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Application of intelligent data management in resource allocation for effective operation of manufacturing systems

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ABSTRACT

Resource allocation has been a critical issue in manufacturing. This paper presents an intelligent data management induced resource allocation system (RAS) which aims at providing effective and timely decision making for resource allocation. This sophisticated system is comprised of product materials, people, information, control and supporting function for the effectiveness in production. The said system incorporates a Database Management System (DBMS) and fuzzy logic to analyze data for intelligent decision making, and Radio Frequency Identification (RFID) for result verification. Numerical data from diverse sources are managed in the DBMS and used for resource allocation determination by using fuzzy logic. The output, representing the essential resources level for production, is then verified with reference to the resource utilization status captured by RFID. The effectiveness of the developed system is verified with a case study carried out in a Hong Kong-based garment manufacturing company. Results show that data gathering before resource allocation determination is more efficient with the use of developed system where the resource allocation decision parameters in the centralize database are effectively determined by using fuzzy logic. Decision makers such as production managers are allowed to determine resource allocation in a standardized approach in a more efficient way. The system also incorporates RFID with Artificial Intelligence techniques for result verification and knowledge refinement. Therefore, fuzzy logic results of resource allocation can be more responsive and adaptive to the actual production situation by refining the fuzzy rules with reference to the RFID-captured data.

1. Introduction

There are several important manufacturing industries in Hong Kong such as the electronics industry, the watches and clocks industry, the toy industry, and the garment industry. Though the economy of Hong Kong is now dominated by the service sector, the manufacturing sector still makes an important contribution to the economy as it generates substantial demand for inputs from the service sectors [1]. Owing to the need for higher efficiency, shorter product life cycle, better product quality and higher customer satisfaction, production planning plays a critical role in manufacturing [2,3]. Production usually involves the participation of more than one individual unit, each performing different functions in the overall production system [4]. Therefore, production planning problems involve determining the amount of resources to be assigned and allocated to all individual units so that each of them can complete its jobs. Effective resource allocation has been called a means to increase productivity by providing efficient usage of limited resources [5,6]. Thus, it is widely accepted as an important factor for gaining competitiveness in the dynamic market. This paper presents a resource allocation system (RAS) induced by an intelligent data management approach, with the aim to provide effective and timely decision making for operations related to resource allocation.

The rationale for selecting the Hong Kong garment industry for the verification of the RAS is that it is generally more time-sensitive than other manufacturing industries. Most of its manufacturing activities are geared to the needs of overseas markets [7], where there is currently a popular concept of "fast fashion" which aims to design and manufacture fashion products quickly and economically. An enhancement of the effectiveness and efficiency of the decision making processes involved in resource allocation is thus of great importance for survival in fast fashion.

This paper is organized as follows. Section 2 presents a literature review related to this study. Section 3 describes the architecture of

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the RAS. Section 4 presents a case study where the RAS is developed and implemented in a garment manufacturing company. Section 5 contains results and discussion of the system. Section 6 presents the conclusion and the future work.

2. Literature review

2.1. Resource allocation

Due to the intense competition in the global market, manufacturers who fail to efficiently allocate and utilize their resources will eventually lose their competitiveness [8]. Numerous benefits brought by effective resource allocation include efficient usage of resources, successful promotion of business performance, optimizing companies' objectives and achieving goals [6,9,10]. This has aroused the interest of many researchers who have investigated various approaches for resource allocation management, such as linear programming [11–13], simulation [14–16] and genetic algorithms [17–19]. However, these approaches no longer meet the challenges in today's manufacturing industries. Firstly, with the increasing technological innovation, the market demand is more unpredictable and the product life cycle has been reduced [20–23]. Existing approaches the operation of which is based on historical data or estimations are not flexible enough to deal with the increasingly dynamic market. Besides, more product options have to be given to customers resulting from mass customization [24], thus increasing the scale and complexity of resource allocation problems in production. However, such large-scale resource allocation problems are often mathematically intractable [25] which make current mathematical approaches not suitable, while other approaches like simulation can only cover a limited number of conditions [26]. Thirdly, conventional quantitative approaches may not be capable of dealing with the actual resource allocation problems in industrial manufacturing environments where most decisions inherently face imprecision and uncertainties [27–29]. Owing to the above highlighted reasons, a more sophisticated approach in resource allocation is a necessity for the survival in the manufacturing sector.

2.2. Fuzzy logic and DBMS

In manufacturing, uncertainties or vagueness could arise from market demand, capacity availability, process times, and costs [30,31]. It is more convenient for the management or decision makers to use subjective judgment and linguistic terms such as "high" and "very high" to describe imprecision [32–35]. Fuzzy logic, one of the Artificial Intelligence (AI) techniques, is a good candidate to deal with uncertain and vague manufacturing variables [36–38]. Fuzzy sets are used to represent linguistic terms and to develop relationships between input and output variables [39–41]. Therefore, many researchers have applied fuzzy logic to solve production planning problems in which linguistic terms are very effective in decision making. Díaz et al. [42] incorporated fuzzy approaches to manage the production priority in roll shop departments in the steel industry. Petrovic and Duenas [43] presented a fuzzy logic based system for production scheduling in the presence of uncertain disruptions. As scheduling involves the allocation of resources to tasks in order to complete those tasks within a reasonable amount of time [16,44,45], many resource allocation problems are addressed during the investigation of production scheduling. There has also been extensive discussion in the literature about the applications of fuzzy logic in manufacturing industries.

To improve information retrieval, fuzzy logic or fuzzy set theory has been introduced into databases for several decades [46]. This involves the concept of Database Management System (DBMS) which is a complex multi-attribute tool used for data processing and supporting different types of business applications with the use of a database [47,48]. Morales et al. [49] proposed a system which stores information in a DBMS that can support the mechanism of fuzzy set theory. Rodrigue et al. [50] designed a fuzzy database which stores imprecise information in a DBMS. In a similar vein, Zhang et al. [51] included both fuzzy and non-fuzzy attributes in their fuzzy databases. While fuzzy data can be handled and managed in a database, the database can also act as a fact-base and so the fuzzy system searches the database when a fact is required [52]. However, there are no standardized approaches incorporating fuzzy logic and DBMS for handling vague decision variables in resource allocation.

There are three different approaches for a fuzzy system to interact with a DBMS [52]. The first one is to incorporate extended data management facilities into the fuzzy system while the second one is to embed deductive rules into DBMS resulting in an intelligent database. The third one is to have both the fuzzy system and DBMS as independent systems with some form of communication between them. Considering that it may not be always practical to construct a new DBMS before one can use it, the third interaction approach is more applicable for designing a generic system for resource allocation as it allows the use of an existing independent DBMS. In such a case, data analysis for resource allocation can be done by an independent fuzzy system after retrieving data from the DBMS.

2.3. Monitoring of resource allocation

After resource allocation, resource utilization can be selected for measurement as it is one of the important factors reflecting the productivity of a production system [9]. Data related to the utilization of resources in one period must not affect the capacity of resources in other periods [53]. This underlines the fact that resource utilization has to be traced over time and be measured dynamically. Radio Frequency Identification (RFID) is widely accepted as a means to enhance data handling processes [54,55] and is able to capture dynamic data [56]. Thus, RFID could be a possible solution for measuring resource utilization.

There are researches applying RFID in manufacturing industries, most of which aimed at keeping track of production processes. Ngai et al. [57] 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. [58] presented an RFID-enabled real-time manufacturing execution system which deployed RFID devices on the shop-floor to track and trace manufacturing objects and collect real-time production data for planning, scheduling, execution and control. On the other hand, with the use of RFID technology, a manufacturing planning and control system proposed by Wang and Lin [59] is 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 [60–65], many of its applications in manufacturing remain to be explored [66] such as its coordination of the resource management process [67].

2.4. Application of fuzzy logic and RFID in resource allocation

Fuzzy logic has been used for allocation of labor resources to manufacturing tasks [68], provision of knowledge support for parameter settings of machinery resources [69], resource demand estimation [70] and determination of order tardiness so as to allocate resources effectively [71]. It has also been applied to determine the amount of machinery resources needed to achieve low work-in-process inventory and eliminate stockouts [72], but this is limited to the application in manufacturing industries where identical machines are used to produce a large variety of components such as the electronic industry. A more generic framework for effective resource allocation in manufacturing has yet to be achieved.

On the other hand, RFID has been applied in resources management in various situations, for example, in warehouses for optimization of resource utilizations [73,74], for victim identification to allow early resource allocation during emergencies [75], in manufacturing processes to track the mobility of resources [76,77], and to detect the location changes of a newly produced automobile [78].

Both the fuzzy logic and RFID seem to be popular in resources management, however, there seems to be no single system that incorporates DBMS with fuzzy logic and RFID, especially for the resource allocation process in manufacturing. This paper presents an integrative DBMS incorporating fuzzy logic for resource allocation analysis, while RFID is applied for real-time production data capturing.

3. Intelligent data managed resource allocation system (RAS)

In this paper, an intelligent data managed RAS, incorporating fuzzy logic for data analysis for intelligent decision making and Radio Frequency Identification (RFID) technology for monitoring, is developed as depicted in Fig. 1. The proposed system consists of two modules, namely (i) a Data Analysis Module, and (ii) a Verification Module. The Data Analysis Module is responsible for resource allocation determination based on input parameters by using fuzzy logic. The input parameters, from various sources, are firstly consolidated to a centralized database in the DBMS and they are then retrieved for analysis in the fuzzy system to generate resource allocation decision parameters which are used for production resource allocation. The Verification Module of the RAS will then evaluate the real-time resource utilization of every single workstation with the aid of RFID technology. The RFID devices visualize and capture the actual resource utilization status of the production lines. Discrepancies between actual and expected resource utilizations can be identified and refinements to the fuzzy rules can thus be made.

The details of the RAS are described in the following sections (Sections 3.1 and 3.2).

3.1. Data analysis module

To determine the resource allocation parameters, different types of production related data are required. Some of these data, such as 'complexity of the products' and 'required skill levels of operators', are manually input into the system, while some others are retrieved directly from other internal information systems such as the Enterprise Resource Planning (ERP) and the Warehouse Management System (WMS). All inputs, such as 'production volume' and 'number of materials' retrieved from ERP and WMS respectively, are consolidated in a centralized database in the DBMS where the Extensible Makeup Language (XML) is the standardized data exchange format. The data set is then converted into fuzzy sets by fuzzification within the fuzzy system before undergoing the fuzzy inference process. The output fuzzy sets are then defuzzified to yield numerical decision parameters, such as 'percentage change in the number of resources required' in different workstations, as they are more suitable for the practical resource allocation purpose in real production environments.

3.2. Verification module

In the verification module, real-time production data is captured by RFID devices, namely, RFID tags, RFID readers and a RFID middleware. The resource utilization rates are thus determined. The real-time data capturing setting requires production materials bundled with RFID tags and readers installed at each resource at different workstations along the production line. The resource utilization rates are determined in accordance with the rates of detection of the material tags. This can only occur when reader-installed resources are utilized to handle materials during production. The detected signals are sent to the RFID middleware for filtering and decoding, before the analyzed 'utilization rates of resources' at various workstations are obtained. If the production performance is found to be unsatisfactory, such as 'low resource utilization rates' it may imply that the output of the Data Analysis Module is not fully responsive to the actual production situations. An adjustment of the stored knowledge, which is in the form of fuzzy rules, is thus required. The adjusted fuzzy rules would then be adopted in the fuzzy system for improvement of the system.

4. Case study

4.1. Case overview

According to the Hong Kong Trade Development Council [79], the total exports in the Hong Kong garment industry decreased by 7% year-on-year in the first four months of 2012 while domestic exports and re-exports declined by 23% and 6%, respectively. This shows the Hong Kong garment industry urgently needs to improve its competitiveness if it is going to survive in the global market. It is facing an additional pressure brought about by the latest trend of "fast fashion". In fast fashion, frequently, new products have to be available in the markets as quickly as possible so as to offer the most up-to-date fashion styles to consumers [80]. Products in the garment industry are ephemeral items which may no longer be saleable or attractive to consumers if the fashion trend changes [81]. As a consequence, production efficiency is one of the major concerns in manufacturing performance. It is thus important to improve the production efficiency for better performance. Effective resource allocation is one way to achieve this.

Unfortunately, the complexity of the garment industry increases the difficulties in achieving effective resource allocation. As depicted in Fig. 2, the amount of resources required for garment production varies according to certain factors, such as different styles, different volume and different delivery schedules. In such cases, various types of information from diverse sources have to be gathered and consolidated for resource allocation determination. It is a time-consuming task, and there is a grave possibility that resource allocation decisions are biased if the decisions are mainly experience-driven without any knowledge support. Therefore, there is a need to have a new algorithm with the purposes of shortening the data collection time frame and enhancing the decision making process relating to resource allocation.

4.2. Background of case company

The case study is carried out in a Hong Kong-based garment manufacturing company founded in 1977. Operating through its eight subsidiaries, the company is engaged in both manufacturing

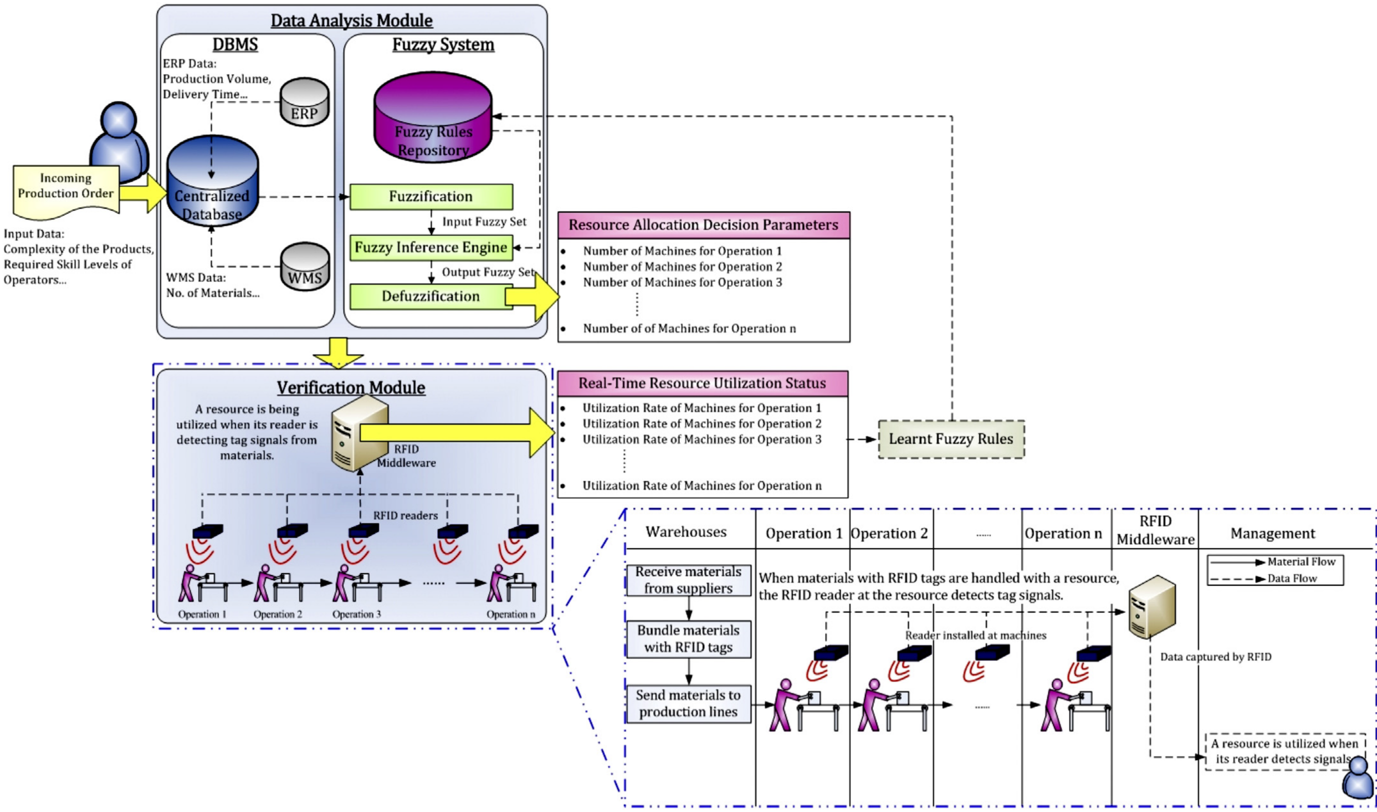

Fig. 1. System architecture of the developed intelligent data-managed RAS.

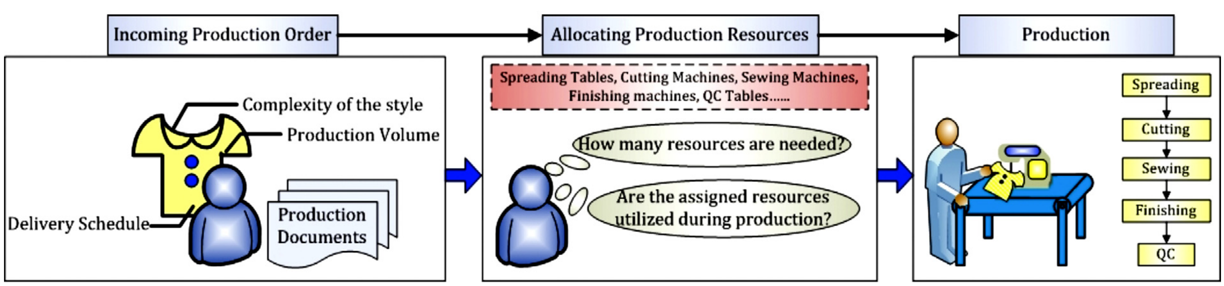

Fig. 2. Problems in production resource allocation in the garment industry.

and sales of garments. Products are mainly ladies' woven apparel, over 15 million pieces of which are exported to different countries such as North America, Europe and Australia annually. The company has manufacturing facilities throughout the Pan Pacific region: Hong Kong, China, Malaysia, Thailand, the Philippines, and Vietnam. To stay competitive in the relentless markets, the company has been expanding its manufacturing capacity: a new factory in Vietnam will start its operation in March 2013. In addition to capacity expansion, a more reliable resource allocation strategy is expected to handle various production orders. It is claimed that the proposed RAS presented in this paper is "tailor made" for this specific purpose.

In the resource allocation determination process in the case company, technical justification of the garment style is the prerequisite as it would definitely determine the requirements and types of resources needed. Together with the production details, the way resources are allocated is generally based on experience. Like most traditional garment manufacturers, the case company is adopting the paper-based manual systems to monitor the production operations as shown in Fig. 3. Three major problems have been observed.

(1) *Bias in resource allocation determination*: In the resource allocation determination process, the production manager takes the responsibility for ensuring the number of resources assigned satisfy the expected specifications. However, without any

Fig. 3. Using paper tickets to record progress in production operations.

knowledge support on resources, the decisions made are heavily reliant on the own intuition and experience of the manager.

(2) *Low visibility in actual resource utilizations*: In the current practice of the company, completed production operation tasks are manually recorded. However, this recording system does not provide thorough details of the actual production performance, such as the actual resource utilization, on a real-time basis. The management thus lacks useful information to justify the effectiveness of the resource allocation decisions determined.

(3) *Huge amount of production data to handle*: In resource allocation determination, different parameters, from various sources, have to be collected before making any decisions. The production manager has to study the related parameters from a list of documents such as production orders, size specification forms, bill of materials and paper patterns. Though these parameters have been identified in the previous pre-production process and are stored in relevant information systems, the production manager can only obtain that information from the paper documents provided by the Sales Development, Sample Room, Purchasing Department and Technical Team. Without a centralized database, the effort used to gather the required parameter information is overwhelming.

4.3. Pilot implementation of the developed RAS

The development of the RAS involves four main stages:

The DBMS and the fuzzy system in the developed RAS are constructed by using Microsoft Office Access 2007 and MATLAB Fuzzy Logic Toolbox, respectively.

4.3.1. System parameters definition for data analysis

With reference to the existing practice of the case company, input and output parameters are predefined for decision making in the resource allocation process. The general practice in the garment industry, is that some specific parameters such as 'number of sewing processes' and 'total sewing distance per garment' have to be verified before production with in-depth verification, according to different product styles. These verified parameters do not exist in any sources before the pre-production justification. Thus, it is essential to have those parameters input into the RAS manually by the system users. Other important parameters in other information sources, such as ERP and WMS, are also identified. Fig. 4 summarizes the system parameters from various sources for data analysis in the RAS.

In the case company, the production operations are mainly classified into five operations (Fig. 5), namely 'Fabric Spreading', 'Fabric Cutting', 'Sewing', 'Finishing', and 'Quality Checking (QC)'. Resources responsible for these operations are 'Spreading Tables', 'Cutting Machines', 'Sewing Machines', 'Finishing Machines' and 'QC Tables'. To fulfill the production demand, the required numbers of these resources have to be determined and are thus defined as the output parameters in the resource allocation process.

4.3.2. Construction of a system database

Microsoft Office Access 2007 is employed as the system database. As previously mentioned (Section 4.2), the production manager obtains resource allocation relating information from other information sources. Necessary parameters to be included in the centralized database are from different sources, including Sales Department, Sample Room, Technical Team, Purchasing Department and Warehouses.

Fig. 6 depicts the data sources and the data structure, storing data in different relational tables. Data in ERP and WMS are imported and can be accessed by users via the system database while the verified parameters are updated manually by users. Users can view the parameters as shown in Fig. 7. Those parameters are ready to be transmitted to the fuzzy system where resource allocation determination is carried out by fuzzy logic.

4.3.3. Construction of a fuzzy system

MATLAB Fuzzy Logic Toolbox is employed as the fuzzy system for the computation. Knowledge acquisition from domain experts including the production manager and experienced production personnel is conducted to define fuzzy sets, membership functions of each fuzzy set, and a list of fuzzy rules indicating the "If-Then" relationship between different input and output parameters. Table 1 shows the defined fuzzy sets and the range of each parameter. For the ease of acquiring knowledge, the input parameters are firstly divided into four categories: the requirements of customers, garments, shell fabrics and operators. Domain experts are asked to provide the linguistic terms they commonly use for parameters description. The identified linguistic terms are then adopted as the defined fuzzy sets of the parameters.

The 'acquired knowledge' is then input into MATLAB Fuzzy Logic Toolbox. The relationship between system parameters and fuzzy rules in MATLAB Fuzzy Logic Toolbox is shown as in Fig. 8. MATLAB Fuzzy Logic Toolbox reads the membership functions, and maps each input parameter to the corresponding fuzzy sets. For instance, the input parameter 'Production volume' may be mapped to fuzzy sets such as 'Large' and 'Very large', which are then used to match the fuzzy rules. Based on the fuzzy rules, the fuzzy sets of output parameters are determined and the actual values of each output parameter can be determined.

In RAS, after identifying of each of the input parameters, users can input them into MATLAB Fuzzy Logic Toolbox to generate the values of the output parameters (Fig. 9). The output parameters, namely (i) percentage change in the number of spreading tables, (ii) percentage change in the number of cutting machines, (iii) percentage change in the number of sewing machines, (iv) percentage change in the number of finishing machines, and (v) percentage change in the number of QC tables, are generated for further resource allocation purposes.

4.3.4. Evaluation of the analysis result

The data output from the Fuzzy Logic component are used to allocate resources for fabric spreading, fabric cutting, sewing, finishing and QC. Utilization of the allocated resources is measured by using RFID devices. Effectiveness of the fuzzy logic application can thus be determined by referring to the resource utilization situation, fuzzy rules can then be finely adjusted and improved fuzzy logic results can thus be obtained.

5. Results and discussion

This study proposes an intelligent system for effective resource allocation, consisting of two modules. The first module, the Data Analysis Module, analyzes data and determines the allocation of resources while the second module, the Verification Module, evaluates the determined results with reference to the real-time captured resource utilization rates.

5.1. The effectiveness of RAS

The Data Analysis Module needs detailed definitions of system parameters and relevant knowledge in the resource allocation determination process. The pilot implementation of the developed RAS carried out in a case company illustrates how such definitions can be arrived at by collecting real data sets and acquiring knowledge from the company so as to build the DBMS and the fuzzy system for the module.

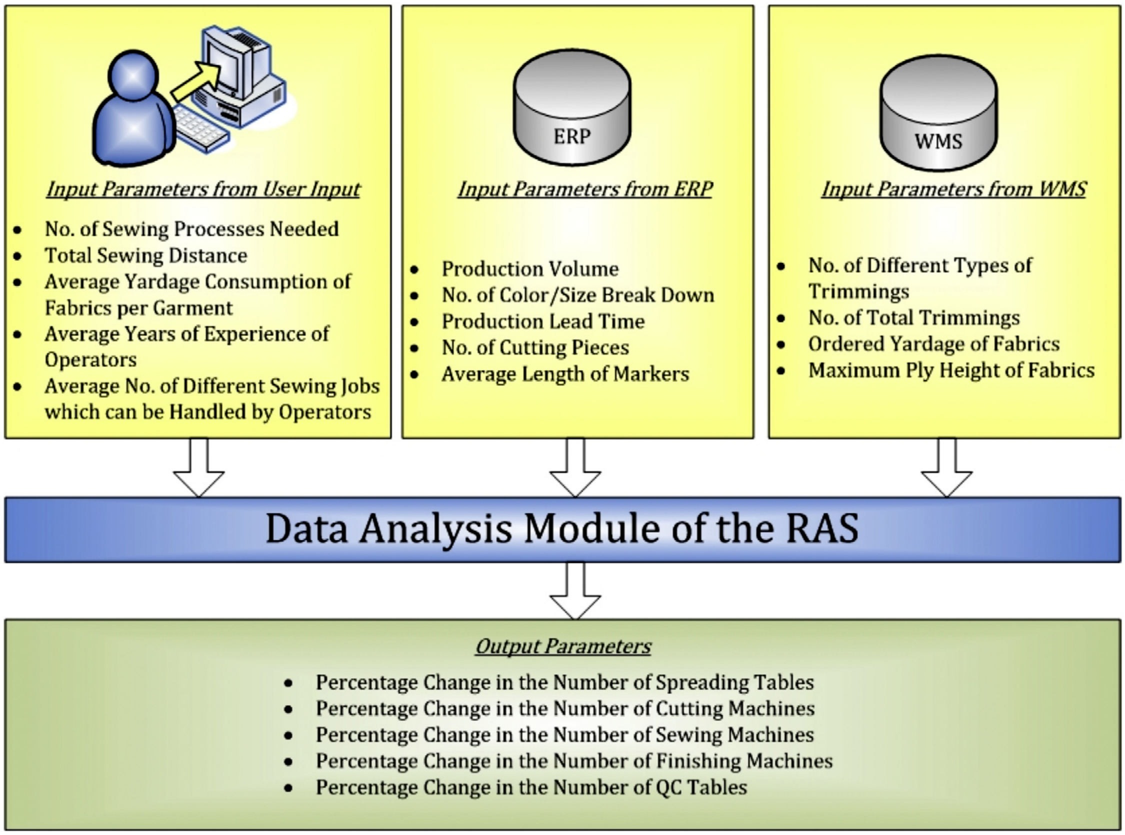

Fig. 4. Input and output parameters for data analysis.

In the case study, a Fuzzy Logic Toolbox is employed to perform simulation of the Data Analysis Module. Table 2 shows the simulation settings and results. Given these input parameters, it is suggested that the number of spreading tables, cutting machines, sewing machines and finishing machines should be increased by 25.4%, 33.4%, 66.6% and 25.8%, respectively, while the number of QC tables should be decreased by 33.4%.

The results are compared with those of the current knowledge-driven (by experienced operators) resource allocation determination. In the comparison, the number of resources determined by the two approaches is represented in the format of a ratio by assuming that the number of each resource is equal to one unit. Table 3 shows the comparison of the results.

The difference in number of resources indicates that the experience-driven resource allocation determination in the current practice is not the optimal solution according to expertise knowledge stored as fuzzy rules. From Table 3, it is found that the difference in the number of QC tables (0.33) is the most significant, followed by that of spreading tables (0.25). When resources are allocated according to the two results in two separate production lines for practical comparison, it is anticipated that two operations, fabric spreading and QC, will contain major discrepancies in production performance as the number of corresponding resources is significantly different. Resource utilization can be used to evaluate the effectiveness of the resource allocation determination by implementing the Verification Module.

The actual production performance after the adoption of the fuzzy logic results can be justified with the RFID-captured resource utilization. Fuzzy rules can be modified according to specific requirements for continuous improvement.

5.2. Integrative DBMS and fuzzy logic

The employment of Microsoft Office Access in the DBMS highlighted two significant features of the system, making RAS outperform other existing approaches for resource allocation. Firstly, the RAS is a user-friendly system as the DBMS itself is devoted completely to the fuzzy system application alone. Unlike other fuzzy database systems, the database in RAS does not store fuzzy data but numerical values for more efficient data input and update, and this makes the system more user-friendly.

Secondly, the RAS has cost advantages over systems which require a total reconstruction of the system. The constructed DBMS and fuzzy system do not require additional investments on software installation.

The fuzzy logic results can be further improved, to be more responsive to the actual production performance, by refining the fuzzy rules regularly according to the real-time production data,

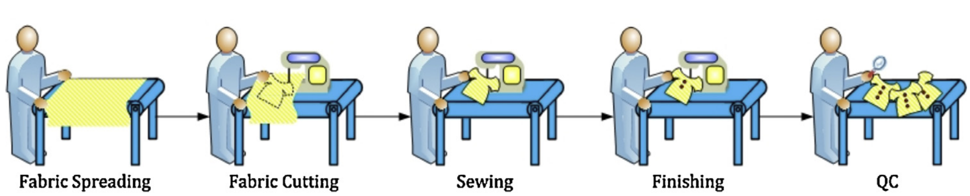

Fig. 5. Production operation flow in the garment industry.

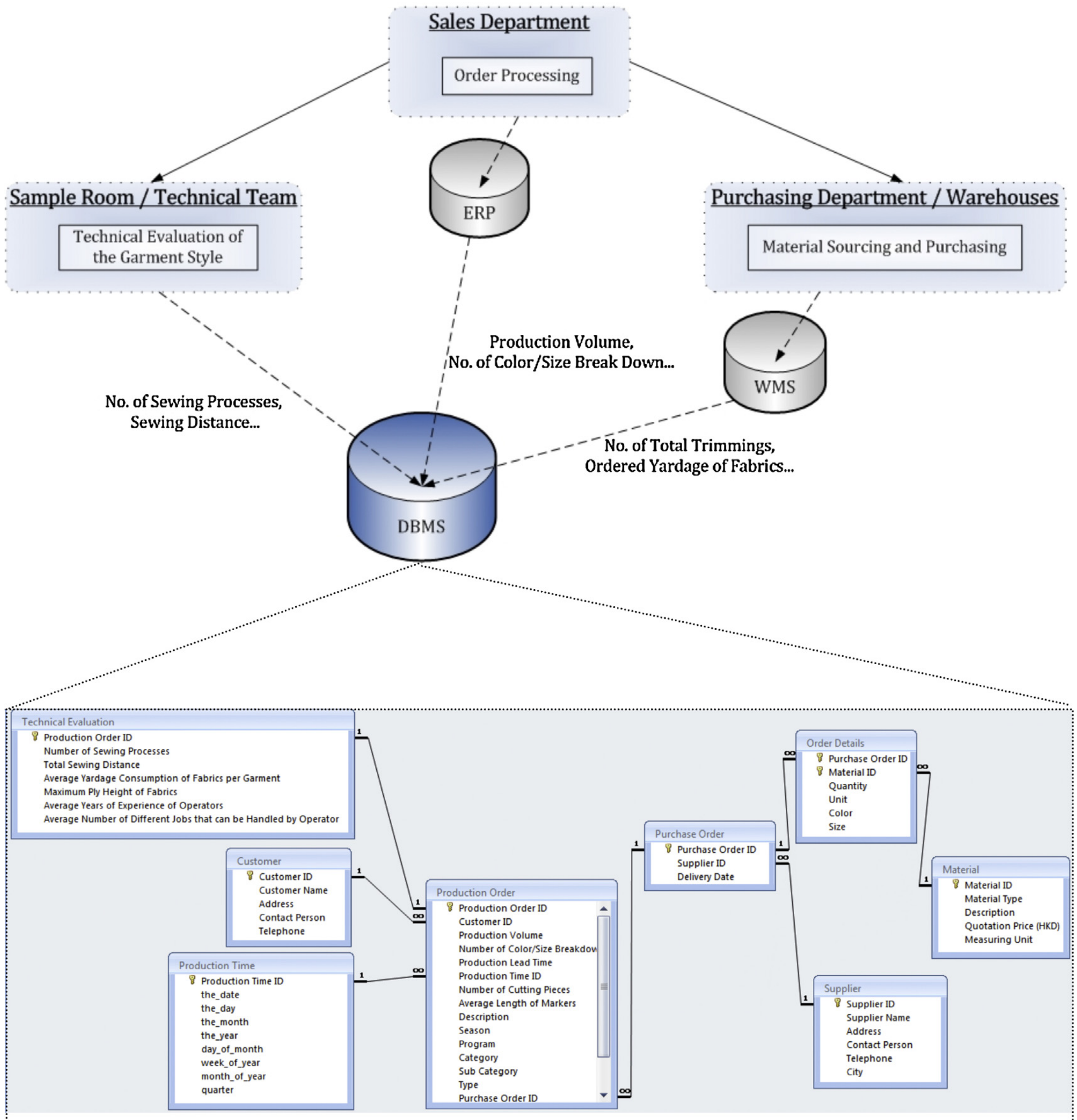

Fig. 6. Data sources and the data structure in DBMS.

Fig. 7. Display of input parameters in DBMS.

Table 1
Defined fuzzy sets and range of parameters.

	Parameter		Fuzzy set	Range
Input	Customer requirement	Production volume	Very small, small, normal, large, very large	0–200,000 pcs
		Production lead time	Very short, short, normal, long, very long	0–240 days
	Garment requirement	No. of color/size break down	Very small, small, normal, large, very large	0–12
		No. of sewing processes needed	Very small, small, normal, large, very large	0–100
		Total sewing distance	Short, normal, long	0–200 m
		No. of cutting pieces	Very small, small, normal, large, very large	0–60
		No. of different types of trimmings	Very small, small, normal, large, very large	0–24
		No. of total trimmings	Very small, small, normal, large, very large	0–36
	Shell fabric requirement	Average Length of Markers	Short, normal, long	0–15 m
		Maximum Ply Height of Fabrics	Low, normal, high	0–10 cm
		Ordered Yardage of Fabrics	Few, normal, many	0–40,000 yds
		Average Yardage Consumption of Fabrics per Garment	Small, normal, large	0–3 yds
	Operator requirement	Average Years of Experience	Few, normal, many	0–40
		Average No. of Different Sewing Jobs which can be Handled by Operator	Very small, small, normal, large, very large	0–36
Output	Change in no. of spreading tables		Substantially decreased, slightly decreased, no change, slighted increased, substantially increased	−100% to 100%
	Change in no. of cutting machines			−100% to 100%
	Change in no. of sewing machines			−100% to 100%
	Change in no. of finishing machines			−100% to 100%
	Change in no. of QC tables			−100% to 100%

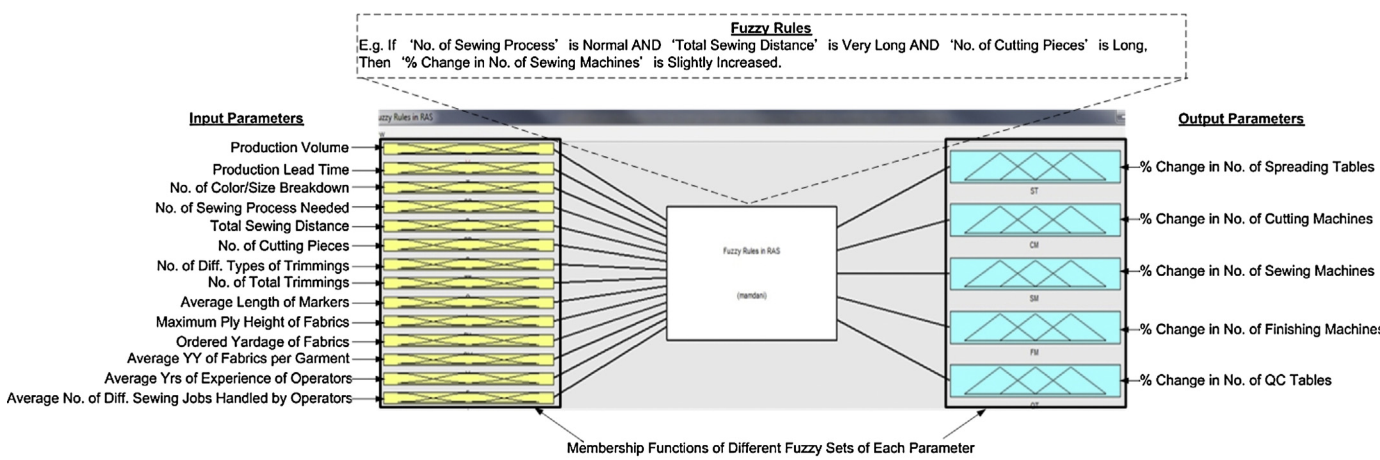

Fig. 8. Relationship between system parameters and fuzzy "If-Then" rules in MATLAB Fuzzy Logic Toolbox.

Table 2
Simulation setting and results.

Input parameters	Input values	Output parameters	Values suggested by MATLAB
Production volume	7700 pcs		
Number of color/size breakdown	8	% change in no. of spreading tables	25.4%
Production lead time	90 days		
Number of cutting pieces	19		
Average length of markers	5.1 m		
Number of different types of trimmings per garment	16	% change in no. of cutting machines	33.4%
Number of total trimmings per garment	29		
Ordered yardage of fabrics	18,000 yds		
Number of sewing processes	28	% change in no. of sewing machines	66.6%
Total sewing distance per garment	105		
Average yardage consumption of fabrics per garment	5.1yds	% change in no. of finishing machines	25.8%
Maximum ply height of fabrics	3.2 cm		
Average years of experience of operators	10	% change in no. of QC tables	−33.4%
Average number of different jobs handled by operators	15		

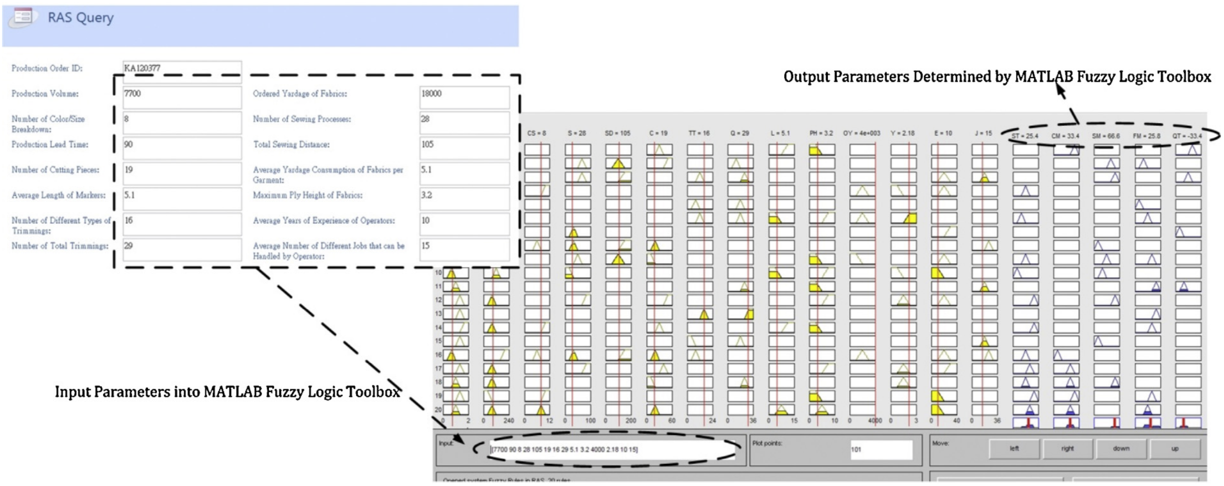

Fig. 9. Output display in MATLAB fuzzy logic toolbox.

Table 3
Comparison of results.

Decision parameter	Fuzzy logic-driven decision	Knowledge-driven decision
Number of spreading tables	1.25	1.00
Number of cutting machines	1.33	1.17
Number of sewing machines	1.67	1.50
Number of finishing machines	1.26	1.25
Number of QC tables	0.67	1.00

such as resource utilization rates, which are captured by RFID devices on the production shop floor. It can be posited that the installation of the entire system is economically applicable as RFID is considered as a cost-saving technology by reducing costs such as labor costs, inventory costs and other costs due to errors, in the long term. In conclusion, the proposed RAS offers a novel but economic approach for effective resource allocation.

5.3. *Monitoring of resource utilization*

The Verification Module is responsible for monitoring the utilization of resources. Compared with approaches which capture offline data, the proposed methodology for capturing real-time data for evaluation achieves a higher level of accuracy and is more responsive to the actual situation than are other methods. The RFID-captured data offers reliable references for the refinement of the stored knowledge in the form of fuzzy rules of RAS. This means that management can use RFID not only to track production operations, but also to improve the efficiency of refining knowledge in the fuzzy logic.

5.4. *Positive impact on the case company*

The system is unique in that the negative impacts induced by the existing problems in the case company can be alleviated.

The use of the DBMS shortens the time used by production managers to gather the required data, while the use of the fuzzy logic reduces human bias in resource allocation determination by offering a standardized procedure for decision making. In addition, the real-time monitoring of resource utilization increases the visibility and accuracy of tracking the actual production performance. However, there are certain problems in this case. The garment industry is one of the most labor-intensive industries so it contains more uncertainties than other manufacturing industries due to a number of human factors such as workmanship and human errors. This is of a great concern when dealing with knowledge issues. When establishing the learnt fuzzy rules, the management has to consider the possible variance of human behavior. Given the same production situation, it is possible that the learnt fuzzy rules may not function equally. However, it is worth bearing in mind that in the future a more comprehensive RAS should be developed, one which considers not only the management of machinery resources, but also human resources.

6. Conclusion

The general structure of an intelligent data management induced resource allocation system (RAS) incorporating DMBS, fuzzy logic and RFID is discussed in this paper, followed by a case study to illustrate its application in the context of resource allocation in a garment manufacturing company. The pilot implementation shows that RAS is a user-friendly and economically applicable system for effective resource allocation. Because it possesses special features, RAS is capable of shortening the time frame of data gathering for deciding the level of resources to be allocated, reducing bias in resource allocation determination by offering standardized procedures, and improving the visibility of the production performance by monitoring resource utilization. It is believed that RAS can be applied in not only the garment industry, but also other manufacturing industries. To improve the fuzzy logic results, future work will be carried out in which the system knowledge will be refined, as it will be based on real-time resource utilization rates captured by RFID devices on the manufacturing shop floor.

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