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A RFID-based Resource Allocation System for garment manufacturing

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ABSTRACT

The emergence of fast changes in fashion has given rise to the need to shorten production cycle times in the garment industry. As effective usage of resources has significant effects on the productivity and efficiency of production operations, garment manufacturers are urged to utilize their resources effectively so as to meet dynamic customer demand. In usual practice, decision makers determine the required level of resources by evaluating technical requirements of garments, subjectively. Since their decision making processes involve concepts which are uncertain and vague, such as "long" and "short", an attempt is made in this paper to apply fuzzy logic for handling imprecise information for determining resource allocation plans. In addition, Radio Frequency Identification (RFID) technology is adopted to capture data which is useful for improving the intelligence associated with the fuzzy logic. This paper presents a RFID-based Resource Allocation System (RFID-RAS), integrating RFID technology and fuzzy logic concept for achieving better resource allocation with particular reference to garment manufacturing. To confirm the viability of the RFID-RAS, a case study is conducted in a Hong Kong-based garment manufacturing company to help manage its resource utilization. Results indicate that the RFID-RAS outperforms conventional approaches with improved effectiveness and efficiency in resource allocation.

1. Introduction

Resource management is always an important issue for all manufacturing sectors. Manufacturers are striking for better resource allocation not only to maximize profits, but also to reduce production cycle times. If insufficient resources are assigned to a particular activity, the entire cycle time will be lengthened. In contrast, if excessive resources are assigned, work in process (WIP) inventory will be increased, resulting in higher inventory costs. At the moment, with additional pressure brought about by a trend called fast fashion, garment manufacturers are being urged to achieve effective and efficient production resource allocation for their survival in the industry. Therefore, owing to the high intensities of both materials and machines involved in garment manufacturing, it is challenging for manufacturers to make decisions on resource allocation for each order, especially given the short response time in the light of the fast fashion trend. Critical decisions include the determination of the appropriate amount of both material and machinery resources. Fig. 1 shows the existing problems in resource allocation which are commonly found in the garment industry.

One of the most common problems faced by the industry is the reliance on experience when determining the number of machines needed. Conventionally, decision makers estimate the number of different types of machines needed by evaluating technical requirements of garment styles, such as the complexity of garments, the number of cutting pieces, the length of markers and the yardage yield of fabric per garment. However, justifications for these technical requirements heavily rely on human experience, causing bias easily to occur and production performance cannot be guaranteed as estimates vary from one decision maker to another.

In addition to machinery resources, sufficient material resources also have to be planned for production. However, in an actual production environment, material wastage due to damage to material or to material lost in factories is very common. In the existing approach in the garment industry, the quantities of materials purchased take certain levels of material wastage into account so that sufficient material resources are available for production. Unfortunately, there are no systematic approaches to determining the material wastage percentages for different types of materials. When the material wastage percentage is set too small, there is a need to re-order materials. Considering that many materials involved in garment manufacturing are "dyed to match", re-ordering of these materials may require another dying process of the materials, resulting in certain levels of quality discrepancies in term of colors of the final products. Therefore, sufficient amount of production material resources has to be determined not only to avoid material shortage, but also to ensure the quality of the final products.

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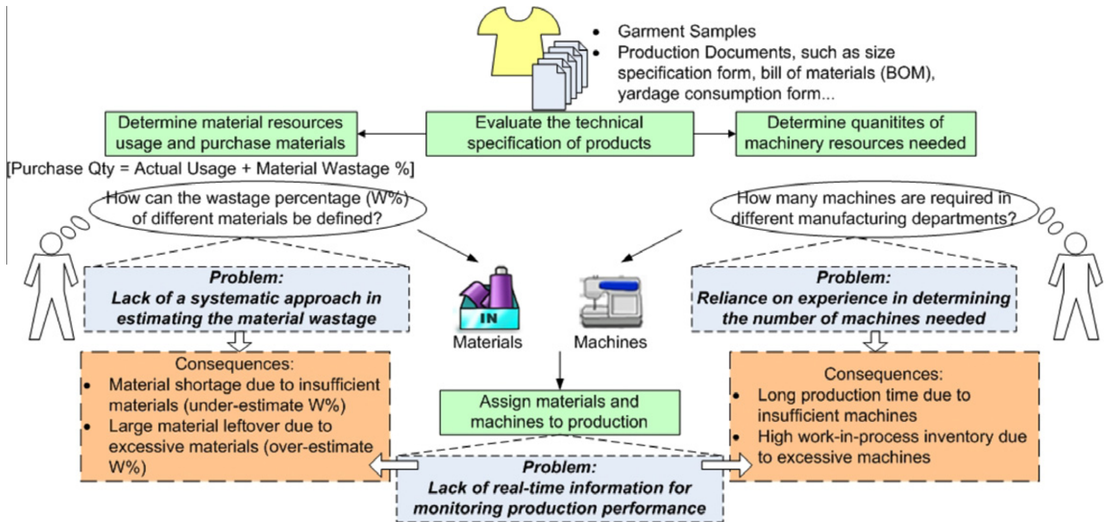


Fig. 1. Existing problems in resource allocation in the garment industry.

Furthermore, the garment industry is lacking real-time information to monitor the actual production performance. Without data, such as that captured by such tools as Radio Frequency Identification (RFID) technology, there is no timely information for manufacturers to keep track of production lines. Problems such as bottlenecks in production operations, which could be caused by excessive or idle machines, as well as material shortage due to high material wastage cannot be identified and solved promptly.

With the aim to solve the above problems, this paper presents a RFID-based Resource Allocation System (RFID-RAS). This integrates RFID technology and fuzzy logic for real-time data capturing and suggestions for machinery resource allocation plans. Actual material wastage is tracked regularly as this also serves as one of the critical considerations in the refinement of the human intelligence that is stored in the system.

This paper is organized as follows: Section 2 contains a literature review related to this study. In Section 3 the architecture of the RFID-RAS for the use in the garment industry is described. Section 4 contains a case study where the developed system was put to the test on a real data set. In Section 5 the result and discussion of the findings are presented. Finally, Section 6 contains the conclusion.

2. Literature review

Resource allocation is regarded as the assignment of appropriate resources to activities so as to obtain an optimal solution in an economic way (Ho, Ip, Lee, & Mou, 2012; Huang, Lu, & Duan, 2011; Lee & Lee, 2005). Effective resource allocation can improve production operations in terms of productivity and efficiency by providing efficient usage of limited resources while avoiding deadline delay (Bastos, Oliveira, & Oliveira, 2005; Hegazy, 1999; Huang et al., 2011). Therefore, manufacturers are attempting to achieve effective usage of resources to gain competitiveness in their industries. Considering the recent market changes, effective resource allocation is of great importance especially for the garment industry. Under the pressure brought by the trend of fast fashion, there is an urgent need for garment manufacturers to shorten lead times for getting new products into stores (Barnes & Greenwood, 2006; Bruce & Baly, 2006). Though effective resource allocation is one of the important criteria for responding to these market changes, it is a complicated task as garment manufacturing involves various machines, skilled labor and thousands of bundles of cut pieces for producing different styles simultaneously, while the specific machines involved in each workstation must be used in a restricted sequence (Chan, Hui, Yeung, & Ng, 1988; Gunesoglu & Meric, 2007). Unfortunately, traditional decision-making processes involved in resource allocation which heavily rely on human experience are time-consuming. In a time-sensitive industry such as the garment industry, any decision delay will lengthen the entire cycle time and cause a company to lose its competitiveness (Pan, Leung, Moon, & Yeung, 2009). Researchers have thus investigated the possibility of increasing the efficiency of the processes involved in garment manufacturing. However, it was found that they mainly focused on solving scheduling and line balancing problems in garment manufacturing (Chan et al., 1988; Wong, Chan, & Ip, 2000). Dessouky, Dessouky, and Verma (1998) aimed at solving the scheduling problems in garment manufacturing with the objective of minimizing the makespan of identical jobs on uniform parallel machines. Guo, Wong, Leung, Fan, and Chan (2006) presented a mathematical model to minimize the total penalties of earliness and tardiness by determining the production start date and the operator assignment method. Wong et al. (2000) focused on the scheduling problem in the operations of fabric spreading and cutting during garment manufacturing. Researchers rarely evaluated the decision making process used for determining the required level of resources for garment manufacturing operations for achieving better resource allocation.

In addition to this, researchers have adopted different AI and data mining techniques, such as clustering algorithms, case-based reasoning (CBR), genetic algorithms (GA) and fuzzy logic, as well as hybrid AI approaches to solve resource allocation problems. Elango, Nachiappan, and Tiwari (2011) attempted to solve balanced multi-robot task allocation problems using the k-means clustering technique to group tasks into clusters so as to minimize the distance in time between tasks. Ho et al. (2012) proposed a GA-based k-means clustering algorithm to classify customers into groups which serves as a point of reference for decision-making in resource allocation. Lam, Choy, Ho, and Chung (2012) developed a hybrid system using GA-based clustering and CBR to suggest resource allocation for cross-border orders in warehouses. Chow, Choy, Lee, and Lau (2006) and Poon et al. (2009) applied CBR for allocating resources for handling warehouse operations orders by retrieving similar past cases. Dai and Wang (2006) used GA to find an optimal solution for allocating resources to different nodes so as to maximize service reliability of grid computer systems. Wang and Lin (2007) applied GA to schedule the order completion dates as close to the customer due dates as possible and used fuzzy logic to guide the resource allocation of each order. Jiang, Cui, and Chen (2009) proposed a dynamic resource selection strategy in a service grid using fuzzy logic. While these techniques are capable of providing decision support in resource allocation processes, only fuzzy logic approaches have the ability to deal with uncertainties which are commonly found in actual industrial situations. In the context of determining the number of machinery resources required in garment manufacturing, justification of technical specifications of garments in human mind are often expressed in linguistic terms such as "long" and "short" that are inherently subjective and imprecise. This makes fuzzy logic an appropriate candidate to provide better solutions to the machinery resource allocation problem.

Fuzzy logic is an effective tool 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, Chen, & Xu, 2006; Novák, 2012; Ordoobadi, 2009). It mimics human decision making by performing approximate reasoning with linguistic terms so to as generate solutions (Liu & Lai, 2009; Wong & Lai, 2011). Judgments in human minds are 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, Ibrahim, & Lochert, 2008). Each of the fuzzy sets is associated with a membership function which allows variables to carry a degree of membership in a fuzzy set within a range between 0 and 1 (Azadeganm, Porobic, Ghazinoory, Samouei, & Kheirkhah, 2011; Otero & Otero, 2012). There are three main components in a fuzzy system; they are (i) fuzzification, (ii) inference engine and (iii) defuzzification (Lau, Cheng, Lee, & Ho, 2008). Fuzzification is responsible for converting crisp input values into fuzzy sets. These fuzzy sets are then input into an inference engine for converting 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. Since decision making in manufacturing always requires the consideration of various uncertainties (Azadeganm et al., 2011; Petrovic & Duenas, 2006), fuzzy logic is a popular decision support tool in manufacturing. Petrovic and Duenas (2006) proposed a fuzzy logic based decision support system to solve production scheduling problems in the presence of uncertain disruptions. Suhail and Khan (2009) adopted fuzzy logic to determine the number of machines to be assigned to production systems so as to achieve low WIP inventory level and no stockouts.

However, those systems lack any mechanisms for tuning the associated knowledge used for decision making. The fuzzy inference engine searches for patterns in the fuzzy rules that match the input patterns, proper tuning of the associated knowledge is thus important for allowing the systems to adapt to the changing environment (Tahera et al., 2008). Probably, a system which can provide real-time feedback on the fuzzy logic output is required for assuring the quality of the fuzzy rules. Radio Frequency Identification (RFID) technology which is able to capture, retain and transmit data about products on a real-time basis (Grüninger, Shapiro, Fox, & Weppner, 2010; Lao et al, 2012) is a probable solution. According to Ngai, Moon, Riggins, and Yi (2008), RFID technology has been applied in at least 14 different industries, including construction, fabric and clothing, food safety warranties, library services, logistics and supply chain management, and retailing. In particular, applications of RFID technology in the garment industry have mainly been confined to retailing such as customer

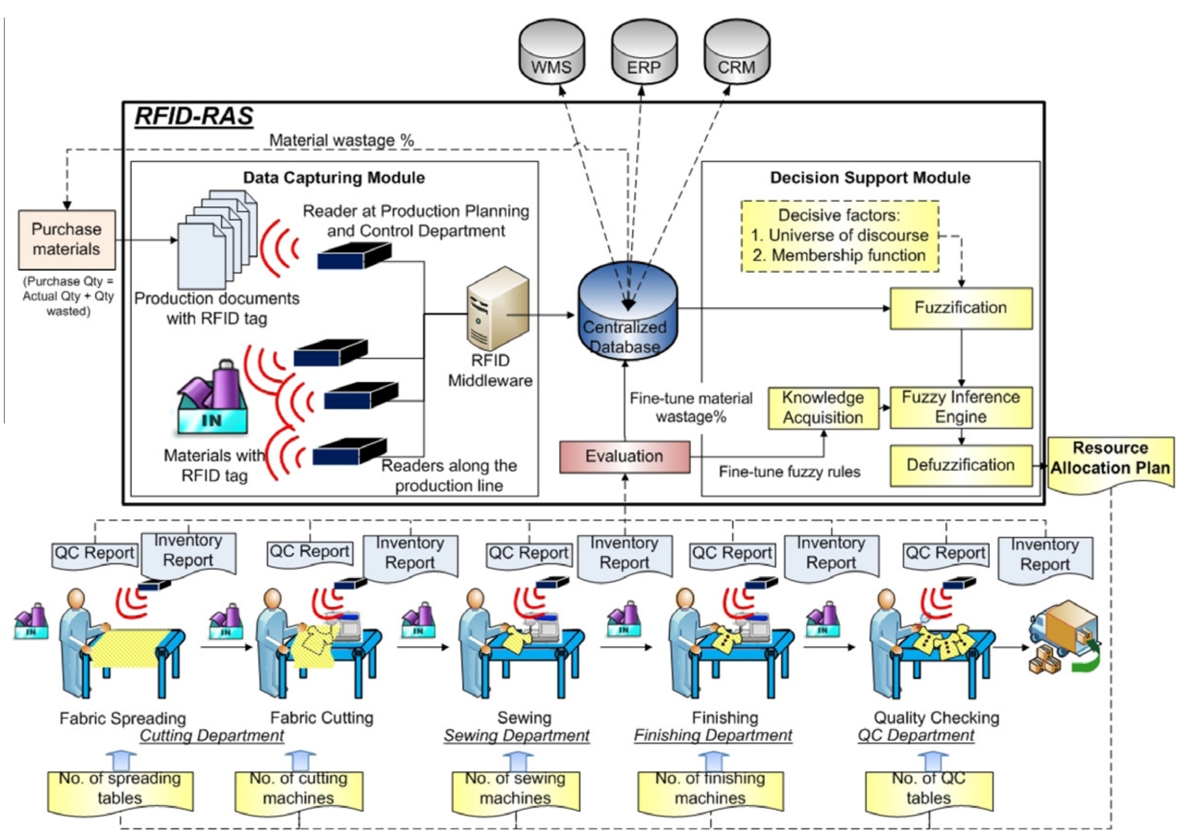


Fig. 2. RFID-based Resource Allocation System.

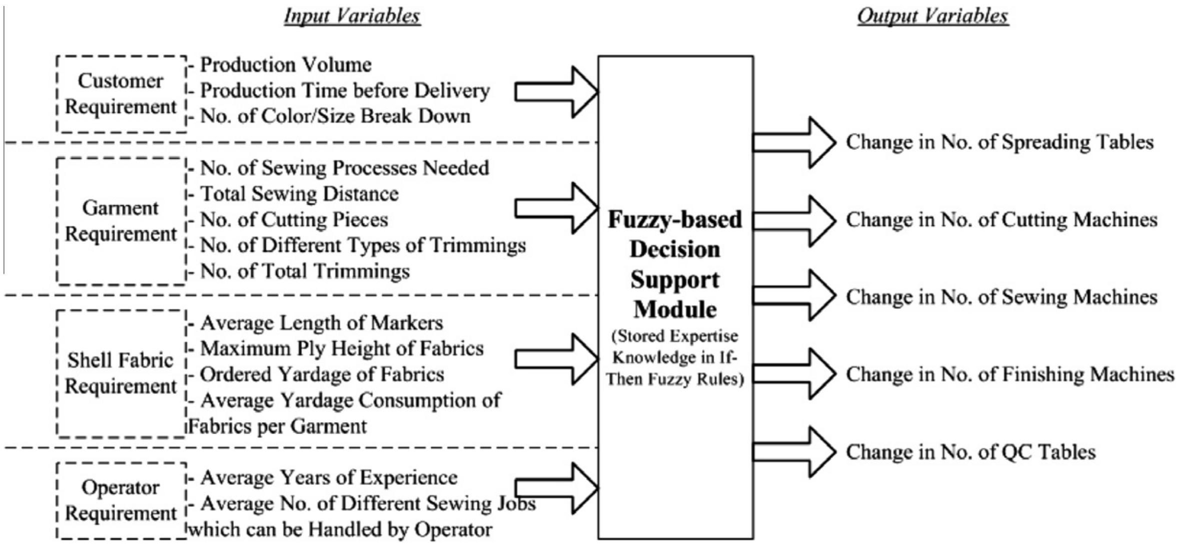


Fig. 3. Input and output variables of the fuzzy inference engine.

relationship management, shop floor management, marketing and promotion, and logistics and inventory management (Moon & Ngai, 2008). According to Ngai, Chau, Poon, and Chan (2012), many garment manufacturers still use paper tickets to manage their operations, causing their production to be invisible to management until the finished garments emerge. It is observed that RFID technology has not yet been widely adopted in manufacturing processes (Ngai et al., 2012). In addition, the real-time data capturing mechanism of the RFID technology rarely coordinates resource management processes of analyzing information, decision support, and knowledge sharing (Poon et al., 2009). Therefore, to help fill this gap, RFID technology is adopted in this paper for monitoring the production operations in garment manufacturing and the actual production performance visualized by the RFID technology will serve as a reference for fine-tuning resource allocation related knowledge associated with fuzzy logic.

After examining the characteristics of the decision making process in resource allocation in garment manufacturing, this study attempts to apply fuzzy logic approaches to machinery resource allocation problems in the garment industry. At the same time, it is observed that RFID technology has the ability to capture real-time data in garment manufacturing processes. Since the garment industry is a labor-intensive industry that is difficult to automate, this highlights a need to adopt RFID technology to keep track of production operations. Real-time information collected is used to perform proper tuning of the fuzzy rules for achieving better resource allocation.

3. RFID-based Resource Allocation System

In our study, the RFID-RAS is developed to help the garment industry achieve better resource allocation for production as shown in Fig. 2. It consists of two modules, namely (i) Data Capturing Module, and (ii) Decision Support Module, to perform the functions of capturing real-time data, and to suggest resource allocation plans, respectively. The Data Capturing Module encompasses RFID technology to capture production related data which are critical for resource planning and production monitoring. The captured information is stored in a centralized database which acts as a bridge between the two modules and is linked with other databases such as the Warehouse Management System (WMS), Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM). To allow data exchange from any databases, Extensible Makeup Language (XML) is used as the standardized format. When a query for resource allocation is input into the system, data are retrieved from the centralized database and transferred to Decision Support Module where fuzzy logic is applied for suggesting resource allocation plans. Input data are fuzzified to obtain fuzzy solutions according to the defined fuzzy rules. Because exact numerical values are preferred in an actual industrial environment, defuzzification is performed for converting the fuzzy solutions into numerical values, for instance, in the percentage change in the number of resources estimated. Evaluation of the fuzzy rules is performed regularly based on the information captured by RFID during production, quality check (QC) reports and inventory reports. With the information from the inventory reports, the actual material wastage percentage of each material is also notified and referred to in future material purchasing processes. Since both fuzzy rules and material wastage percentages are recursively refined to better ones, this provides the system with learning capabilities, so continuous improvement of resource allocation is thus achieved. The detailed functions of each module constituting the RFID-RAS are described as follows.

3.1. Data Capturing Module

This module adopts different RFID devices to capture relevant production data for resource planning and production monitoring. RFID tags are attached to production documents and to bundles of raw materials. When production documents are sent to the Production Planning and Control (PPC) Department, readers at the department detect signals from the tag, then relevant parameters which are useful for resource allocation such as production volume, production time and number of color/size breakdown are then retrieved from a centralized database to join the Decision Support Module. The centralized database allows the retrieval of related data as it is seamlessly integrated with other internal information systems such as WMS, ERP and CRM, using XML as the standardized data format for data exchange. On the other hand, raw materials for a production order which are previously bundled with RFID tags are sent to the production line for production. When readers, installed at each manufacturing department, detect signals from the material tags, this indicates that the materials have arrived at the corresponding department for production; visualizing the actual production operations. From the RFID signals, bottlenecks of production operations can also be identified. Using a RFID middleware, signals received from all the readers are transformed into meaningful information, which is then stored in the centralized database systematically. With the use of XML, information captured by the RFID is shared in real-time with other functional parties through the RFID-RAS.

3.2. Decision Support Module

This module is composed of an inference engine using fuzzy logic to generate resource allocation plans for garment manufacturing. The input and output variables of the fuzzy inference engine are depicted in Fig. 3. Input variables which are retrieved from the centralized database include data related to the requirements of customers, garments, shell fabrics and operators. In order to convert the input variables into fuzzy sets, two decisive factors, namely the universe discourse and the membership function, are previously specified by domain experts. Membership functions are set according to the characteristics of input variables and give the degree of membership for each element of the universe of discourse. They allow the conversion of any possible numeric input variables into natural language. Such fuzzy sets are then input into the inference engine to generate output fuzzy sets by matching the fuzzy input and fuzzy output variables using "IF–THEN" fuzzy rules which are previously defined through knowledge acquisition. Output fuzzy sets are finally converted into numerical values through defuzzification. Output numerical values such as changes in the numbers of spreading tables and cutting machines are then referred to when assigning resources for production.

Continuous improvement in resource allocation is achieved by recursively challenging the fuzzy rules in the Decision Support Module and replacing them with better ones based on the actual production performance. Based on the information captured by RFID devices during production, inventory reports and QC reports, resource allocation plans are evaluated. If the evaluation result contains discrepancies with the expected result in terms on production progress, material wastages and the quality of products, there is a need to refine the corresponding resource allocation plan by adjusting the stored fuzzy rules for decision making. From the inventory reports, the actual material wastage percentages are also reflected and will be taken into consideration in future material purchasing processes.

4. Case study

4.1. Company background

The viability of the proposed framework of the RFID-RAS was evaluated by means of a case study in which the RFID-RAS was developed and implemented in a Hong Kong-based garment manufacturing company. With eight subsidiaries and seven joint ventures in China, the case company is one of the largest garment manufacturing companies in China. The company, founded in 1977, 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 is also expert in making silk garments as well as producing different types of fabric such as linen, cotton, wool and synthetic fibers. However, the profitability of the company 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,

Fig. 4a. Fabric spreading operation.

Fig. 4b. Fabric cutting operation.

Fig. 4c. Sewing operation.

companies not only have to guarantee the quality of finished garments, but also deliver the garments as fast as possible. These industrial changes have made the business environment in which the case company operates a tougher one. In addition, owing to China's becoming a member of the World Trade Organization, 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 operation efficiency so as to remain competitive in the industry. Facing the challenges in the market, the company decided to have a pilot run of the RFID-RAS in one of its manufacturing plants located in Shenzhen, China, in an attempt to solve the existing problems which are described in the next section.

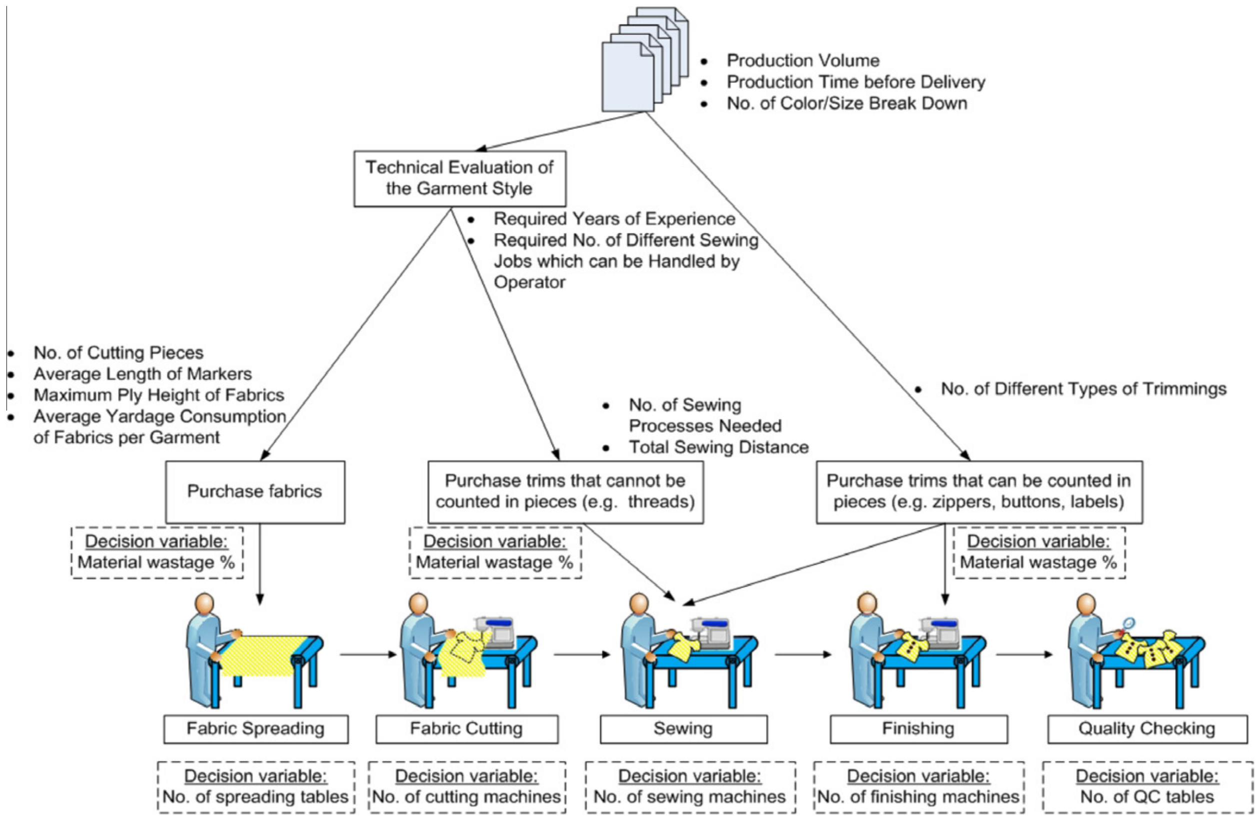


Fig. 5. Existing workflow of resource allocation in the case company.

4.2. Existing problems faced by the company

The company is currently facing the following problems.

4.2.1. Low visibility of actual production operations

The company is now lacking real-time data for keeping track of production operations, some of which are depicted in Fig. 4. Instead, it monitors production operations by manually recording the number of completed tasks in different production lines every hour. Since the actual production operations are not visualized on a real-time basis, the production manager frequently fails to identify the bottlenecks in the operations promptly. Problems arising during production such as unsatisfactory production progress due to insufficient resources, cannot be identified at an early stage.

4.2.2. Reliance on human experience in resource allocation

To estimate the resources needed for fulfilling production demand, decision makers in the company evaluate the requirements of the garments from the garment samples and from the production documents, such as the size specification forms and the technical packages provided by customers. Decisions are heavily reliant on the experience of particular individuals and are made without referring to actual production situations. Without a systematic approach to capturing the tacit knowledge of resource allocation from experienced staff, less experienced staff may not be able to make appropriate decisions and the company eventually loses the relevant knowledge.

4.2.3. Variance between expected and actual material wastages

The company estimates the amount of each production material required to be purchased by considering 1%, 2% or 5% material wastage, depending on the normal material amount listed in the bill of materials (BOM). For example, when the BOM quantity of a material is not more than 500, 5% material wastage will be applied. Therefore, in this case, the company will purchase 25 pieces of the material more than the amount listed in the BOM. After materials have been purchased and sent for production, there is no feedback mechanism for detecting the actual material wastage of each material and verify the percentages used. Therefore, the company usually suffers from material shortage when the actual material wastage percentage is higher than expected, and a large amount of material is left over when the actual material wastage percentage is lower than expected.

4.3. Existing workflow of resource allocation in the company

Prior to the implementation of the system in the case company, the existing workflow of resource allocation in the company is studied as shown in Fig. 5. Input parameters and decision variables involved in resource allocation are identified and serve as the inputs and outputs of the fuzzy-based Decision Support Module. Input parameters such as the production volume, production time before delivery, the number of color/size breakdown and the number of different types of trimmings can be collected from production documents. After that, materials such as zippers, buttons and labels that can be counted from the garments easily are firstly purchased according to the BOM quantities, and include the material wastage percentages. On the other hand, considering that the consumption of some materials, including threads and fabrics, cannot be easily verified from the BOM, technical evaluation of the garment style is performed so as to determine the actual material usage per garment. Through the technical evaluation process, important input parameters such as the number of sewing processes, total sewing distance as well as the length of markers are generated. It is found that, in addition to the actual material usage per garment, material wastage percentages have to be decided when purchasing. This can

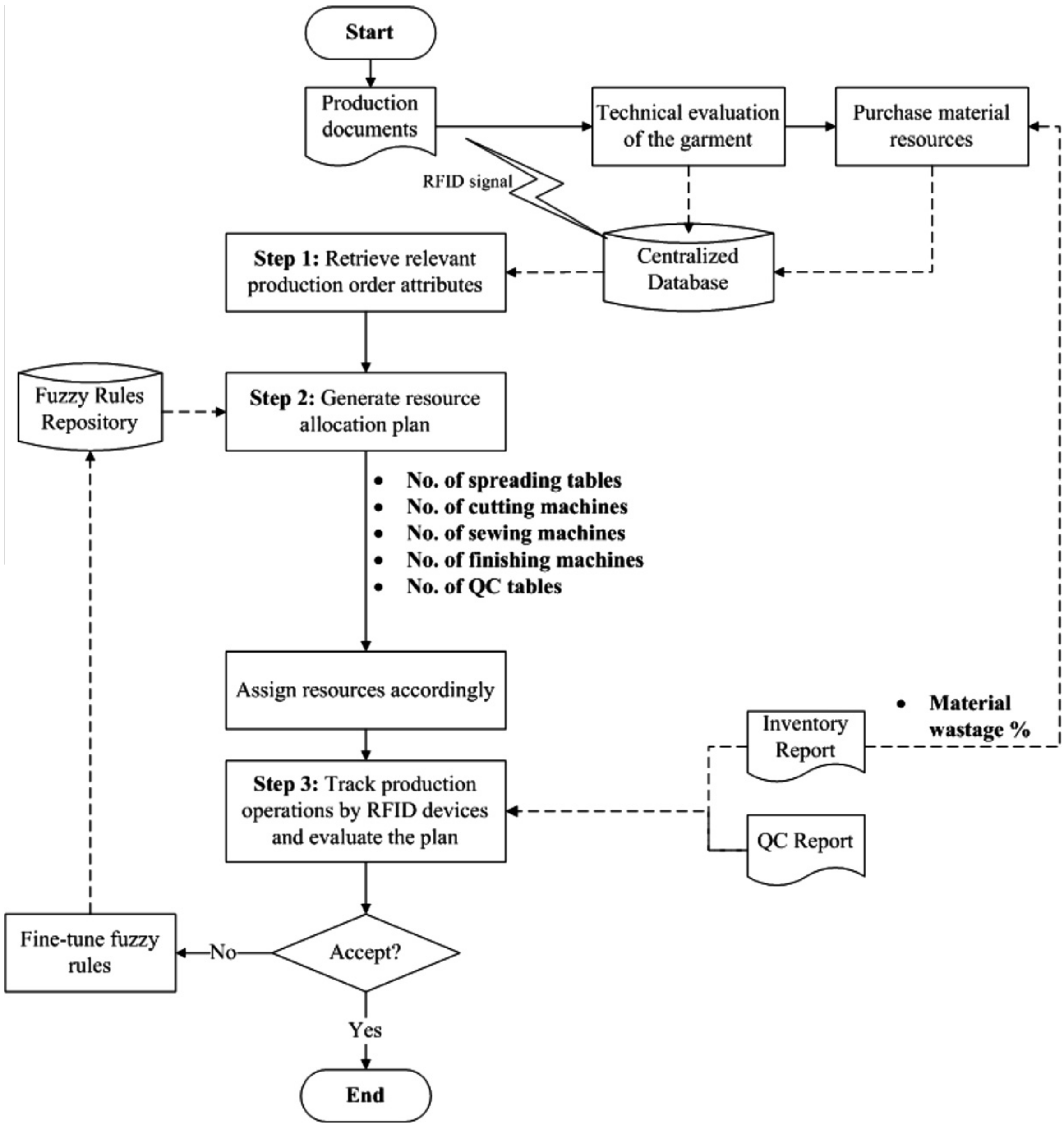


Fig. 6. Operation flow of the RFID-RAS.

guarantee that sufficient materials are available for production even if some of the materials are wasted due to material damages or material lost during production. Finally, with reference to all these input parameters, a resource allocation plan is generated by determining the required number of spreading tables, cutting machines, sewing machines, finishing machines and the QC tables.

It is observed that decisions involved in resource allocation heavily rely on the experience of individual decision makers. They are made without any objective knowledge support and thus their quality cannot be guaranteed. This highlights a need to develop an intelligent system to provide decision support in resource allocation. With the use of the proposed system, it is expected that the decision variables can be determined in a shorter timeframe and decisions will be of better quality.

4.4. Implementation of the RFID-RAS

After the identification of both input parameters and decision variables, the RFID-RAS is constructed and implemented in the company. As shown in Fig. 6, the operation flow of the RFID-RAS involves three main steps. It starts with the retrieval of relevant order attributes for generating resource allocation suggestions based on the stored fuzzy rules. Evaluation of the plan is carried out by tracking the production operations and referring to the inventory reports and QC reports. The fuzzy rules are adjusted if necessary, for improving the resource allocation plans. Details of each step in the operation flow are described as follows.

4.4.1. Step 1: Retrieve relevant production order attributes

Relevant production order attributes collected from technical evaluations and material purchase processes are initially stored in the centralized database. When the production documents with a RFID tag arrives at PPC department, the RFID reader at the department identifies the production order and the RFID signals induce the system to extract all the relevant order attributes which are helpful for making resource allocation decisions from the database. Fig. 7 shows the data input interface of the RFID-RAS. Users are able to view the retrieved attributes and send them to generate a

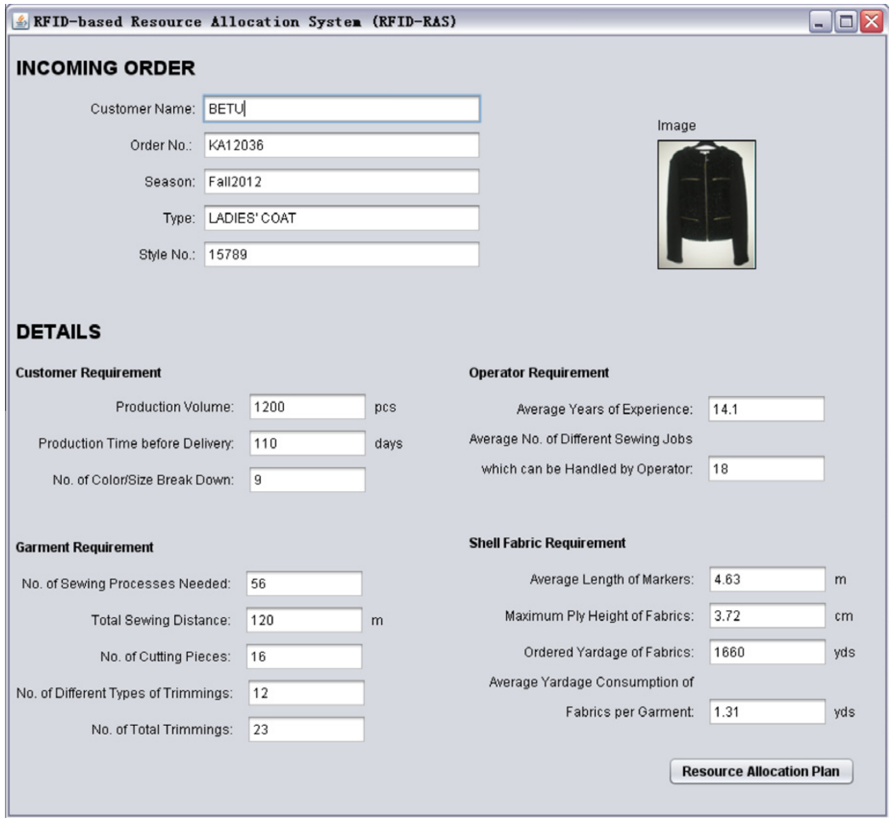


Fig. 7. Data input interface of the RFID-RAS.

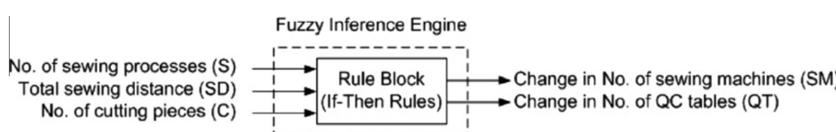


Fig. 8. Input and outputs variables of the fuzzy inference engine for resource allocation used for illustration.

resource allocation plan by clicking the "Resource Allocation Plan" button.

4.4.2. Step 2: Generate resource allocation plan

This is the core function of the Decision Support Module of the RFID-RAS where fuzzy logic is adopted to generate resource allocation plans. In order to demonstrate how fuzzy logic is used for resource allocation, three inputs, the number of sewing processes (S), total sewing distance (SD) and the number of cutting pieces (C), and two outputs, change in number of sewing machines (SM) and change in number of QC tables (QT), of the fuzzy logic model are selected for illustration as shown in Fig. 8. Fuzzy sets and membership functions associated with each variable are shown in Table 1.

Given that the input crisp values of S, SD and C are 81, 114.2 and 49, respectively, the resultant membership values of input fuzzy sets are then calculated as shown in Fig. 9. When the number of sewing processes is 81, it has a membership value of 0.14 to Large and 0.86 to Very Large. When the total sewing distance is 114.2 m, it has a membership value of 0.28 to Normal and 0.72 to Long. When the number of cutting pieces is 49, it has a membership value of 0.1 to Large and 0.9 to Very Large.

After membership values are determined, fuzzy rules stored in the inference engine are referred to. In the rule-firing process, rules are displayed in a rule block format as shown in Fig. 10 for the ease of search. Examples of some fuzzy rules in the rule block format are shown in Fig. 11. Four of the successfully fired rules are extracted for calculating the crisp values of the output parameters to illustrate this.

The composite membership value in each rule is the minimum of the memberships of input fuzzy sets. Therefore, the composite membership of Rule 1 is the minimum values of 0.14, 0.72 and 0.9 which is 0.14. Similarly, the composite memberships of Rule 2, 3 and 4 are 0.1, 0.1 and 0.28, respectively. These values are then used to determine the consequent fuzzy region, a region that is a combination of the individual fuzzy regions in each rule, of each output fuzzy set as shown in Fig. 12. In order to convert output fuzzy sets into crisp values, the center of area method is selected due to its simplicity and ease of use. The method returns the center of area (Y) of the consequent fuzzy region by the Eq. (1):

$$Y = \frac{\sum_{j=1}^{N} w_j \overline{C_j A_j}}{\sum_{j=1}^{N} w_j \overline{A_j}} \quad (1)$$

where w, C and A denote the weight, center of gravity and area of the individual fuzzy region of rule j, respectively. According to the equation, the center of areas of the consequent fuzzy regions of SM and QT are +53.29 and +22.04, respectively. Therefore, in the illustration example, the fuzzy logic approach suggests manufacturers to increase the number of sewing machines and QC tables by 53.29% and 22.04%, respectively.

In the RFID-RAS, Fuzzy Logic Toolbox of Matlab was employed to compute the output values given the different input values retrieved in Step 1. With all the input parameters sent to Fuzzy Logic Toolbox of Matlab for determining the resource allocation plan, the result is displayed in the data output interface of the RFID-RAS as shown in Fig. 13. The result shows that the company is recommended to increase the numbers of spreading tables, cutting machines, sewing machines and finishing machines by 13.5%, 33.4%, 29.1% and 41.4%, respectively, while at the same time to decrease the number of QC tables by 22%. Users are allowed to study the rule viewer and the surface plot generated by the Fuzzy logic Toolbox by clicking the "Rule Viewer" and "Surface Plot" buttons, respectively. The rule viewer, as shown in Fig. 14, shows the fuzzy regions of input and output variables in each rule. It allows users to view how each rule impacts the final output values. In addition, Fig. 15 shows some examples of output surface plots given by two input variables 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.

Based on the resource allocation plan generated, the number of different resources required is determined and assigned to the corresponding manufacturing departments.

Table 1
Fuzzy sets and membership functions of input and output variables.

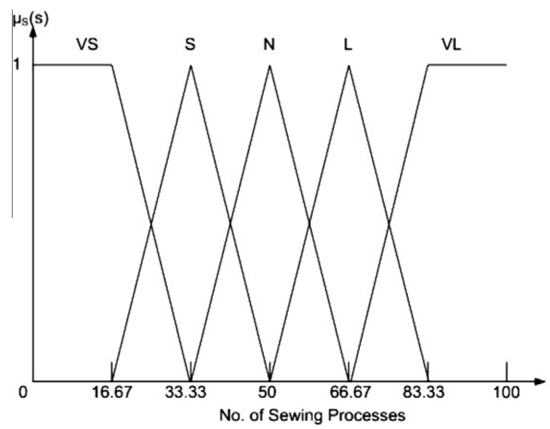
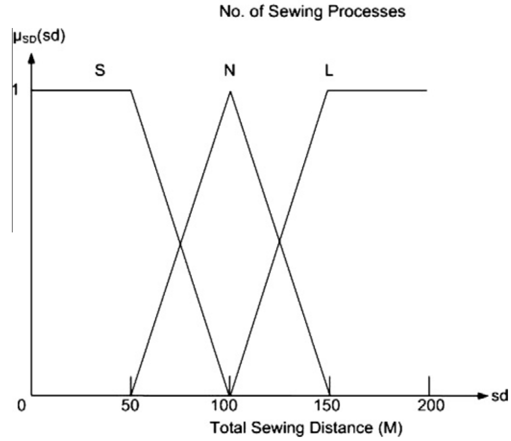
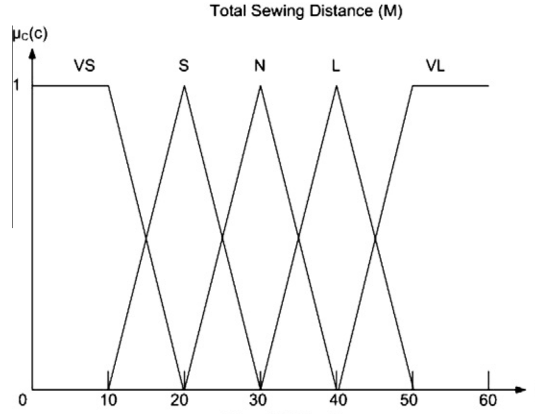
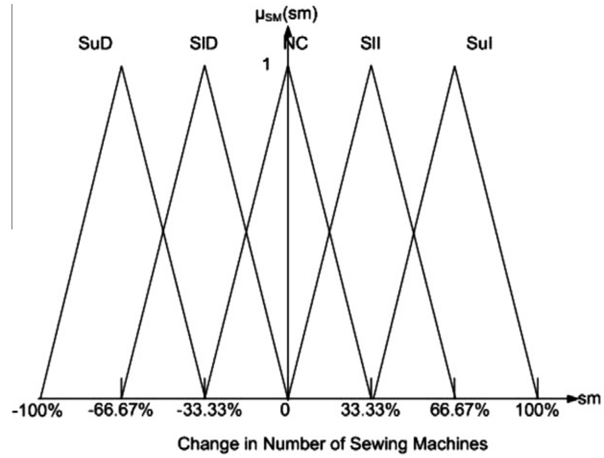
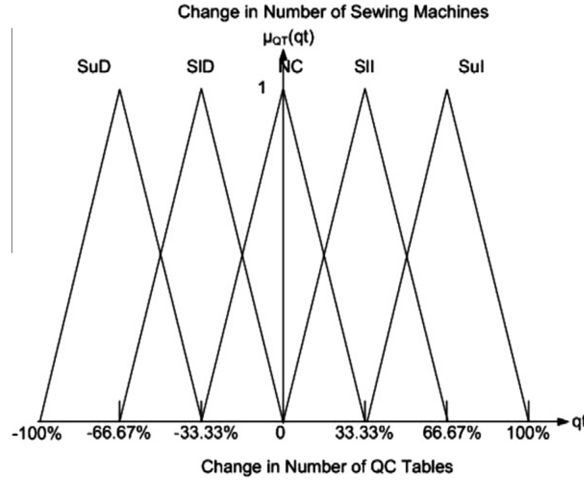
Variable	Fuzzy set	Membership function
Input		
No. of sewing processes (S)	S = {VS, S, N, L, VL} where VS is very small, S is small, N is normal, L is large and VL is very large	
Total sewing distance (SD)	SD = {S, N, L} where S is short, N is normal, L is long	
No. of cutting pieces (C)	C = {VS, S, N, L, VL} where VS is very small, S is small, N is normal, L is large and VL is very large	

Table 1 (*continued*)

Variable	Fuzzy set	Membership function
Output		
Change in No. of sewing machines (SM)	SM = {SuD, SlD, NC, SlI, SuI} where SuD is substantially decreased, SlD is slightly decreased, NC is no change, SlI is slightly increased and SuI is substantially increased	
Change in No. of QC tables (QT)	QT = {SuD, SlD, NC, SlI, SuI} where SuD is substantially decreased, SlD is slightly decreased, NC is no change, SlI is slightly increased and SuI is substantially increased	

4.4.3. Step 3: Track production operations using RFID devices and evaluate the plan

In each manufacturing department, RFID devices are installed to detect tag signals from materials which are bundled with RFID tags, and are sent to manufacturing departments for production. With this physical setting, the movements of materials representing the production progress are visualized in real time. The company is able to identify any bottleneck in production operations which could be due to there being insufficient resources. Using this information captured by RFID devices, the company evaluates the effectiveness of the existing resource allocation plans.

The evaluation of resource allocation plans is based on three sources of information: (i) real-time feedback on production performance based on the information captured by the RFID devices, (ii) QC reports in manufacturing departments generated during production, and (iii) inventory reports recording the inflow and outflow of materials between manufacturing department and warehouses.

4.4.3.1. Real-time feedback on production performance based on the information captured by the RFID devices. By referring to the information captured from readers in every manufacturing department, the company is able to monitor production operations on a real-time basis and adjust resource allocation strategies if needed. When a relatively high percentage of materials remains in a particular department, this may indicate that the number of machines in that department may fail to meet the actual production demand. An increase in the number of corresponding machines may thus be needed. Such feedback is obtained by refining fuzzy rules so as to improve resource allocation plans generated by the RFID-RAS.

4.4.3.2. QC reports in manufacturing departments generated during production. The quality of the semi-products or final products created in each department reflects the appropriateness of the resource allocation plans, as some defects could be due to inaccurate estimation of the job complexity of the products, insufficient resources or the use of inappropriate resources. In such cases, adjustment of fuzzy rules is required to improve the resource allocation plans. For instance, increasing the number of resources is able to alleviate the defect rate by increasing the average processing time in each manufacturing task so that the workers have sufficient time to handle complicated tasks.

4.4.3.3. Inventory reports recording the inflow and outflow of materials between manufacturing departments and warehouses. Inflow and outflow of materials between manufacturing departments and warehouses recorded in inventory reports are important data for computing the actual quantity of materials handled in each department and the actual material wastage. When there is a discrepancy between the expected and actual material wastage, there is a need to refine the fuzzy rules so that an improved resource allocation plan can be suggested for handling the actual amount of materials. In view of that, the inventory reports are referred to in the evaluation process not only to compute the actual material

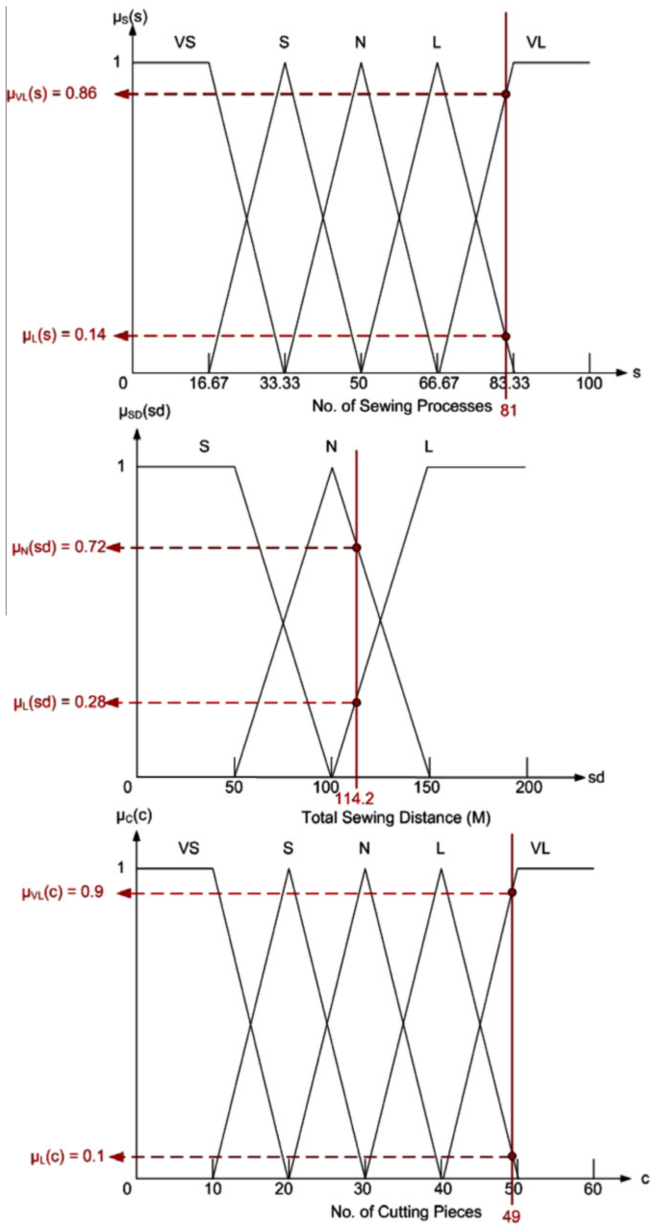


Fig. 9. Membership values of the input fuzzy sets S, SD and C.

	No. of Sewing Processes
	Total Sewing Distance
No. of Cutting Pieces	Change in No. of Sewing Machines / Change in No. of QC Tables

Fig. 10. Rule block format.

wastages which can be useful in the material purchasing processes, but also when revising the fuzzy rules to meet the actual production demand.

Fuzzy rules stored at the Fuzzy Logic Toolbox of Matlab can be adjusted by changing the fuzzy terms of the variables in each rule as shown in Fig. 16. An improved resource allocation plan can be obtained based on well-adjusted fuzzy rules.

5. Results and discussion

With the output from Fuzzy Logic Toolbox of Matlab, production resources parameters are determined and assigned to corresponding production operations. During a three-month trial and

	L		
	S	N	L
VS	SuD/SID	NC/SID	SII/NC
S	SuD/SID	NC/SID	SII/NC
N	NC/SID	NC/NC	SII/NC
L	SID/NC	SII/NC	SuI/NC
VL	SID/NC	SII/SII	SuI/SII

	VL		
	S	N	L
VS	SID/SID	NC/SID	SII/NC
S	SID/NC	NC/NC	SII/NC
N	NC/NC	SII/NC	SuI/NC
L	NC/NC	SII/NC	SuI/NC
VL	SII/NC	SuI/SII	SuI/SII

Rule 2
Rule 1
Rule 3
Rule 4

Fig. 11. Examples of the fuzzy rules.

error process, the fuzzy rules are recursively challenged and revised until better ones are obtained. The actual amount of materials wasted is also traced and recorded so that more accurate material wastage percentages of different types of materials can always be referred to when estimating the required amount of materials for future use in material purchasing. The improvements achieved by the use of the system are shown in Table 2. During the three-month period of time, there was a substantial growth in improvements as regards the reduction in average planning time per order, reduction in average material shortage per order, reduction in average material leftover per order, and an increase in average utilization rate of resources. This shows that continuous improvement of the system is achieved successfully by the regular refinement of the stored knowledge in the form of fuzzy rules.

Results show that the RFID-RAS outperforms conventional approaches in resource allocation by offering a series of benefits which include:

5.1. Higher efficiency in the resource allocation decision making process

With the adoption of RFID technology, orders arriving for production are notified in real-time. Relevant production information is then retrieved from the centralized database and automatically sent to the Decision Support Module where fuzzy logic is applied for resource planning. The average order planning time is reduced by 10.30% with the use of the system as time spent on human-driven activities such as manual consolidation of data from different production documents, data input, as well as analysis of data for resource allocation based on experience, is eliminated.

5.2. Reduced material shortage and material leftover

Inventory reports reviewed in the evaluation process record the actual material usage and wastage during production which serve as a good reference for planning material resources for production. In particular, the actual material wastage is traced and is used in the material purchasing processes. With more accurate material wastage estimation, an appropriate amount of material resources can be ordered. This can help reduce material shortage during production as well as the material left over after production. From Table 2, the average amounts of material shortage and material left over are reduced by 3.28% and 1.55%, respectively. It is hard to achieve 0% material shortage and 0% material leftover as there are other factors, in addition to poor material wastage estimation, affecting material wastage or material leftover such as the calculation of yardage consumption of fabrics per garment, material lost, material defects or damage. Therefore, though the reductions in average material shortage and material left over are not very high, the results are still satisfactory.

5.3. Higher effectiveness in production operations with better resource allocation

Before the launch of the RFID-RAS, the quantity of resources needed for production was determined on the basis of

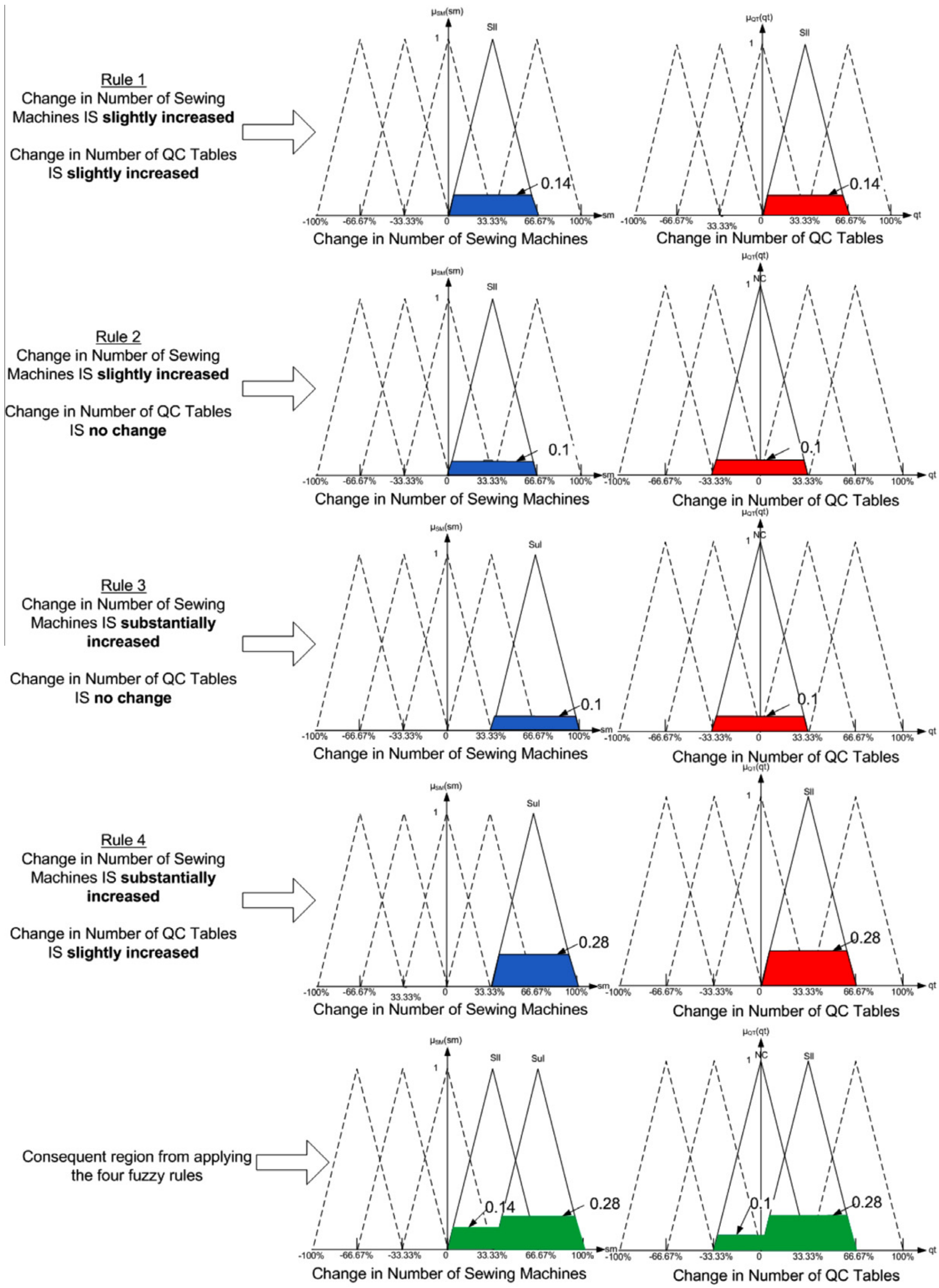


Fig. 12. Consequent fuzzy regions of output variables.

the experience of particular individuals. Bias could easily occur as different decision makers may have different judgments on problems. There were no standardized approaches to evaluating the effectiveness of their decisions. With the use of the RFID-FAS, the number of resources needed is determined according to the expert knowledge stored in the system. With proper knowledge acquisition for capturing and storing the relevant knowledge, the RFID-RAS is capable of providing objective and accurate decisions. In addition, with the use of RFID technology, production operations are tracked according to the movement of materials with RFID tags

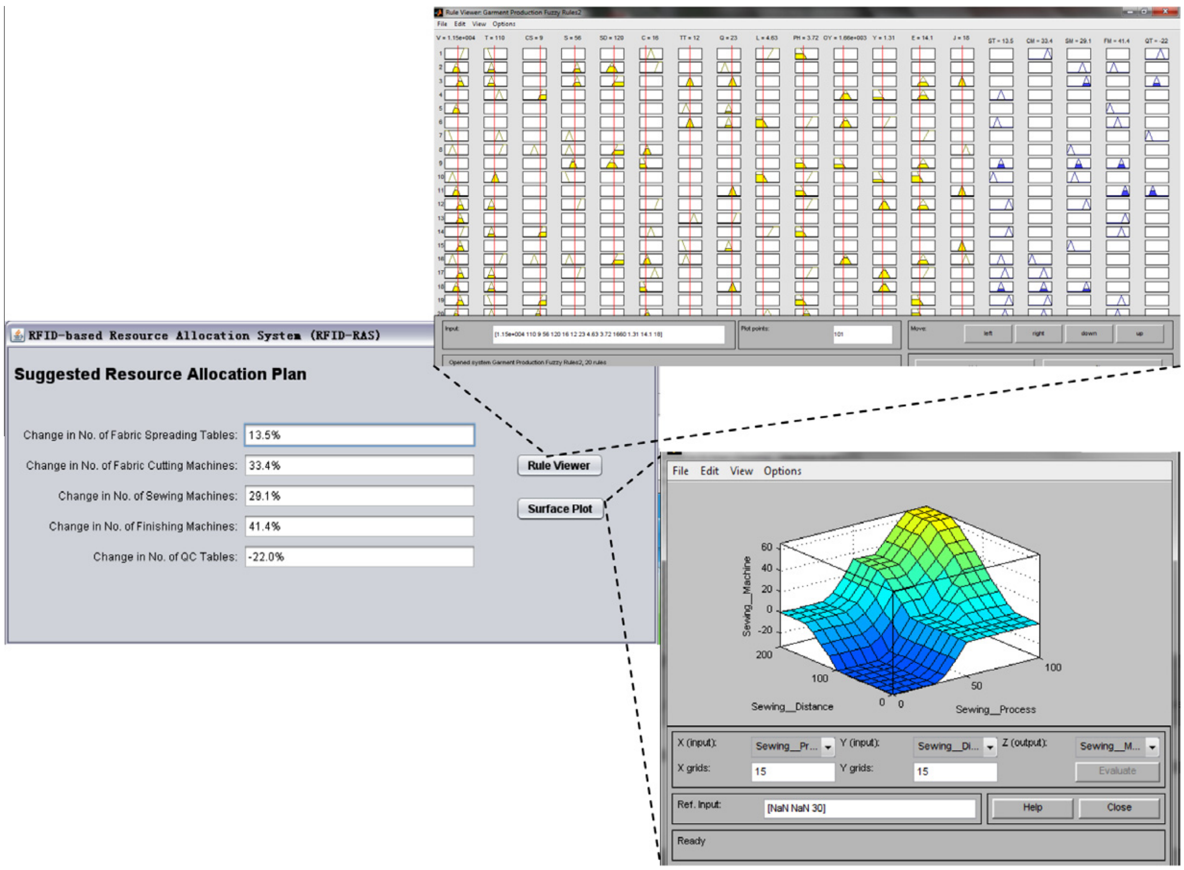


Fig. 13. Data output interface of the RFID-RAS.

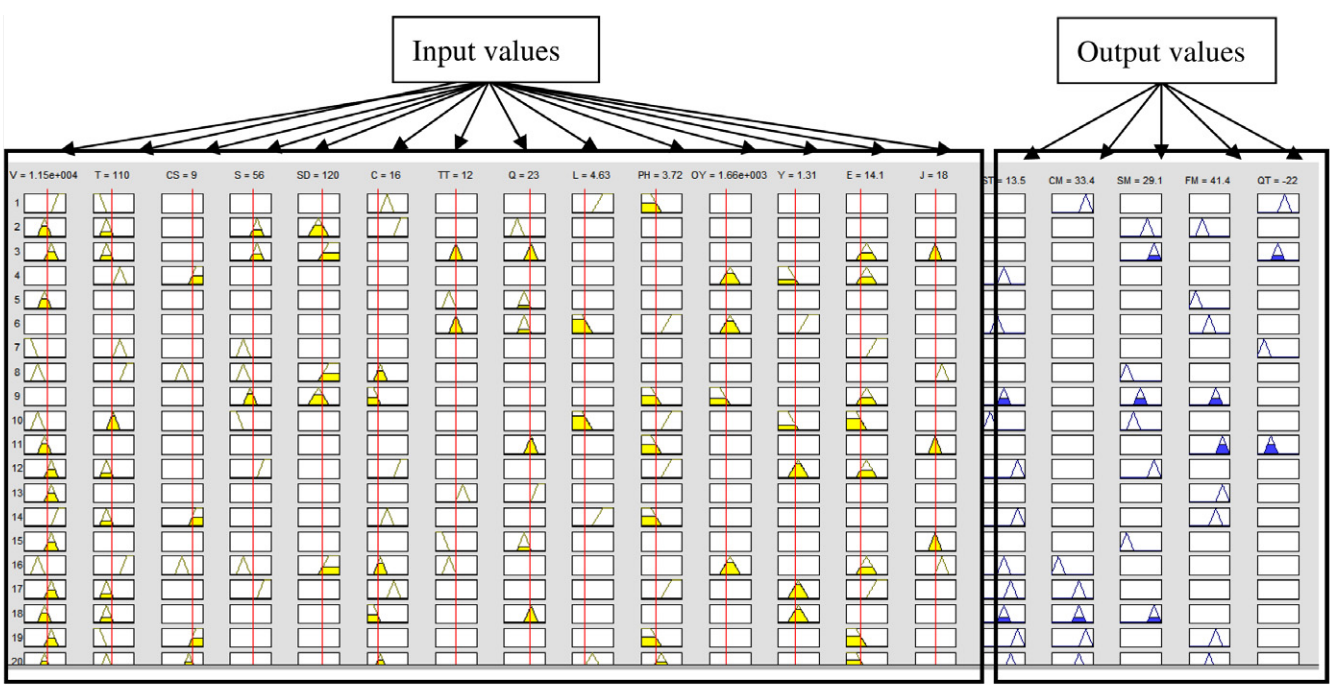


Fig. 14. Rule viewer generated by Fuzzy Logic Toolbox of Matlab.

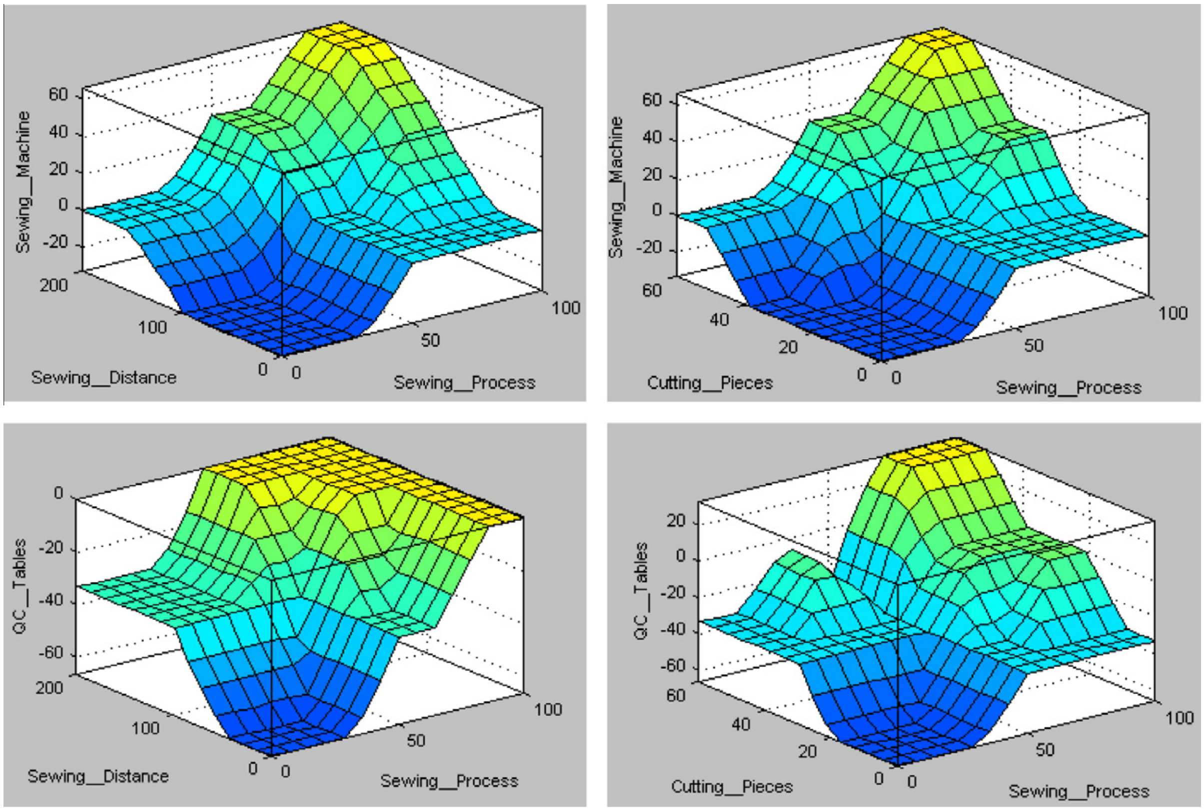


Fig. 15. Examples of output surface plots given by two input variables.

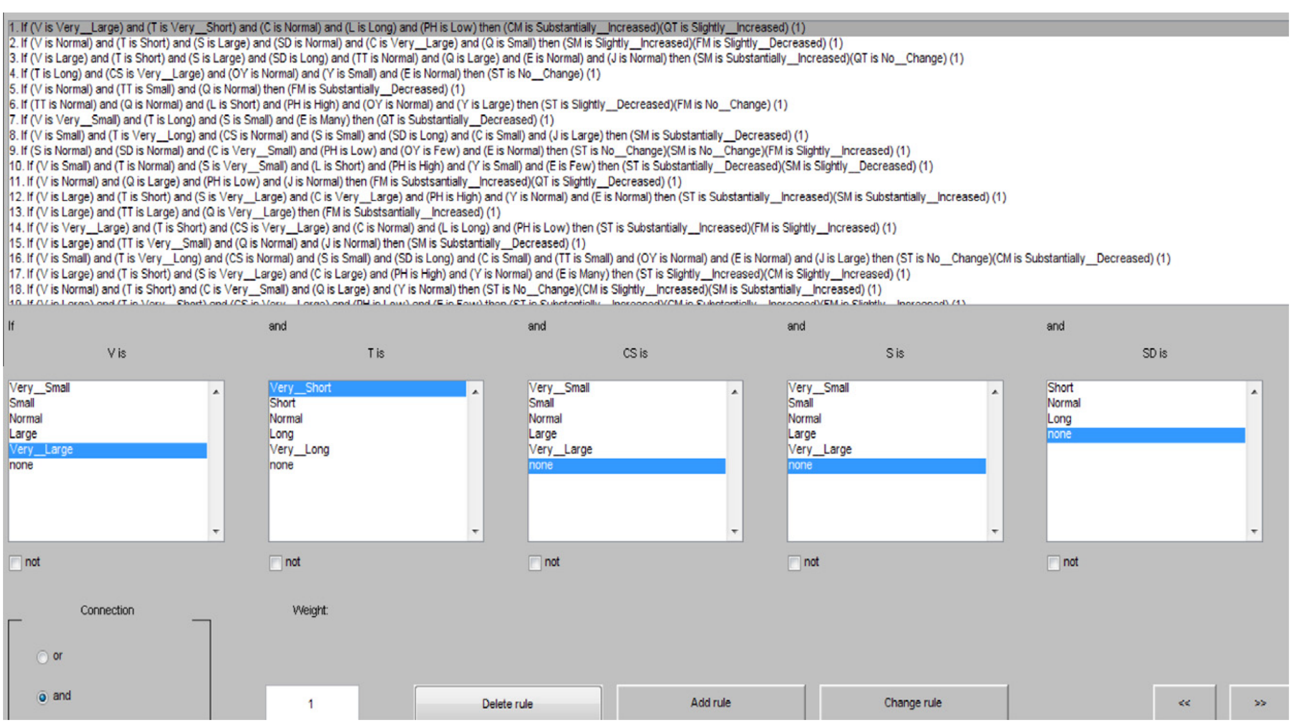


Fig. 16. Adjustment of fuzzy rules.

whenever they pass through the system for manufacturing. As a result, the company can identify production problems and refine the fuzzy rules accordingly so that a more effective resource allocation plan can be utilized for solving production problems. With regular refinement of the fuzzy rules during the three-month period of time, the effectiveness of resource allocation plans in terms of utilization rate of resources are increased by 4.36% on average.

Table 2
Improvements achieved by the use of the RFID-RAS.

Improvement	Without RFID-RAS	With RFID-RAS		
		1 Month	2 Months	3 Months
Reduction in average planning time per order (from order arrival to final decision made) (%)	0	5.11	8.57	10.30
Reduction in average material shortage per order (%)	0	1.46	2.07	3.28
Reduction in average material left over per order (%)	0	0.62	1.13	1.55
Increment in average utilization rate of resources per order (%)	0	1.83	2.74	4.36

6. Conclusion

This paper presents an intelligent system with the integration of RFID technology and fuzzy logic for providing decision support in resource allocation specifically for the garment manufacturing industry. The Fuzzy logic approach is used to determine resource allocation decisions using the knowledge of domain experts by employing a set of "IF–THEN" fuzzy rules. To accurately estimate resources needed for particular production orders, proper acquisition of relevant knowledge is important but is, as yet, difficult and challenging. To overcome this challenge, the proposed system applies RFID technology to capture data during production. Appropriate adjustments allow the knowledge stored in the system to be challenged, revised and improved recursively so that the system can adapt to rapid market changes. The system was developed and tested on real-world production data related to garments. Results show that it can significantly enhance operation efficiency by estimating the required quantities of appropriate resources for different tasks. There are two major contributions made by this study. First, fuzzy logic is adopted to compute the resources needed for garment manufacturing based on the requirements of customers, garments, fabrics and skill levels of operators. This study differs from many others in the literature in which fuzzy logic is commonly applied in the garment industry for determining process parameters such as initial setting of process mean and conducting hand evaluation of fabrics. It proves the possibility of applying fuzzy logic in providing decision support for achieving better resource allocation. Second, this study demonstrates the use of RFID technology in allowing continuous improvement of fuzzy-based decision support systems where the fuzzy rules can be refined based on actual production performance. This provides an implication to manufacturers who are interested in adopting RFID technology that RFID technology can be used not only to track production operations, but also to be integrated with other AI techniques so as to improve the associated human intelligence. While the discussion of this paper is confined to the garment industry, the methodology developed is also applicable to other industries. Future research will focus on hybridizing the proposed system with GA for determining optimal sets of the fuzzy rules as well as the associated membership functions.

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