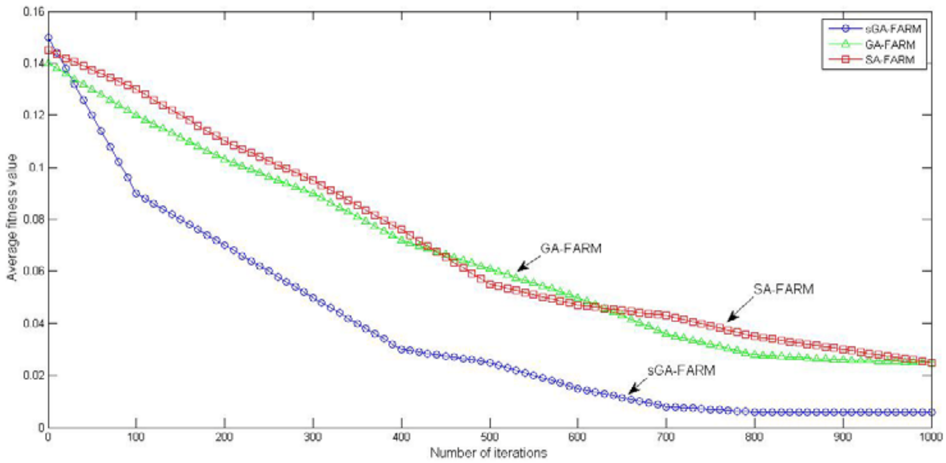

Fig. 6. 7 – Comparison of the three approaches in parameter setting 3

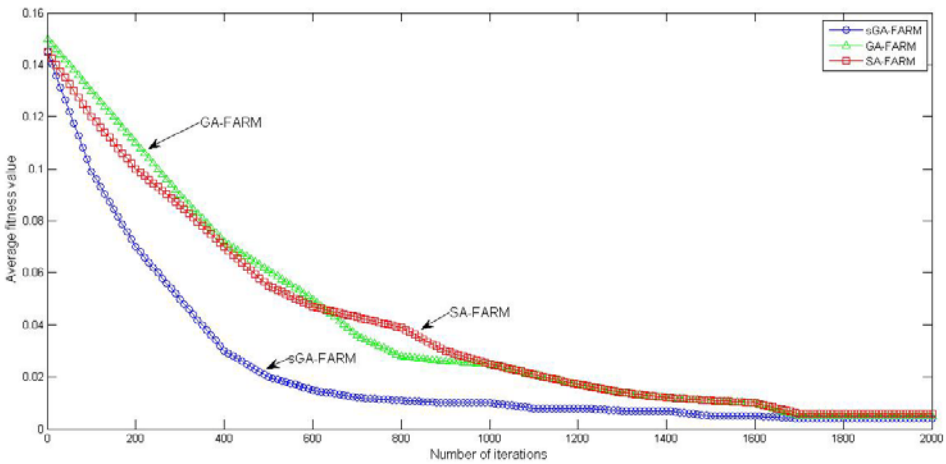

Fig. 6. 8 – Comparison of the three approaches in parameter setting 4

With the addition of the slippage concepts, the optimization performance is improved because of the two slippage mutations, insertion and deletion. Insertion allows an increase in the length of individual chromosomes so as to create more diverse solutions. The increase in chromosome length indicates that there are additional parameters being considered in the rules. On the other hand, deletion creates a decrease in the length of individual chromosomes by removing a certain number of consecutive genes from the chromosomes. In the case that most of the genes in a chromosome representing a decision rule do not predict the product quality with minimum error, slippage mutations may help in exploring the relationship between the product quality and other parameters in order to increase the fitness of a solution. The results revealed that the sGA-FARM outperforms the fixed-length GA and SA to a larger degree when the population size is increased and the number of iterations is decreased.

6.2.3 Discussion of the DSM

The DSM is a fuzzy inference system in which fuzzy logic is applied to determine the quantitative values of the output parameters based on the fuzzy association rules obtained via the FARRM and sGAOM. In the FRRMS, the output parameters are defined as the quality features of the garment products. When a set of quantitative values of the input parameters are entered in the DSM, the input values are fuzzified and the generated fuzzy sets are used to map with the stored rules. With reference to the triggered rules and the predefined membership functions, the fuzzy sets of the output parameters are obtained. Through the defuzzification process, the quantitative values of the output parameters are generated. In order to improve the quality features of the garments, users can input the process parameters to be used into the DSM. Based on the input values, the DSM informs them of the resultant quality features. If the quality features estimated by the DSM are satisfactory, the production operators can adopt the process parameters in production accordingly. If the quality features estimated by the DSM is not desirable, users are able to fine-tune their input values of the process parameters, for example, by adjusting the speed of the sewing machines and cutting machines. These learnt process parameters can help the production operators to determine the appropriate process parameters for production in order to achieve desire quality features of the products.

In addition, the mining algorithm embedded in the FRRMS is a recursive one. More and more decision rules of improved quality can be generated, enhancing the accuracy of the quality features estimated by the DSM. Hence, reliable knowledge support can be given to the production operators, and a set of effective QA strategies can be formulated. In the long term, a continuous improvement of the processes and product quality of the garment manufacturing company can be achieved.

6.3 Experimental Results and Discussion of the Case Studies

In the earlier section, a general discussion of the three modules involved in the FRRMS is presented. It is observed that each module possesses critical features in enhancing QA in the garment industry. In this section, the major findings obtained in the two case studies are presented. The improvements achieved in the case company after the system implementation are discussed. Based on the results, the effectiveness of the system in supporting QA in the garment industry can be verified.

6.3.1 Results and Discussion of the Use of the System in Case Study 1

The results and discussion of case study 1 are divided into two parts. The first part is a cost analysis regarding the investment on RFID devices for real-time data collection. The second part is the improvement achieved in the case company, measured in terms of the KPIs.

6.3.1.1 Cost Analysis

Since RFID technologies are employed for data collection, a cost analysis was conducted to illustrate the cost-effectiveness of the system. The total cost of system implementation was around HK$580,000 in terms of RFID equipment and system set-up. In the garment industry, the revenue of a manufacturer is significantly affected by the labor cost for quality inspection and the rework cost due to product quality problems. Other penalty costs incurred by production delays and late shipments should also be considered when manufacturers have to bear the shipment costs to meet customer deadlines. Table 6.7 shows the costs associated with the system and a comparison of labor costs, rework costs, and penalties before and after system implementation. From Table 6.7, it is found that the total amount saved per year is:

[(*labor cost for quality inspection per month before implementation – labor cost for quality inspection per month after implementation*) + (*rework cost per month before implementation – rework cost per month after implementation*) + (*penalty per month before implementation – penalty per month after implementation*) – (*system maintenance cost per month after implementation*) x 12

= HK$[(60,000 - 35,000) + (35,000 - 20,000) + (12,000 - 4,500) – HK$10,000] x 12

= HK$450,000.

Based on money saved, the expected break-even point is:

Money invested / money saved = HK$580,000 / HK$450,000 per year = 1.3 years.

Table 6. 7 – Cost Analysis of the FRRMS with the Use of RFID in THC

	Implementation Cost	Before Implementation	After Implementation
RFID equipments including antennas, tags, readers and a middleware	HK$500,000	/	/
System set up	HK$80,000[a]	/	/
System maintenance cost per month	/	/	HK$10,000
Average labor cost for quality inspection per month	/	HK$60,000	HK$35,000
Average rework cost per month	/	HK$35,000	HK$20,000
Average penalty per month[b]	/	HK$12,000	HK$4,500

[a] Labor costs of two full-time system developers

[b] Penalty incurred by production delays and late shipments

From the analysis, it is expected that the company will require around 1.3 years to get back the money invested. However, as the system provides continuous improvement of the processes and product quality, because of its recursive mining feature, it is not surprising that continuous improvement in cost saving in rework costs and penalties over time result. Accordingly, the company can likely take less than 1.3 years to get back the money invested.

6.3.1.2 Measurement of KPIs

QA activities require an understanding of the factors affecting the final product quality. As the garment industry is time-sensitive, these activities must be proactive enough to solve quality problems without contributing to production inefficiencies. This research presents an intelligent system to effectively discover the hidden relationships between process parameters and product quality in terms of fuzzy association rules, and then determines appropriate process parameters for production based on the discovered knowledge. Fig. 6.9 shows the improvement achieved by the use of the system after three months and after six months. It is found in case study 1 that the FRRMS combining DM, AI and RFID technologies can offer significant benefits to the garment industry, which include:

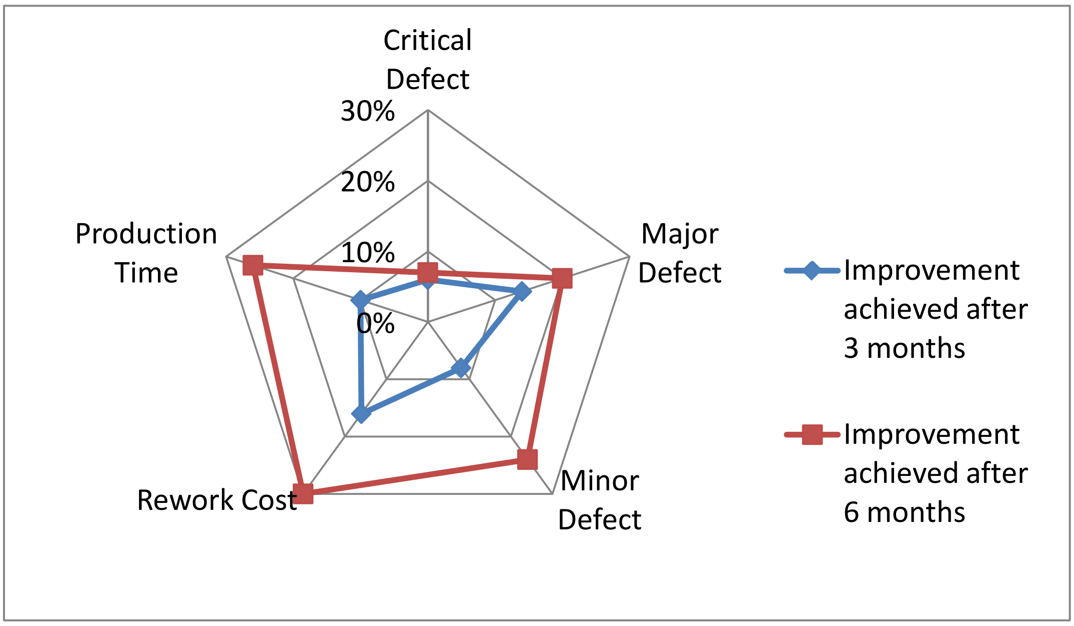

Fig. 6. 9 – Improvement achieved by the use of the FRRMS in case study 1

(i) Increased production efficiency

It is found that the production time is significantly shortened by 10% and 26% after the three-month and six-month pilot run of the system respectively. This can be attributed to the use of RFID devices on the production shop floor tracking the production processes on a real-time basis. This allows the manufacturers to identify any bottlenecks in production and take proactive measures to refine the process settings.

(ii) Improved product quality in terms of the number of defects and rework cost

The product quality is improved in terms of the number of defects and rework cost. Firstly, the numbers of critical defects are reduced by 6% and 7% after the three-month and six-month pilot run of the system respectively. At the same time, the numbers of major defects are reduced by 14% and 20% after the three-month and six-month pilot run of the system respectively. Among different types of defects, minor effects are reduced the most. The numbers of minor defects are reduced by 8% and 24% after the three-month and six-month pilot run of the system respectively. Defects are reduced because the data captured by the RFID devices not only visualize the production operations, but also the product quality achieved. The integration of fuzzy association rule mining and fuzzy logic allows the quality analysis to be undertaken at a parameter level for achieving effective quality assurance. By looking at the mined relationship between the processes and finished quality, quality engineers are able to identify root causes of quality problems and adjust the process parameters for improved QA. As a result, defects found on the products are reduced, lowering the rework cost by 16% and 30% after the three-month and six-month pilot run of the system respectively.

(iii) Continuous improvement of processes and product quality

From Fig. 6.9, it can be observed that there is a substantial growth in the improvement during the six-month pilot run of the system. As the mining algorithm embedded in the system is a recursive one, more and more fuzzy association rules can be generated over time, taking the initial process settings and the resultant product quality as inputs to discover the hidden knowledge. Based on the discovered knowledge, users are able to adjust their process parameters for achieving better quality with the use of fuzzy logic. The newly obtained parameters are applied in production and become new inputs of the mining algorithm for discovering new knowledge. This leads to a continuous improvement of the processes as well as the resultant product quality.

6.3.2 Results and Discussion of the Use of the System in Case Study 2

In case study 2, the fuzzy association rules obtained in case study 1 are optimized with the use of the sGAOM. The results and discussion of case study 2 are divided into two parts. The first part is the comparison of the sGA-FARM with variable-length of GAs, and the second part is the measurement of KPIs, followed by a comparison with that in case study 1.

6.3.2.1 Comparison of sGA-FARM with variable-length of GAs

Due to the error-prone nature of garment manufacturing operations, it is challenging to guarantee the quality of garments. Case study 1 covers the determination of process settings for improving the garment quality by fuzzy association rule mining. Case study 2 serves as an enhancement to case study 1 as it focuses on optimization of the rules obtained. The capability of conventional GAs in rule optimization has been well proven. Wang et al. (2000) applied GAs for the integration of multiple fuzzy rules sets. If some features were not used in individual rules, dummies would be inserted into the rules to ensure that all chromosomes were of the same length. In addition, Lau, Ho et al. (2009) used GA to generate an optimal or nearly optimal fuzzy set and membership functions for the process parameters. After the domain knowledge was represented with a fuzzy rule set, the obtained fuzzy rules and the associated memberships were encoded into chromosomes. Each chromosome represented one fuzzy rule and the related problem. Through the crossover and mutation operations, an optimal or nearly optimal fuzzy set and membership functions for the process parameters were discovered. Furthermore, Chen et al. (2009) integrated GAs and fuzzy concepts to discover suitable minimum supports, membership functions and useful fuzzy association rules from historical transactions. Each chromosome in the population represented a possible minimum support and membership functions for an item. The chromosomes in the same population were of the same length. In a similar vein, Yan et al. (2009) designed a

GA-based strategy for identifying association rules without specifying actual minimum support. However, in their design, only Boolean association rules were considered. In the abovementioned work, only classical GAs with fixed length chromosomes were used. As a result, previous knowledge was required to define constraints, for instance the number of rules in the rule base (Rajesh & Kaimal, 2008). Furthermore, the best achievable fitness was inherently limited by the chromosome length and it was difficult to define an optimal chromosome length, especially for design optimization problems (Kim & De Weck, 2005).

To overcome this limitation, different variable-length GAs have been proposed to increase the diversity of the chromosome lengths. This can be done by introducing additional mutation operators to vary the length of the chromosomes and to perform crossover on chromosomes of differing lengths (Hutt and Warwick, 2007). The earliest example of a GA with variable length was the messy GA proposed by Goldberg et al. (1989). In addition, Han et al. (2002) designed an adaptive length chromosome hyper-GA (ALChyper-GA) with two new mutation operators

This research proposes sGA-FARM to optimize rules with variable-length chromosomes. By so doing, different combinations of parameters can be considered in a rule, increasing the diversity of the solutions. The comparison of sGA-FARM with existing variable-length GAs is shown in Table 6.8.

Table 6. 8 – Comparison of sGA-FARM with existing variable-length of GAs

	sGA-FARM	Messy GA (Goldberg et al., 1989)	ALChyper-GA (Han et al., 2002)
Biologically inspired	Yes, inspired by the slippage phenomenon in DNA replication	No	No
Crossover	Uniform crossover	No	Best-best crossover
New mutation operators	Slipped insertion, slipped deletion	Cut, splice	Removing-worst mutation, inserting-good mutation
Application area	Industrial process parameter optimization	Elimination of bit positional dependencies in a standard GA	Personnel scheduling

The sGA-FARM is compared with two existing variable-length GAs, namely the messy GA (Goldberg et al., 1989) and ALChyper-GA (Han et al., 2002). Among these variable-length GAs, only sGA-FARM is biologically inspired, in particular, by the slippage phenomenon in DNA replication. Therefore, it more appropriately matches biological genetic representation. Besides, the messy GA replaced crossover with cut and splice operators to produce variable-length chromosomes. It was developed to eliminate the bit positional dependencies in a standard GA. Bit values in a messy GA chromosome, each of which is tagged with a name indicating its position, are extracted from the chromosome and reordered based on their names. As a result, bits are no longer in fixed positions and can move around on a chromosome. However, one of the limitations of the messy GA is that it focuses on bits. If there are n variables, each of which need k bits, there will be $n2^{nk}$ additional bits in the messy GA. In this sense, the messy GA may not be a feasible solution if the problems to be solved are complicated, involving a large set of variables. On the other hand, Han et al. (2002) designed the ALChyper-GA with a new crossover method, best-best crossover. The best group of genes in chromosomes are selected and exchanged during crossover. Followed by the crossover were two new mutation operators, namely the removing-worst mutation and the inserting-good mutation. The former one removes the worst group of genes in the selected chromosome while the latter one inserts the best group of genes from a randomly selected chromosome to a random point in the desired chromosome. As genes are removed or inserted, the length of the chromosomes in each generation changes. The ALChyper-GA was applied to solve the personnel scheduling problem. Problems such as allocation of staff to timeslots and possibly locations can be solved by the ALChyper-GA. Only quantitative values were considered in the chromosomes, nevertheless, the sGA-FARM integrates fuzzy set concepts into the GA. It solves optimization problems while taking the fuzziness of data into consideration. Though the use of sGA-FARM in the research is applied to the garment industry, it can be easily modified for other manufacturing applications for industrial process parameter optimization. Considering that real data possess many forms of uncertainties, the application areas of the sGA-FARM are more diverse than that of the messy GA and ALChyper-GA as the fuzziness of data can be embedded into the sGA-FARM chromosomes.

6.3.2.2 Measurement and Comparison of KPIs with Case Study 1

In case study 2, improvement achieved by the use of the FRRMS is measured in terms of KPIs. The results are compared with those achieved in case study 1 in which QA was supported solely by FARMM and DSM without the application of sGAOM. Therefore, it is believed that the differences found in the comparison are mainly due to the introduction of sGA-FARM in the system for optimization purposes. Table 6.9 compares the results obtained after a six-month pilot run of the system, and the results are discussed in the following sections.

(i) Reduced Rework cost

After a six-month pilot run of the system, the FRRMS reduced the rework cost by 34%, which is 4% higher than that obtained in case study 1. By looking at the mined relationship between the process parameters and the quality features, quality engineers are able to conduct causal analysis of the defect problems and provide feedback on the performance of different production workstations so as to avoid rework of garments. The FRRMS achieved better cost reduction than that in case study 1 because more parameters can be considered in the fuzzy association rules with the use of the sGAOM. In case study 2, parameters which are initially ignored in the FARMM can have a chance to be re-considered during rule optimization. Because of the slippage concepts in the sGA, different combinations of production process parameters can appear in the rules by insertion and deletion, allowing knowledge to be discovered for quality assurance in a more comprehensive way. On the contrary, case study 1 only considers parameters based on their frequent association. As a result, the knowledge mined in case study 1 is limited.

(ii) Increased production efficiency

The production efficiency is improved by 27% after the inclusion of the sGAOM in case study 2. One of the reasons is that the time for rework of garments is significantly reduced. As a consequence, the average production lead time is shortened. Furthermore, RFID was employed for data collection, allowing the manufacturers to identify any bottlenecks in production and take proactive measures to adjust process settings on a real-time basis.

Table 6. 9 – Improvement achieved by the use of the sGAPMS and the RFID-RPMS

KPI	With sGAOM in case study 2	Without the sGAOM in case study 1
Rework cost	34%	30%
Production efficiency	27%	26%
The number of critical defects	9%	7%
The number of major defects	22%	20%
The number of minor defects	27%	24%

(iii) Improved quality features

The quality features are improved after the implementation of the sGAOM in case study 2. In particular, the numbers of critical defects, major defects and minor defects are reduced by 9%, 22% and 27%, respectively. This reveals that the knowledge discovered by the sGAOM is useful for improving the resultant quality of the garments. As the condition part of the fuzzy association rules concerns the production process parameter settings, the QA is supported by the system at the parameter level. This allows garment manufacturers to adjust the process parameters directly in order to achieve the desired product quality. Through the defuzzification process, the system can predict the resultant quality features based on adjustment of the parameters. Compared with case study 1, the FRRMS in case study 2 improves the quality features to a larger extent. This is because the diversity of rules is increased with the use of the sGA-FARM and the overall quality of the rules can be improved eventually. These rules with better quality can predict the quality features with less deviation. As a result, more reliable QA activities can be carried out.

6.4 Implications for Quality Assurance in the Garment Industry

Fig 6.10 shows how DM and AI are used to ensure quality in the garment industry. Currently, the quality in the garment industry is managed by means of QC. Garment defects are detected, identified and corrected by inspection-based approaches which are product-oriented and solely focuses on defect identification. Nothing has been done to improve the processes by which the products are produced. In view of this, a more proactive approach, such as QA, is required to improve the underlying processes. QA is process-oriented and focuses on defect prevention. It requires the collection and analyses of data to identify the weaknesses of processes. Considering that there are a large number of processes involving in garment production, QA in the garment industry involves many input and output parameters that are not easy to optimize. Therefore, DM and AI are necessary to analyze the data. They are used to extract knowledge from a large set of raw data for providing decision support for QA. In this research, fuzzy association rule mining and GA are applied to perform two major quality tasks, which are quality prediction and parameter optimization. To summarize, the management of quality in the garment industry is originally at the product level. However, with the introduction of QA, it can be shifted to the process level. With the use of DM and AI, it can be further extended to the parameter level, providing a more sophisticated approach to ensure the quality in the garment industry.

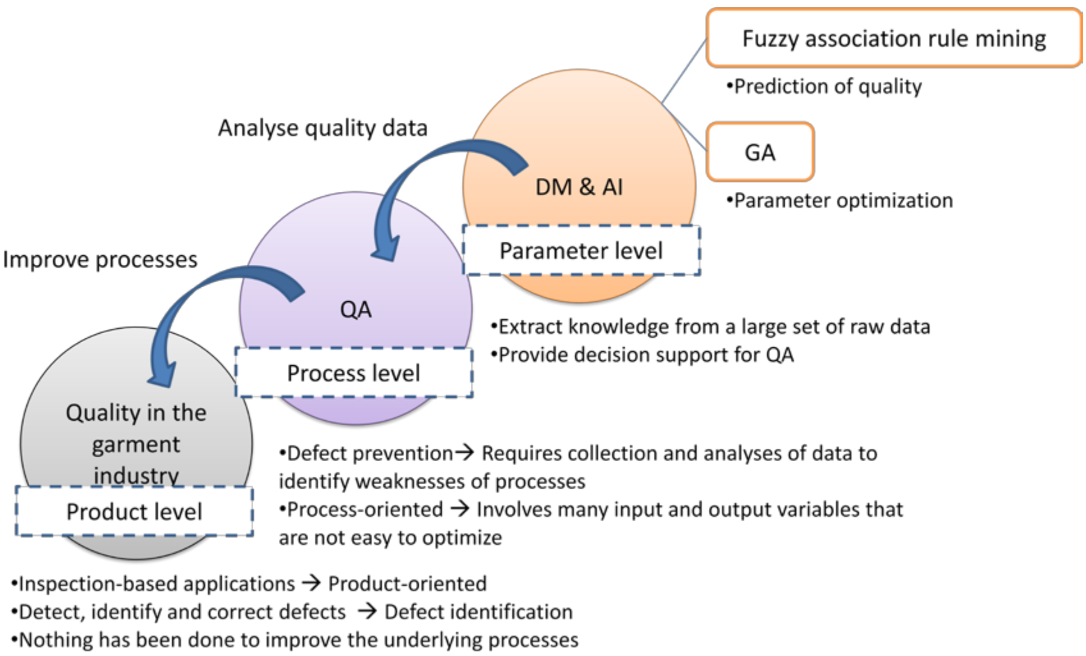

Fig. 6. 10 – The use of DM and AI for ensuring quality in the garment industry

Existing publications have shown that traditional association rule mining without integrating fuzzy set concepts can only discover the relationship between items. For instance, Chougule et al. (2011) used association rule mining to detect anomalies in the field that causes customer dissatisfaction, and the knowledge discovered was used for root cause identification. In a similar vein, Lee, Choy, Ho, Chin et al. (2013) applied the same tool to detect the correlations among different garment defects which served as useful knowledge for defect prediction. However, the knowledge discovered by traditional association rule mining is not sophisticated enough to provide decision support on quality management. Thus, it is a drawback to use traditional association rule mining for solving quality problems because one of the critical aspects of planning for quality improvement is to discover the relationship between items at the parameter level (Lau, Ho et al., 2009). On the contrary, fuzzy association rule mining approaches are able to discover knowledge at a parameter level by describing the quantitative values of the parameters in fuzzy terms. Lee, Ho at al. (2014) applied it to investigate the relationships between production parameters and the resultant product quality. Their goal was to help the operators to determine the appropriate process parameters for production. However, in their study, the decision rules obtained might not be optimal. On the other hand, Ho et al. (2008) used GAs to optimize the fuzzy association rules. The GA they applied was a classical GA with fixed chromosome length. As a result, the best achievable chromosome fitness is inherently limited by the fixed chromosome length. Comparing with the above mentioned work, the FRRMS integrates fuzzy set concepts to traditional association rule mining, and its performance is better than that of tradition association rule mining approaches as it allows the planning for QA to be conducted at the parameter level. In addition, it also outperforms some existing FARM-based approaches, as proposed by Ho et al. (2008) and Lee, Ho at al. (2014), because the fuzzy association rules obtained in the FRRMS are optimized by a variable-length GA. Limitations caused by the fixed-length chromosome length can thus be eliminated.

Table 6.10 compares the FRRMS with the Kaisen quality management tool. In general, Kaisen signifies small improvements made in the status quo as a result of ongoing efforts. It is a process-oriented approach to solve problems in a rational way. In usual practice, suggestions for improvement are generated from workers and the number of suggestions is posted on a wall in the workplace in order to encourage competition among workers. It is expected that each suggestion, once implemented, leads to a revised quality standard. In Kaisen, when a quality problem occurs, the organization will check with the resources, such as machines, tools and workers, and find out the root cause. Elimination of waste is encouraged so as to ensure that all existing activities can add value to the organization. Standardization is also carried out for prevention of recurrence. It can be seen that the cycle time for conducting a Kaisen project is relatively long and is also dependent on the self-discipline of the workers.

Table 6. 10 – Comparison between Kaisen and the FRRMS

	Kaisen	FRRMS
Approach	Process-oriented	Parameter-oriented
Suggestion for quality improvement	Generated from workers	Generated based on historical data
Way of achieving ongoing improvement	Elimination of waste, and standardization	Adoption of learnt process parameters recursively
Cycle time	Longer	Shorter

On the other hand, the FRRMS designed in this research is a parameter-oriented approach for managing the product quality. Suggestions for quality improvement are generated through a series of mining procedures based on historical data. In particular, different combinations of parameters can be considered because of the variable-length sGA scheme. Once the hidden relationships between process parameters and the quality features are discovered, learnt process parameters are available for adoption in the actual production environment, achieving ongoing improvement. As the quality problems are analyzed quantitatively, followed by solutions determined by the FRRMS, the time for root cause identification is eliminated. As such, the time for QA with the use of the FRRMS is shorter than that of Kaisen. In any time-sensitive industry such as the garment industry, the FRRMS is a better choice for formulating QA strategies.

6.5 Summary

In this chapter, the results and discussion of the research are presented. Firstly, an overview of each module of the FRRMS is presented. The FARRM is compared with other existing fuzzy logic-based approaches and association rule mining-based approaches. The sGAOM is also tested with different parameter settings, followed by a comparison with sGA-FARM and GA-FARM, and the major findings of the two case studies are discussed. Improvement in product quality and production efficiency is confirmed. Finally, a number of implications for QA in the garment industry are presented.

Chapter 7 Conclusions

7.1 Summary of the Research

The garment industry has been in a transformation since the emergence of the fast fashion trend. For business survival, garment manufacturers are required to shorten their time to market and develop products which can meet the changing expectations of customers. This exerts a great pressure on the industry which needs to assure the quality of the products and to increase the production efficiency. Historical data related to production process parameters and the quality of the products thus provide important information for supporting process parameter determination with the resultant product quality taken into consideration. Nevertheless, only a small number of research studies have been reported investigating the discovery of this kind of knowledge with the use of DM techniques. Meanwhile, the capabilities of DM for quality management have still not been exploited in the garment industry.

Motivated by these issues, the aim of this research is to design and develop an intelligent system, with a newly-designed algorithm, i.e. sGA-FARM, and a fuzzy association rule mining approach, to overcome the challenges of demanding customers who seek high-quality products at fast fashion pace. The principle of the

FRRMS is developed to conduct recursive process mining analyses based on the historical production data, thereby discovering the hidden patterns among the process parameters and quality features. The knowledge discovered by the FRRMS is adopted as a set of decision rules for the formulation of effective QA schemes in the garment industry.

The extensions made in this research can be viewed at both the application and theoretical levels. At the application level, this research applies DM for QA in the garment industry. From the literature review, it is found that DM applications have not been observed in the garment industry. As a result, the research has made an extension by applying DM techniques for QA, focusing on the garment industry. At the theoretical level, this research designs a variable-length GA which is inspired by the biological slippage phenomenon in the DNA replication. This novel GA mechanism is also the first variable-length GA hybridized with fuzzy association rules. In view of this, the research has made an extension at the theoretical level by creating a novel GA mechanism, called the slippery GA, which can be hybridized with fuzzy association rules for optimization.

7.2 Contributions of the Research

This research proposes a generic methodology for the development of an intelligent system to provide knowledge support for QA in the garment industry. This allows the garment manufacturing companies to consider the resultant quality features while determining the process parameters to be used during production. The contributions of this research are summarized below.

(i) The FRRMS is developed as a new framework for the garment industry to discover the relationships between the production process parameters and quality features of the products. Through the hybridization of DM and AI tools, effective QA schemes supported by the FRRMS are parameter-oriented, providing clues for the operators to improve their determination of the production process parameters. The unique features of the FRRMS provide the garment industry with specific solutions in response to the increasing concerns about product quality, extending the concept of quality management at the parameter level.

(ii) The mining algorithm designed in the FRRMS is a recursive one because it allows its outputs to be returned to the mining procedures as new inputs. After the determined learnt process parameters, based on the knowledge supported by the FRRMS, are adopted in production, their relationships with the resultant product quality are again investigated through the algorithm. As a consequence, new knowledge is continually discovered. In particular, the decision rules are recursively challenged, revised and improved, supporting more effective QA strategies in the long run.

(iii) This research is a pioneering work in imitating and transcribing the biological slippage into a GA framework. The aim is to propose a new scheme involving the variable-length GA in order to overcome the limitations caused by fixed-length GAs to enable enhancement of the garment quality. In the FRRMS, a novel nature-inspired algorithm, sGA-FARM, is introduced to optimize a set of fuzzy association rules with variable lengths of chromosomes. It imitates the biological slippage phenomenon during DNA replication to enhance the search for superior solutions. The results show that the sGA-FARM can increase the diversity of solutions and discover knowledge more comprehensively thereby achieving better product quality. This is a significant contribution in applying the laws of nature for providing solutions to QA problems in the garment industry.

(iv) It is widely recognized that assuring the quality of garment products is a challenging task due to the error-prone nature of the garment manufacturing processes. There are limited technical applications currently used in the garment industry for assuring the quality of products. Comparing to other manufacturing industries, the technological capability of the garment industry is relatively low.

This research applies DM and fuzzy set theories to develop better products by considering the relationships between process parameters and quality features. The techniques embedded in the FRRMS increase the innovation and technological capability of the garment industry, encouraging more researchers to explore the possibilities of applying diverse DM or AI techniques for the garment industry.

(v) The FRRMS is successfully implemented in a garment manufacturing company. Based on the results obtained in the case studies, the overall production efficiency and product quality are improved. This confirms that the FRRMS proposed in this research is feasible in the actual garment manufacturing environment.

7.3 Scope of the Research

Despite the contributions made by this research in both academia and the garment industry, there are some limitations in the scope of this research, which are highlighted below.

(i) The two case studies in this research were conducted in the same garment manufacturing company. The selection of process parameters and the quality features were specifically tailor-made for the company. Though the company is well regarded as representative of the garment industry as a whole, review and modification may still be required before the system can be implemented in other garment manufacturing companies.

(ii) The relationships between the process parameters and the resultant quality features are discovered in terms of fuzzy association rules. They serve as knowledge support for the garment industry to assure better product quality. However, the determination of the appropriate process parameters still relies on the system users to some extent to analyze the rules mined, and to test and input different combinations of process parameters into the system for estimating the quality features. Therefore, extra investigation may be required to assist the users in their analysis.

(iii) In the FRRMS, the threshold values of the parameter support counts, the slippage rate, the crossover rate and the mutation rate are defined by trial-and-error approaches. To ensure the suitability of their definition, it could be a time-consuming task to have the system users determine the appropriate values of these parameters before a set of useful fuzzy association rules can be generated by the FRRMS. Hence, automatic methods for determining these values could be considered in order to avoid the trial-and-error approaches.

7.4 Suggestions for Future Work

The future research directions regarding the proposed algorithm and the system framework are suggested to further improve the overall capabilities of the system. They are summarized as follows.

(i) In the FARRM, the choice of membership functions of the parameters is based on subjective decision criteria and the initial values rely on trial and error approaches. In addition, the membership functions are assumed to be static. In view of these, particular learning methods, such as ANNs, should be incorporated to dynamically determine the optimal membership functions for the parameters so as to respond to the actual production environment.

(ii) In the sGA-FARM algorithm, each parameter has the same possibility of being inserted into or removed from the chromosomes. Considering that some parameters could have more significant impacts on the resultant quality features, weightings should be considered to give higher priorities to those parameters for being considered in the fuzzy association rules.

(iii) In reality, a process parameter setting is a crucial issue due to its great impact on the finished quality. Small changes of the process parameters are regarded as less complex, and manufacturers are always willing to minimize this complexity by reducing the number of process parameter settings in different departments and processes. However, in this research, the fitness function of the chromosomes in the sGAOM only considers the minimization of the variance between the actual and estimated quality features of the products. It is thus suggested that other factors such as the complexity of the process change should also be incorporated when evaluating the fitness of chromosomes.

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