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# An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment

Z.X. Guo [a,*], E.W.T. Ngai [b], Can Yang [a], Xuedong Liang [a]

[a] Business School, Sichuan University, Chengdu 610065, PR China
[b] Department of Management and Marketing, The Hong Kong Polytechnic University, Hunghom, Kowloon, Hong Kong, PR China

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ABSTRACT

Global manufacturing companies have some pressing needs to improve production visibility and decision-making performance by implementing effective production monitoring and scheduling. This paper proposes a radio frequency identification (RFID)-based intelligent decision support system architecture to handle production monitoring and scheduling in a distributed manufacturing environment. A pilot implementation of the architecture is reported in a distributed clothing manufacturing environment. RFID and cloud technologies were integrated for real-time and remote production capture and monitoring. Intelligent optimization techniques were also implemented to generate effective production scheduling solutions. A prototype system with remote monitoring and production scheduling functions was developed and implemented in a distributed manufacturing environment, which demonstrated the effectiveness of the architecture. The proposed architecture has good extensibility and scalability, which can easily be integrated with production decision-making as well as production and logistics operations in the supply chain. Lastly, this paper discusses the difficulties encountered and lessons learned during system implementation and the managerial implications of the proposed architecture.



## 1. Introduction

Labor-intensive manufacturing companies in China, such as those specializing in clothing and footwear, face unprecedented global competition and unpredictable demand fluctuations. These companies must determine methods to improve supply chain management. Global uncertainty and business complexity in supply chain operations have recently increased and various leagile supply networks have been proposed (Purvis et al., 2014). "The Smarter Supply Chain of the Future" released in 2010 (Butner, 2010) by IBM Corporation suggests that a smart supply chain is instrumented, interconnected, and intelligent. To possess these core characteristics, information visibility and transparency, as well as decision-making performance in supply chain operations need to be improved.

Companies have developed and implemented various information systems to increase information visibility and transparency (Francis, 2008). The accuracy of production data in these systems relies on the effectiveness of production data capture and monitoring. In labor-intensive manufacturing industries in China, the collection of production data mainly relies on manual recording, barcode scanning, and radio frequency identification (RFID)-based techniques (Wong and Guo, 2014). Manual recording and barcode scanning usually result in incomplete and lagged data, and barcode labels easily become wrinkled or smudged during labor-intensive production. Meanwhile, RFID technology involves a simple process and can be used in these environments because the electronic components of RFID tags are adequately protected inside.

Most information systems for labor-intensive manufacturing are intended to facilitate various business operations and activities. However, these systems fail to automatically provide users with production decisions. Production decision-making, such as production scheduling, relies on the experience and the subjective assessment of production management, which is rarely optimal. Thus, effective production scheduling in labor-intensive manufacturing needs to be investigated.

This study focuses on the production monitoring and scheduling problem faced by distributed labor-intensive manufacturing companies with multiple production plants. This company aims to effectively track and monitor the progress of each production order and determine where and when to produce each order on

* Corresponding author. Tel.: +86 28 85417867; fax: +86 28 85415628.
*E-mail address:* zx.guo@alumni.polyu.edu.hk (Z.X. Guo).

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the basis of real-time production data. An RFID-based intelligent decision support system (RIDSS) architecture is developed in which RFID and cloud technologies are integrated for real-time production capture and remote production monitoring, whereas intelligent optimization techniques are applied to generate effective production scheduling solutions.

The remainder of this paper is organized as follows: Section 2 reviews related studies on RFID-based production monitoring and production scheduling. Section 3 presents the production monitoring and scheduling problem faced by labor-intensive manufacturing companies with multiple production plants. In Section 4, the RIDSS architecture is proposed to address this problem. Section 5 describes the implementation of the RIDSS architecture in a distributed manufacturing company with multiple plants. Sections 6 and 7 present the performance evaluation and discussion of this system. Finally, Section 8 summarizes this paper and suggests future research directions.

## 2. Literature review

### 2.1. Previous studies in RFID-based production monitoring

RFID technology enhances information visibility and traceability in supply chains (Delen et al., 2007). Studies have been conducted on the application of RFID in monitoring production processes (Huang et al., 2007; Lee and Park, 2008) and concluded that RFID technology can improve supply chain performance (Sari, 2010). Effective production decisions are driven by accurate and real-time production data.

Various RFID-based systems have been developed and implemented to track and monitor production and logistics operations in manufacturing industries. Several studies have focused on production monitoring in shop-floor environments (Chen et al., 2010; Liu and Chen, 2009; Ngai et al., 2007; Poon et al., 2007). Ngai et al. (2007) developed an RFID-based traceability system for monitoring and tracing aircraft repairable items in an aircraft engineering company in Hong Kong. Poon et al. (2007) presented an RFID-based decision support system to monitor the real-time state of equipment and products in a shop floor. Liu and Chen (2009) suggested an RFID-based electronic control framework for improving production efficiency in an integrated-circuit packaging house. Chen et al. (2010) proposed an RFID-based integration framework for facilitating real-time management of dynamic production operations. This framework provides the enterprise with an effective technique to integrate RFID-based solutions into its information technology infrastructure and manufacturing environment. These systems can effectively handle production monitoring in various shop floor environments but not in distributed manufacturing environments. Studies have rarely been reported on the applications of RFID-based systems in distributed manufacturing environments across multiple plants.

RFID-based remote monitoring systems by integrated RFID and Internet technologies have been developed for monitoring and control of production systems within a manufacturing company (Wang et al., 2011; Zhou et al., 2007). These systems allow real-time transfer and storage of production data on the database via the Internet. With a remote connection feature, these systems can also potentially monitor distributed manufacturing environments. In these systems, RFID terminals are installed at the entrance and exit of each shop floor or assembly line to collect information on materials and parts at a frequency of 915 MHz, which can read RFID tags at a distance in the range of 5–10 m. However, these systems fail to collect and track detailed production information from workstations at each shop floor or assembly line. This limitation is attributed to the longer reading distance (5–10 m) compared with the distances between workstations in labor-intensive assembly lines (usually less than 1 m). Reading distance within such a range enables terminals to read the information on workpieces (not being processed and those being processed) in neighboring workstations. This problem results in chaotic and inaccurate production information collected. Labor-intensive manufacturing with many manual operations need to collect production information from each workstation and then monitor its production status because production in assembly lines substantially affects production performance.

Numerous studies have evaluated the effects of RFID in production management and scheduling (Chen et al., 2010; Fan et al., 2014; Liu and Chen, 2009; Zhou et al., 2007; Zhou and Piramuthu, 2013) and demonstrated that RFID can significantly improve scheduling performance and productivity, as well as reduce production costs. However, studies on the integration of the RFID technology with production scheduling have rarely been reported. Chongwatpola and Shardab (2013) presented an RFID-based scheduling approach to improving the production scheduling performance in a job shop environment. Real-time production data, which were collected using the RFID-based system, were used to adjust production schedules. Their study indicated that the performance of RFID-based scheduling rule was superior to that of traditional scheduling rules in terms of cycle time, machine utilization, backlogs, and penalty costs. However, the RFID-based scheduling rule in their study is only applicable to the job shop environment investigated. Thus, RFID technology needs to be integrated with production scheduling in complex labor-intensive production environments.

### 2.2. Production monitoring in distributed labor-intensive manufacturing

Compared with highly automated industry (e.g., the automobile industry), labor-intensive manufacturing industries, such as those specializing in clothing and footwear, have installed and implemented RFID-based production and monitoring systems only recently because of their low-automation and low-profit features. RFID-based data capture and monitoring systems have been developed for gathering real-time and accurate production data and monitoring production progress as RFID technology has become economically feasible for application in labor-intensive manufacturing industries. The effectiveness of these systems has been proven by various industrial applications and practices (Wong and Guo, 2014). However, existing data capture and monitoring systems are designed for a separate plant. RFID-based systems need to be installed separately in each plant to collect the production data in each plant. Consequently, the production data collected in various plants are isolated. Meanwhile, labor-intensive global manufacturing companies in China currently generate production orders in multiple subordinate and collaborative plants located in different regions.

In order to track and monitor production in all plants effectively, companies develop additional systems to integrate production data from different plants and save these data to a central database located at headquarters. However, real-time synchronization of the headquarter database with subordinate plant database is characterized by technological complexity and entails additional costs for secondary development and maintenance. In addition, these systems can only track and monitor production in subordinate plants but not the progress of material and outsourcing production. Unfortunately, material and outsourcing production substantially affects the entire production performance of the company in certain labor-intensive manufacturing industries such as clothing and footwear. In the clothing industry, the majority of raw materials are customer order-dependent, which usually cannot be pre-prepared before confirming customer orders. As a result, uncontrollable material production processes may lead to poor production performance. Hence, a clothing manufacturer must monitor the material production process.

Therefore, an effective system must be developed for tracking and monitoring production in distributed production manufacturing companies with multiple production plants in different regions. In recent years, cloud-based systems and applications have emerged as an important trend in information technology. This technology has been applied successfully in various government organizations (Smitha et al., 2012) as well as the manufacturing (Xu, 2012), healthcare (Lai et al., 2012), and education (Sultan, 2010) sectors. Cloud-based applications benefit the distributed manufacturing environment through cost reductions and applicability. Despite the benefits provided by these applications, studies on the use of cloud-based technology for production monitoring and decision-making in labor-intensive manufacturing industries have been rarely reported.

### 2.3. Previous studies in production scheduling

The existing data capture and monitoring systems installed in each plant can collect large quantities of real-time production data from production frontlines in labor-intensive manufacturing. However, these abundant data are chiefly used in payroll recording and simple production reporting and fail to facilitate effective production decisions in production management.

Numerous comprehensive reviews have been published in the field of production scheduling (Biskup, 2008; Hart et al., 2005; Koulamas, 2010; Panwalkar et al., 2013). These studies include many scheduling problems: single machine scheduling (Koulamas, 2010; Wang et al., 2010), parallel machine scheduling (Vallada and Ruiz, 2011; Yanga et al., 2012), job shop scheduling (Weng and Ren, 2006), flow shop scheduling (Panwalkar et al., 2013), flexible manufacturing system scheduling (Tomastik et al., 1996; Xing et al., 2010), and order scheduling at the company and supply chain levels (Chen and Pundoor, 2006; Guo et al., 2013a, 2013b). Some of these studies consider labor-intensive manufacturing environments, such as the fabric-cutting (Rose and Shier, 2007) and sewing (Tomastik et al., 1996; Wong et al., 2014) processes in clothing production.

Previous studies limited their scope to independent scheduling problems in a separate production unit, such as a machine, a shop floor, or a plant, where each type of production units corresponds to a management level. Thus, the scheduling problems were investigated independently and separately at each management level. In real-world production, production scheduling decisions at different management levels, such as company and plant levels, are based on correlative dependence and interplay. Production scheduling problems at multiple management levels in a distributed manufacturing company have not been simultaneously examined based on a holistic view. Methods in which the use of real-time production data would suffice to make scheduling decisions remain undetermined. A scheduling mechanism that can generate effective scheduling solutions to real-world production scheduling problems in the distributed labor-intensive manufacturing environment needs to be established based on real-time production data.

Most production scheduling problems are non-deterministic polynomial-time hard (Hart et al., 2005). Current labor-intensive manufacturing is characterized by short production lead-time, short life-cycles, volatile customer demands, small quantities with frequent product change, and distributed multi-plant production environments. These characteristics inevitably increase the complexity of production scheduling problems in the global labor-intensive manufacturing environment. Traditional approaches, such as simulation, mathematical programming, and heuristic methods, fail to address these complex problems. Intelligent optimization algorithms have been widely used in handling scheduling problems because they can potentially determine the global optimum (Hart et al., 2005).

Previous related studies are generally limited despite the pressing need to improve production visibility and scheduling performance in current labor-intensive manufacturing industries in China. Production scheduling problems in distributed manufacturing environments with multiple plants that involve material and outsourcing production have not been examined from a holistic perspective. Demirkan and Delen (2013) have pointed out that further research is required to explore the integration of database management system and decision-making methodology. However, the integration of RFID-based management system with these production scheduling activities have not been reported. Cloud technology and intelligent optimization techniques can feasibly handle distributed production monitoring and complicated production scheduling, respectively.

Consequently, an effective decision support methodology based on RFID technology, cloud technology, and intelligent optimization techniques is worthwhile for development. This methodology should provide effective real-time remote production monitoring, as well as effective production scheduling solutions for a real-world labor-intensive manufacturing environment with multiple plants.

The present study proposes the development of an RIDSS architecture in which RFID and cloud technologies are integrated for real-time production capture and remote production monitoring. Intelligent optimization techniques are also applied to generating effective scheduling solutions.

## 3. Problem statement

This study aims at proposing an effective RIDSS architecture for production monitoring and scheduling, which is faced by a typical distributed labor-intensive manufacturing company in China. This architecture can be achieved by assisting the production management in monitoring the production progress of each customer order and assigning the production for each order to appropriate production units on a real-time basis. Numerous similar manufacturing companies are operational in China, especially in global make-to-order clothing and footwear manufacturing.

The production tasks in this kind of manufacturing companies are completed in $m$ production plants, including collaborative or self-owned plants located in different regions. These plants involve $N$ production departments. These production departments comprise two categories: ordinary category and special category. Each category consists of multiple production departments. The ordinary departments are fully contained in all plants, whereas the special departments may be only partly included (or not included) in some plants. Each production department consists of multiple shop floors, with each shop floor having either multiple workstations or multiple assembly lines that consist of workstations. Fig. 1 shows the structure of the manufacturing company and the production task allocation flowchart after customer orders are received. $PD_m^n$ denotes the $n$th production department of plant $m$ and $SF_m^{np}$ denotes the $p$th shop floor of $PD_m^n$.

The manufacturing company receives various production orders from different customers. Each group of production orders with the same due date from a same customer are called as an order group. After customer orders of an order group are confirmed, the manufacturer needs to purchase raw materials from material suppliers according to the material requirement of the customer orders. Labor-intensive manufacturing industries, such as those specializing in clothing and footwear, are usually characterized by quick response manufacturing. The timely acquisition of raw materials is important because lack of supply significantly affects production decision-making. Thus, monitoring is crucial to effectively monitor and control the progress of material production in supplying plants. All production processes of customer orders need to be effectively tracked and monitored as well. In particular, manual operations can be potential production bottlenecks, thereby influencing production performance in labor-intensive manufacturing. For instance, manual sewing operations are the most important production activities in clothing production. This situation requires monitoring of production in workstations with key manual operations. Production management at different levels has different monitoring requirements according to responsibilities. For example, production management at the head company needs to track and monitor all orders, whereas shop managers only need to monitor orders at their respective shop floors.

In a distributed labor-intensive manufacturing environment with multiple plants, the purpose of production scheduling aims

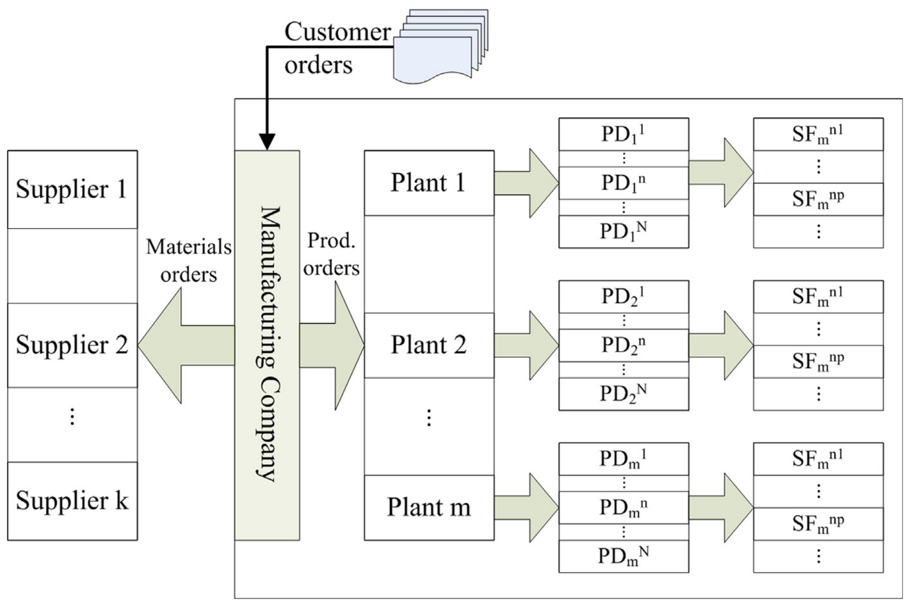


**Fig. 1.** Flowchart of production task allocation after receiving customer orders.

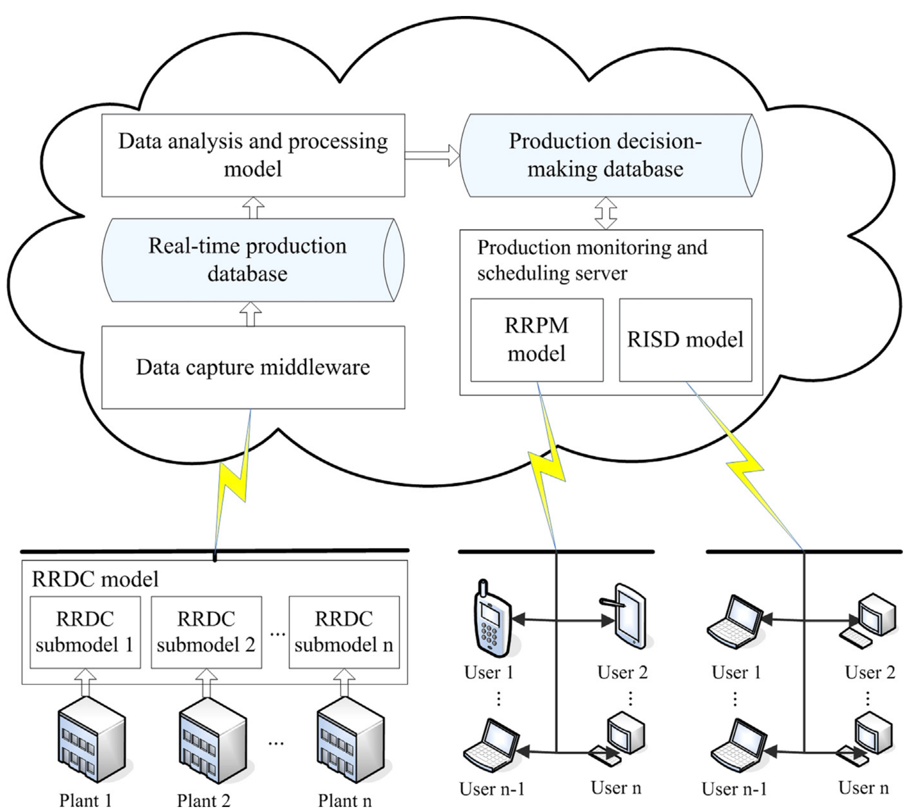


**Fig. 2.** RIDSS architecture for production monitoring and scheduling.

to assign production orders to their appropriate production units at different management levels: the company level, plant level and shop level. At the company level, each production order from a customer is assigned to its appropriate plant. The production orders are assigned to appropriate shop floors at the plant level whereas the production orders are then assigned to appropriate assembly lines or workstations at the shop level. Each order consists of a maximum of $N$ production processes, which must be performed in production departments 1 to $N$, respectively. Each production process of an order is assigned to only one plant. Different production processes of an order should be performed in different plants if a plant does not include all production departments required. Several real-world problem features in production scheduling, including multiple scheduling objectives and various production uncertainties need to be addressed. Possible scheduling objectives include minimizing total tardiness, total throughput time of production orders and total idle time in production plants or floors. Potential production uncertainties include uncertain production orders and uncertain production efficiencies.

This research aims to propose an effective system architecture for tracking and monitoring the production progress of each production order – from material production to packing process – in a real-time manner, and for determining the time and place for the production of each order on the basis of real-time production data.

## 4. RFID-based intelligent decision support system architecture

This section presents the establishment of the RIDSS architecture to implement effective production monitoring and scheduling in a distributed labor-intensive manufacturing environment. Fig. 2 shows the structure of the RIDSS architecture. This architecture uses RFID technology to collect production data from distributed manufacturing environments real-timely while intelligent optimization techniques are implemented to make effective production scheduling decisions. The RIDSS architecture comprises an RFID-based real-time data capture (RRDC) model, data capture middleware, a real-time production database, a data analysis and processing (DAP) model, a production decision-making database, a remote real-time production monitoring (RRPM) model, and a remote intelligent scheduling decision-making (RISD) model. All models are run remotely from the servers located at the company headquarters, except for the RRDC model, which is run in distributed plants. The proposed system architecture fits the concept of a community cloud because this architecture provides ubiquitous, convenient, and on-demand network access to the cloud infrastructure, shared production data from plants, as well as production monitoring and scheduling services, and because it is shared by multiple production plants and supports a specific community with shared concerns.

The RRDC model collects real-time production records from workstations of each shop floor or assembly line in material supplying plants and product assembly plants. The production records are transferred to the data capture middleware, which receives data from the RRDC model, enters the production data into the real-time production database, and provides access to the data. The real-time production database stores production data by using MySQL, MS SQL Server, or Oracle according to specific data processing requirements. The DAP model extracts necessary summary data from the raw data collected, and stores them to the production decision-making database. The RRPM model is proposed based on the information on this database to monitor the production progress of each production order in production plants. The RISD model generates effective production scheduling decisions by using intelligent optimization techniques. These models provide user-friendly interfaces that allow Web-based remote interaction with users from different production units.

The following subsections describe four key models under the RIDSS architecture: RRDC, DAP, RRPM, and RISD.

### 4.1. RFID-based real-time data capture (RRDC) model

In labor-intensive manufacturing, each shop floor or assembly line comprises certain workstations. Each workstation is typically a physical location that accommodates an operator, a machine and a buffer. The RRDC model collects production records of each workpiece and each operator from workstations based on RFID technology. The model then transfers the collected data to the remote data capture middleware through the Internet. The RRDC model is composed of submodels installed in each plant. Fig. 3 shows the structure of the RRDC submodel installed in a shop floor or assembly line. Each shop floor or assembly line uses the same method of collecting production records. An RFID terminal is installed on each workstation processing key or bottleneck operations of each production process. If it is necessary to collect all production and processing records from all workstations, RFID terminals can also be installed on each workstation although this installation would be more costly. Collecting the production information from key operations or key workstations is sufficient for implementing effective production tracking and monitoring in practice. The RFID terminal reads the RFID tag attached to each workpiece and captures its beginning and completion processing time at a given workstation during production in a real-time manner. In each submodel, access switch and internet access are performed by network switches, which connect the RFID terminals into an intranet and channels incoming data from any multiple-input ports to the specified output port. The number of RFID terminals collected from a network switch depends on the number of switch ports. The data of output port are sent to a remote data capture middleware via internet access. TCP/IP protocol is used to implement data communication between the switch and the middleware. The production progress of materials and outsourced parts can be tracked and monitored by installing RRDC submodels on related supplying and outsourcing plants workstations.

To avoid reading RFID tags wrongly attached on workpieces not being processed, we use passive RFID tags with a low frequency of 125 KHz in this model. Compared with the high frequency tag of 915 MHz, such a low frequency tag provides a shorter read range ($<5$ cm) and stronger capability of resisting disturbance, which is also low-cost and technically mature for industrial use. The ID number of each RFID tag is stored in the memory of this tag. All other relevant information is stored on the remote real-time production database. These information include the information of the workpiece this tag attached to, such as corresponding order number, operation number and precedence of this workpiece. Each tag ID is linked with its corresponding additional information through the real-time production database.

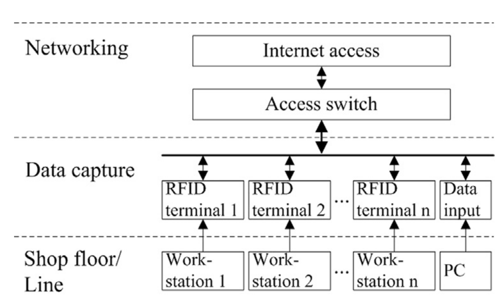


**Fig. 3.** Structure of RRDC submodel for a shop floor or an assembly line.

Except for the data collected by the RFID terminals, some data are also input directly by computer operators from each shop floor through a Web-based computer program embedded into the RRDC model. These data include the data of production orders, shop floors, assembly lines, workstations, and operators. The program provides a user-friendly interface to the computer operator in the production frontline to input related production information.

The RFID-based data capture process cannot be replaced by a barcode-based capture process in labor-intensive manufacturing environments such as clothing and footwear production due to the following two reasons. First, the production beginning and completion times of key operations of each workpiece need to be recorded during production in a real-time manner. It is time-consuming and unacceptable to use barcode scanning to collect real-time production records. Comparing with scanning barcode, reading RFID tags is much faster and acceptable. Second, RFID tags are rugged and reusable because they are protected by a plastic cover. Meanwhile, barcodes can be wrinkled and damaged easily, which would make scanning impossible.

### 4.2. *Data analysis and processing (DAP) model*

The purpose of the DAP model is to efficiently generate necessary data for the RRPM and the RISD models. A large amount of real-time production data is collected from the production frontline, affecting the efficiency of database operations. In addition, high-level production management is not concerned with the detailed production information. Despite a large collection of real-time production records, only these raw data are insufficient to implement production monitoring and production decision-making. Some necessary parameters need to be extracted from the real-time production database according to specific monitoring and scheduling requirements.

These necessary parameters, which are used by the RRPM and the RISD models, include the following: (1) operator and machine configuration of each production department, shop floor, and assembly line; (2) information on each production order, including the production operations of each order and the standard allowed minutes of each operation; (3) daily working records of each operator, including the number of operations completed by this operator and this operator's daily average operative efficiency for each operation. Based on these parameters, several other parameters need to be calculated further and used in monitoring reporting and scheduling decision-making. These parameters include the workload of each production process in each order, available production capacity and production efficiency of each production unit, and completion time of each production process in its corresponding production unit. The extracted parameters are saved in the production decision-making database for further production monitoring and decision-making.

Before these necessary parameters are calculated, raw production data must be preprocessed because they are collected by frontline production operators scanning RFID tags attached to workpieces. The scanning of RFID tags cannot be fully automated and can only be performed by the frontline operator because only the operator knows the actual beginning and completion processing times of a workpiece at a given workstation. Hence, some production data collected are possibly inaccurate because of the difficulty in obtaining 100% accuracy in the scanning operations of each operator. To reduce the side effects of inaccurate raw data, we use the median of a parameter as the average value of the parameter. For example, an operator's average operative efficiency in a day is set as the median of all operative efficiencies of the operator on the same day.

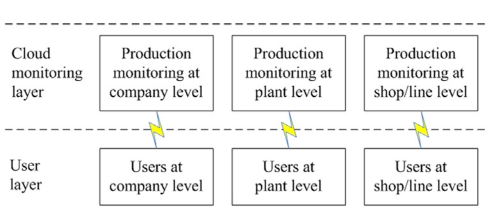


**Fig. 4.** Structure of the RRPM model.

### 4.3. *Remote real-time production monitoring (RRPM) model*

Production management at different management levels – that is, company, plant, and shop levels – must track and monitor the production progress of customer orders in a timely and accurate manner according to job responsibilities. The RRPM model is thus designed and developed by integrating production monitoring functions at three different levels: the company, plant and shop floor levels. Although RFID-based production monitoring has been successfully applied to monitor production within a plant, successful applications of remote and distributed production tracking and monitoring have not been reported in the current industrial practice of labor-intensive manufacturing.

The structure of the RRPM model is shown in Fig. 4. At the cloud monitoring layer, three monitoring submodels at different management levels are included, which provide a user-friendly Web portal to help production management at different management levels monitor the progress of each order. Production management at different levels can easily access to information on job requirements. For example, the production management at the headquarters needs to track and monitor the progress of each order group in subordinate and supplying plants but not the production details of each operation. At the shop floor, the frontline supervisors must focus on the details of each operation for the orders produced in the shop. At the user layer, the users at each management level can browse information related to their responsibilities in accordance with their access rights, through Web browsers in Internet-ready microcomputers and intelligent mobile devices. This RRPM model is implemented by a Web-based production monitoring program that connects with the remote production decision-making database.

### 4.4. *Remote intelligent scheduling decision-making (RISD) model*

This subsection presents the development of the RISD model by a scheduling mechanism based on an intelligent technique to handle production scheduling tasks at different management levels from a holistic perspective.

Production management at different levels needs to determine the assignment of orders to appropriate production units, as well as the processing sequences of these orders. Fig. 5 shows the flowchart of the RISD model for a distributed labor-intensive manufacturing environment involving multiple plants. The scheduling mechanism in this model implements production scheduling in the distributed environment by dividing the scheduling task into three-order scheduling problems at the following management levels:

(1) Company level: after the confirmation of new production orders from a customer, the order scheduling submodel at the company level assigns each order to an appropriate plant.
(2) Plant level: after the confirmation of production orders assigned by the head company, the order scheduling submodel at the plant level assigns each order to one or more appropriate shop floors.
(3) Shop level: the scheduling submodel at this level schedules the production of orders in the shop floors. In some production

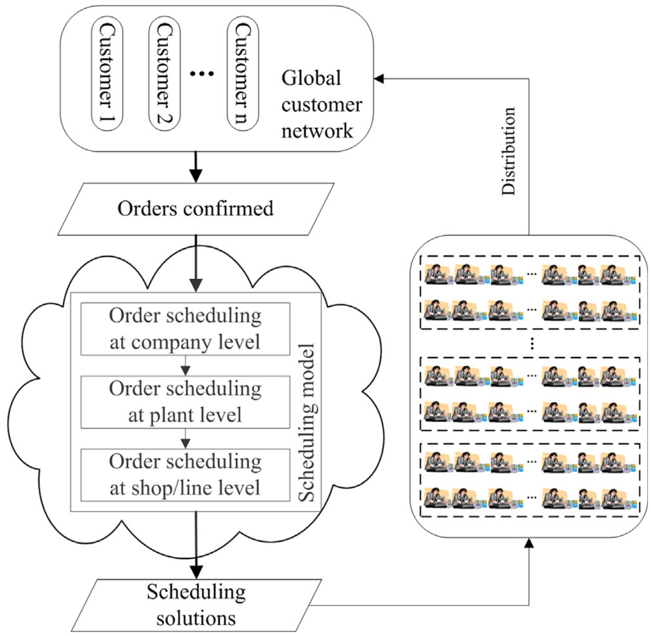


**Fig. 5.** Flowchart of the RISD model.

environments, such as sewing, in which each shop floor comprises multiple assembly lines, assigning orders to each assembly line is also necessary.

Production orders are assigned according to the scheduling solutions generated. After the production of a group of orders from a customer, the finished products are delivered to the specified destinations. Users at different management levels can access these scheduling submodels through the Internet. Scheduling solutions at each management level are stored real-time on the production decision-making database. These scheduling solutions are also used as input parameters of scheduling and decision-making processes at lower management level to achieve transparent and timely information sharing.

In real-world production, the three scheduling problems at different levels need to consider various labor-intensive production features. These characteristics include multiple plants, multiple shop floors, multiple orders, multiple production objectives, and production uncertainties. These features transform these problems into complex, uncertain, and multi-objective combinatorial optimization problems, for which traditional optimization techniques, such as mathematical programming and heuristic techniques, cannot provide optimal or near-optimal solutions. Guo et al. (2013a) proposed a hybrid intelligent decision-making model to solve an order allocation problem considering multi-objective production uncertainties. Various production uncertainties, such as uncertain order arrival time and uncertain processing time, are represented by random variables. Multi-objective intelligent optimization and Monte Carlo simulation techniques are integrated to generate Pareto-optimal solutions. The decision-making model proposed by Guo et al. (2013a) developed a general framework of optimum-seeking process for complex, uncertain, and multi-objective combinatorial optimization problems, which can be thus used to address production scheduling problems at different levels. The main procedures involved in this optimum-seeking process are described briefly, as follows:

(1) A multi-objective intelligent optimization submodel is adopted to generate initial Pareto-optimal solutions to the deterministic production scheduling problem. The deterministic problem disregards production uncertainty by these assumptions: all uncertain orders need to be produced and the processing time of an order equals the mean of its processing time in a production department. Multi-objective intelligent optimization algorithms, such as the non-dominated sorting GA-II (Deb et al., 2002) and the memetic Pareto archived evolution strategy (Knowles and Corne, 2000), can be used to search for Pareto-optimal solutions.
(2) The stochastic production scheduling problem is addressed using the Monte Carlo simulation submodel to evaluate the performance (fitness) of each initial Pareto-optimal solution under various uncertainties in production scheduling.
(3) Based on the fitness of initial solutions for the stochastic problem, the heuristic pruning submodel is employed to generate the final optimal solutions for production scheduling.

## 5. Prototype system development and implementation

A pilot system was developed to evaluate the effectiveness of the RIDSS architecture proposed in Section 3. A distributed labor-intensive manufacturing company with multiple plants was selected as the pilot company in which this system was evaluated. The pilot manufacturing company is a medium-sized clothing manufacturer producing casual wear and sportswear. The company consists of four production plants located in four different cities. This type of labor-intensive manufacturing company exists widely in mainland China. The company receives production orders from global customers and processes these orders in four plants according to customer requirements.

These plants include six production departments: cutting, embroidering, printing, sewing, finishing, and packaging. Each production department occupies one or more shop floors. Each sewing shop floor comprises multiple assembly lines, whereas other shop floors comprise multiple workstations. Each production plant consists of different production departments. Table 1 shows the production departments in each plant. Plant 1 includes six production departments, plants 2 and 3 do not include embroidering and printing departments, and plant 4 does not include cutting and embroidering departments.

The pilot system contains remote production monitoring and production scheduling functions at the company level. In the pilot manufacturing company, one shop floor in each production department of each plant was selected to implement and test the pilot system.

The production performance of each clothing production plant is most affected by the sewing department. Six to ten RFID terminals are installed in sewing workstations to collect the production records of key sewing operations in each sewing production line. A sewing production line consists of about 30 workstations usually. In the cutting department, RFID terminals are installed in each cutting bed to capture the outputs of cutting process of each production order. In the embroidering and printing departments, the outputs of embroidering and printing processes of each order are collected by installing an RFID terminal in each embroidering and each printing workstation. In the finishing department, three RFID terminals are installed to collect the

**Table 1**
Production departments included in each plant.

| | Cutting | Embroidering | Printing | Sewing | Finishing | Packaging |
|---|---|---|---|---|---|---|
| Plant 1 | √ | √ | √ | √ | √ | √ |
| Plant 2 | √ | × | × | √ | √ | √ |
| Plant 3 | √ | × | × | √ | √ | √ |
| Plant 4 | × | × | √ | √ | √ | √ |

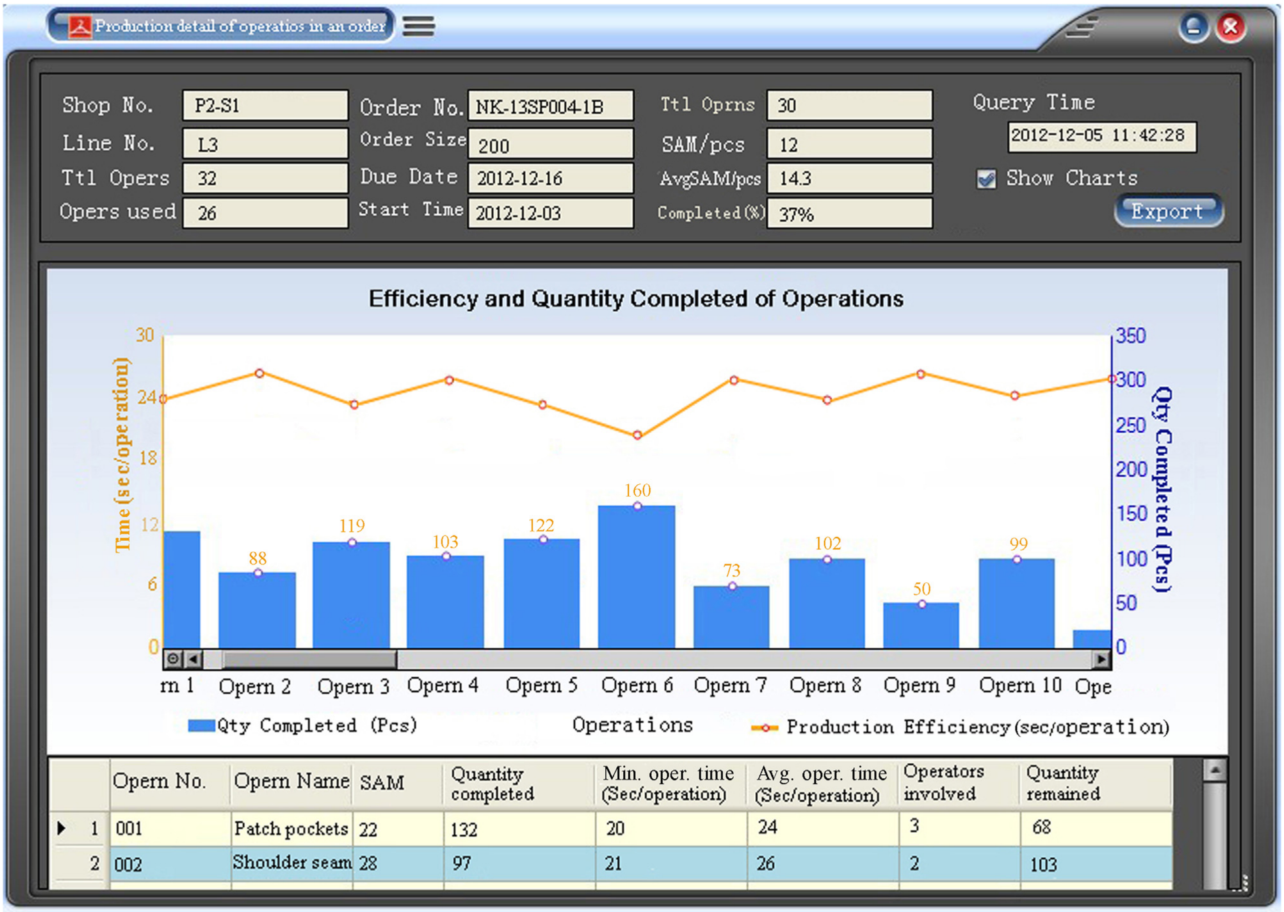


**Fig. 6.** Interface 1 – production detail of operations in an order.

production record for each piece of garment while an RFID terminal is installed to collect the records of each carton of garments in the packing department. Three RFID terminals are installed in the shop floors of the fabric supplier to monitor the production progress of the main fabric materials.

The production scheduling problem at the company level involves the determination of the optimal allocation of a production process for each order to an appropriate plant and the optimal time for processing. The scheduling solutions are generated based on the hybrid intelligent optimization model presented by Guo et al. (2013a).

The pilot system was based on Java/J2EE, SQL Server 2005, and Web technologies. The production management at different levels can monitor the production progress for each order by using summarized production reports and can assign each order to an appropriate plant. Some examples of the pilot system interfaces are shown in Figs. 6–8.

Fig. 6 presents an interface comparing the production efficiency and progress of different operations in a production unit. The average efficiency and progress of different operations involved in processing a production order in a plant, production department, shop floor, or assembly line are compared. The completed quantity from operation 11 is lower than those from other operations, indicating that Operation 11 is a bottleneck operation and can inevitably lower the production efficiency of this order. Operations need to be adjusted to achieve a balanced production flow. This interface clearly shows whether the production flow of an order in a production unit is smooth. By using this interface, the actual operating time can be compared with the standard allowed minute. For example, the average time of operation is "001" and the standard allowed minute is 20 and 22 seconds. This interface is used by production management at different levels to monitor production details of individual orders.

Fig. 7 presents an interface comparing the production progress of all orders in a group. As shown in this figure, the order group NKE-SP01B1 comprises 21 production orders. On the whole, 55% of the total workload of this group is completed. The completed workload of Order 2 is 89%, whereas that of Order 9 is only 18%. In addition, Plant 2 has 625 workers, but only 172 are involved in the production of this order group. By using this interface, the production progress and the average efficiency (average operating time for each product) of different orders in a group are compared. This interface is designed for production management at plant and company levels to monitor the production progress of each order and order group.

Fig. 8 presents an interface showing the solution for assigning production orders to different plants as a result of production scheduling at company level. The orders of group OKY-WI12-2B are assigned to Plant 3, and those of group GNT-SP13-1S are assigned to Plant 1 for processing. Each production order can only be assigned to one plant because of its small-batch feature. In addition, the sequence of orders shown in the interface represents their production sequence in the corresponding plant.

## 6. Evaluation

The effectiveness of the proposed architecture is evaluated by the benefits this system provides the pilot company. Prior to the development and implementation of the pilot system in the pilot

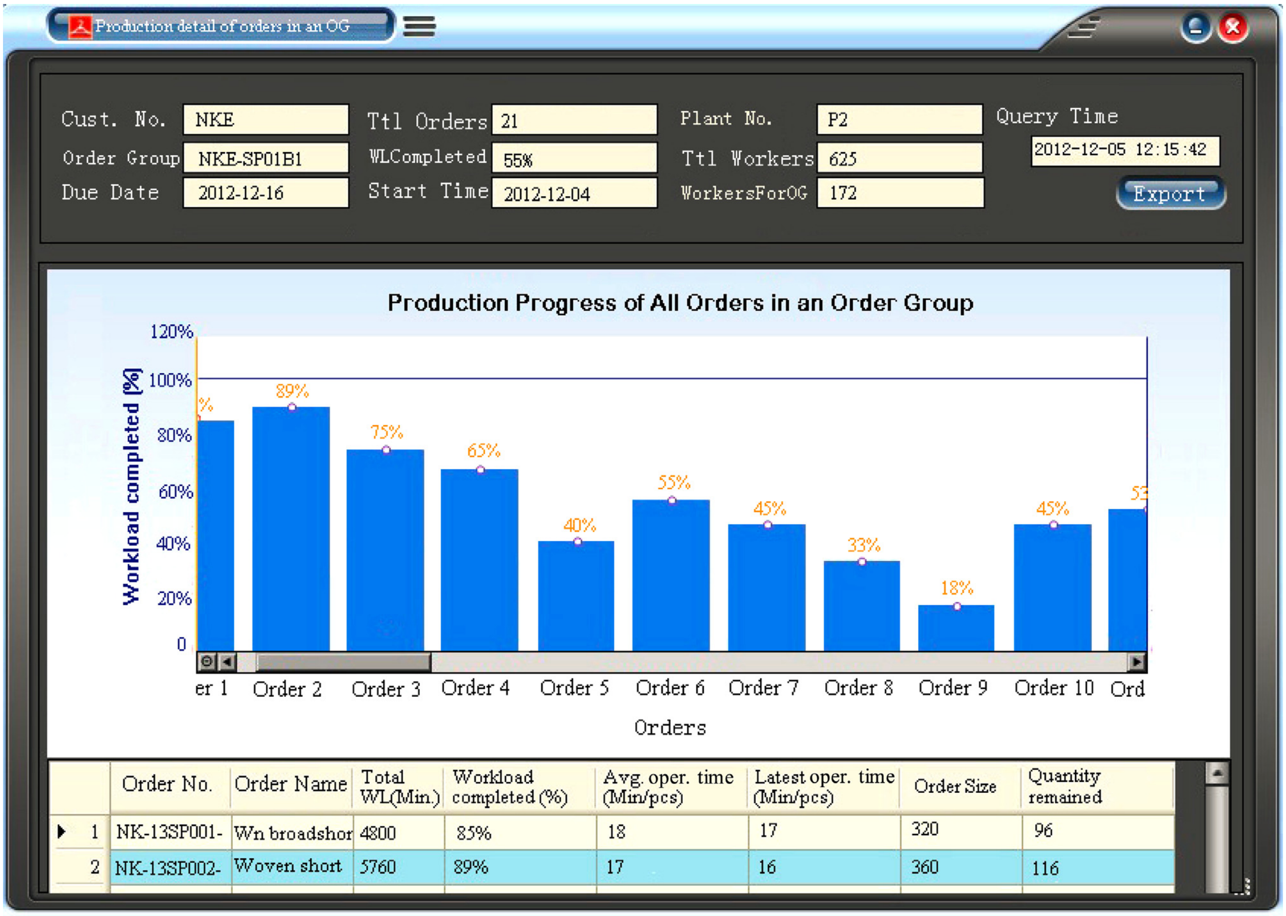


**Fig. 7.** Interface 2 – production detail of orders in an order group.

method of operation before implementation of RIDSS

manufacturing company, manual recordings were used to collect production data. There is a computer operator to input daily job tickets into the computer in each shop floor of sewing department. The production management failed to monitor the production progress of each order in material supplying plants and clothing production plants in a real-time and accurate manner. A large amount of time is required to read and analyze daily summary reports from each plant. The reports are not updated and unreliable because manual recordings and inputs often lead to data errors. In addition, the production schedulers at the headquarters assign each order to an appropriate plant based on experience and subjective judgment, which usually generates inconsistent and low-efficient solutions.

After implementing the pilot system for 6 months, performance was analyzed and evaluated by comparing the production performance of the latest 3 months with that of corresponding 3 months in the previous year. Such comparison was conducted for the following reasons:

(1) The system was confirmed as stable after several months of operation in the pilot company. Therefore, production performance in the last 3 months represents the overall performance of the system since implementation.
(2) Similar product types are produced in each plant in the same months each year because of the seasonal characteristics of clothing production. Comparison of the production performances in the same months for two consecutive years can reduce production performance variations attributed to different product types.
(3) In the two selected periods, full-capacity production is achieved, and the labor force is stable in each shop floor.

Variation in performance can be attributed to the system after elimination of factors that disturb production performance. Comparison of the two selected periods indicates that the pilot company obtained the following tangible benefits:

(1) 25% Increase in production efficiency: production efficiency is defined as the production workloads completed/number of working hours, that is, the average production workloads completed per hour. The production workload completed in a period equals the total standard allowed minutes of all operations completed within this period. The real-time and accurate production data collected lead to a higher visibility and transparency of production operations in distributed manufacturing, which is a motivation for frontline operators to reduce the possibility of loafing on the job. In addition, more accurate progress monitoring of raw material production is helpful to improve the effectiveness of production scheduling decision-making and effective production scheduling decisions generated by the pilot system can improve production efficiency as well.
(2) 12% Reduction in production waste: overproduction, defects, and unnecessary inventory are identified as factors that lead to production waste, which is defined as the total cost incurred by these three factors. Overproduction costs are incurred when the company produces more products than required by a customer. Defect costs are incurred when bad production

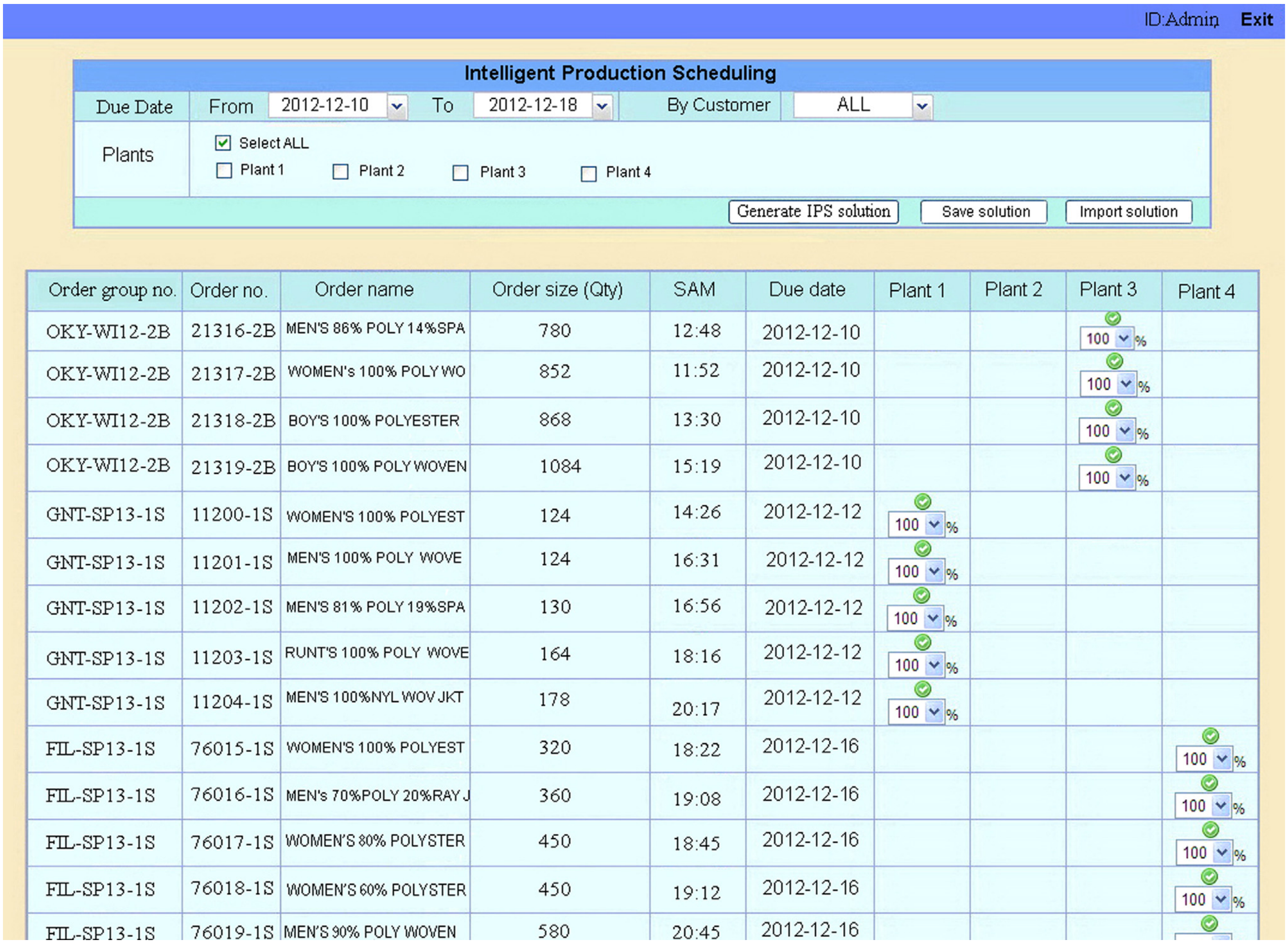


**Fig. 8.** Interface 3 – intelligent production scheduling at company level.

processes lead to substandard products that need repair. Effective order tracking and monitoring result in a more transparent production process, thereby preventing overproduction, defective products, and in-process inventory. More effective monitoring of material production can reduce material inventory. Higher production transparency is also helpful to make operators reduce production waste. Effective production scheduling reduce the probability of rush production, thereby reducing defects.

(3) 8% Reduction in labor and system costs: no computer operator is required to input job tickets. The improvement of production visibility is helpful to reduce IE-related manpower for production management. In addition, the pilot system with cloud-based architecture requires fewer computer servers, lower installation and maintenance costs, as well as less IT-related and IE-related manpower as compared to other data collection systems which were independently installed on each plant. The intangible benefits of using the pilot system include more timely production reports, more effective production scheduling performance, and faster production quick speed.

The case company continued to run the pilot system because of the benefits described above. The company is also planning to further implement the system in all its production departments and to develop and integrate additional functions into the structure.

## 7. Discussion

### 7.1. Cloud-based architecture

A production data capture and monitoring system designed for one plant cannot implement effective integration and sharing of production data collected from different plants. With the development of global manufacturing and in the presence of fierce market competition, this system fails to meet the needs of a distributed global manufacturing network. New and improved architectures are needed to integrate and process a large amount of production data collected from distributed plants and meet actionable decision-making requirements in a very short time. The proposed RIDSS architecture, which adopts a cloud-based system architecture, can provide effective and real-time production monitoring and decision-making functions. The cloud-based system architecture exhibits the following advantages:

(1) Easy-to-access portal to integrate RRDC models. The models are developed to collect real-time production data from different plants, particularly from collaborating or outsourcing plants. Without cloud-based architecture, such data collection can be difficult. Real-time production data result in real-time production monitoring and effective decision-making, thereby improving response time.
(2) Completion of system installation and maintenance in the company headquarters rather than in individual plants. It results in reduced labor and system costs for production plants since

the main system components of the RIDSS architecture are installed and maintained in the company headquarters.

(3) System access from anywhere via the Internet for users at 3 different management levels. Such access allows these users to remotely track and monitor production progress and make production scheduling decisions, which leads to a higher production visibility, transparency as well as decision-making performance.

### 7.2. Extensibility and scalability of the RIDSS architecture

The proposed RIDSS architecture can be used to effectively monitor production processes at different production units and to schedule orders to their appropriate production units. This architecture is extensible, which can easily be modified to include additional functions. For example, the proposed system architecture can be enhanced to integrate with production processes of subcontractors. This enhancement improves visibility of production progress in subcontractor floors. The real-time and accurate production data collected can also be used in other decision-making processes in supply chain operations, such as production planning, order acceptance negotiation, and supply chain scheduling. These decision-making functions can be integrated into the proposed RIDSS architecture. In-depth data analysis and data mining can be conducted based on the collected production data. More useful data are revealed for production decision-making.

Based on the proposed RIDSS architecture, considerable amounts of production data can be collected from its subordinate and collaborative plants and saved into a central database, which enables the provision of timely production data and information on demand to the users at different management levels of the entire company. That is, data as a service function can be implemented in the manufacturing company based on the proposed system architecture.

The proposed RIDSS architecture is also scalable, which can be used in various manufacturing environments, including multi-plant production and partial or complete production outsourcing. In addition to manufacturing companies, the system can be used by trading companies and branders to track and monitor the production and logistics of orders simply by monitoring the status of several key logistics nodes. For example, the proposed architecture is applicable to the tracking and monitoring of clothing supply networks described by MacCarthy and Jayarathne (2013).

Despite the initial intention of using the system for distributed manufacturing with multiple production plants, the proposed architecture can also be applied in simple labor-intensive manufacturing environments such as single-supplier and single-plant environments.

### 7.3. Difficulties encountered and lessons learned

The following are the difficulties encountered and the lessons learned during system implementation in the pilot company:

(1) Employee resistance: resistance by employees was the biggest problem during system implementation. In clothing production, the operator in each workstation must scan RFID tags attached on each workpiece to collect real-time production records. Operators in production floors were comfortable with routine procedures. In particular, certain workers (e.g., sewing operators) resisted the system because their wages directly depend on the number of completed workpiece, which is a common management practice in China's labor-intensive manufacturing company. They consider tag-scanning process a waste of work time and a cause of output reduction. Consequently, managers had to frequently handle workers' resistance. This resistance was gradually exhibited by frontline managers as well. Thus, operating procedures must be kept simple and easy to demonstrate. Pilot production floors for trial runs must also be appropriately selected. Effective measures to prevent employees from reverting to the outdated operation are also required. The system can be implemented in other production floors once the trial run is completed successfully.

(2) Employee training: compared with employees in high-automation industries, the majority of employees in China's labor-intensive manufacturing industries have achieved a relatively low level of education. As a result, frontline management personnel and operators often encounter difficulty of learning a new technology and accepting a new system in daily operations. Thus, effective methods must be adopted to educate relevant participants. The functions and benefits of the new system must be explained carefully to the participants for developing their interests in actively using the system.

(3) Inadequate planning and lack of top management commitment: prior to system implementation, a comprehensive plan can be created by developing step-by-step implementation procedures. The plan needs to consider various potential difficulties during system implementation and corresponding measures to cope with these difficulties. In China's labor-intensive production, lack of motivation to implement the new system can be expected from frontline production management (or even senior management) personnel because they are always preoccupied with daily work. Therefore, commitment and support of top management must be obtained.

### 7.4. Implications

This study has implications for practitioners and academic studies. First, this study can help production management understand the significance of RFID integration and cloud technology in improving production performance and reducing costs.

Second, the proposed RIDSS architecture is capable of making data and information available quickly to people, processes and applications in a distributed manufacturing environment, which is helpful to eliminate data silos existing in systems and infrastructure of different plants, to enable real-time production information sharing for production monitoring and decision-making.

Third, the proposed RIDSS architecture is capable of providing decision support capabilities in the cloud, which is one of the major trends for manufacturing enterprises in hopes of becoming more agile. The proposed RIDSS architecture is a service-oriented decision support system architecture characterized by such distinct features as extensibility, scalability, reusability and customizability. Reusability indicates that the production monitoring and scheduling services provided by the RIDSS can be re-used in many business processes. Customizability represents the ability to be changed by system users in order to adapt it to a specific manufacturing context. For example, manufacturing enterprises with different plant configurations and different decision-making requirements can customize their own RIDSS on the basis of the proposed RIDSS architecture.

Fourth, this study reveals that cloud technology is crucial to real-time production monitoring and scheduling. An increasing number of labor-intensive manufacturing enterprises currently produce their customer orders in distributed manufacturing environments. Thus, production management must consider the implications of more effective production monitoring and scheduling in this scenario. For instance, production outsourcing is a common practice in distributed manufacturing. However, many enterprises did not think about the risks of production outsourcing when they outsourced their production processes to reduce their production cost. RFID and cloud-based production monitoring and scheduling are helpful to reduce this risk by improving the visibility and transparency of distributed production operations and generating integrated scheduling decisions.

Fifth, this study provides a decision support system architecture for monitoring and scheduling the production processes of customer orders in distributed manufacturing environments on the basis of three different management levels. We encourage more researchers to develop cloud-based production monitoring and scheduling systems for different manufacturing environments and integrate various decision-making functions into this system architecture. The applicability, extensibility, and effectiveness of the proposed system architecture requires further evaluation in different manufacturing sectors and supply chain environments, such as supply networks with different types of flexibilities described by Purvis et al. (2014).

Lastly, from the implementation case of the proposed system architecture described above, some key factors of successfully implementing the system architecture in China's labor-intensive manufacturing industry can be suggested. These factors include (1) strong incentive policy that will encourage frontline workers to accept and use the new system, (2) consistent commitment and support from both top management and frontline workers to ensure that the system will be implemented well, and (3) effective employee training to educate relevant management and workers and (4) ensure that they will learn about the system so that they could use it effectively.

## 8. Conclusions

An RIDSS architecture was proposed for effective production monitoring and scheduling in a distributed labor-intensive manufacturing environment on the basis of three different management levels. RFID technology was utilized to collect real-time production records from workstations. An intelligent optimization technique was employed to generate effective production scheduling solutions.

This study is the first to investigate production monitoring and scheduling in distributed labor-intensive manufacturing environments in an integrated manner. The proposed RIDSS architecture is a community cloud-based architecture that can effectively monitor production progress in distributed labor-intensive manufacturing. The cloud-based and easily accessible feature allows the convenient collection of real-time production data from supplying and outsourcing plants but not from subordinate plants. Data collected are transferred to remote real-time production database via the TCP/IP protocol, and subsequently analyzed and extracted for use in production scheduling and decision-making. The scheduling mechanism based on an intelligent technique in the RISD model can handle production scheduling tasks in distributed labor-intensive manufacturing environments from a holistic perspective.

The effectiveness of the proposed architecture is verified by developing and implementing a pilot system in a distributed labor-intensive manufacturing company with multiple plants. The evaluation of the pilot system clearly demonstrated the benefits of the system, including a 25% increase in production efficiency, and a 12% reduction in production wastes, and an 8% reduction in labor and system costs. Improved supply chain coordination and production scheduling decisions can be achieved by implementing this system, which ultimately leads to enhanced customer service.

The proposed RIDSS architecture can help develop an interconnected, visible, and intelligent supply chain because (1) interconnectivity of different plants and business partners is improved. This increased interconnectivity can facilitate collaboration among plants and partners, in addition to creating a more holistic view of production progress. (2) The proposed system can improve visibility in production and supply chain operations. This architecture enables production management at different levels to "see" more events and witness these events as they occur. (3) RIDSS architecture can improve the production decision-making process by using intelligent optimization techniques to generate effective scheduling decisions.

This study presents an effective and promising system architecture for production monitoring and scheduling; however, the following research limitations must be addressed in the future:

(1) The proposed RIDSS architecture only includes production monitoring and scheduling functions. Future studies can extend the scope of this architecture to allow integration with more extensive supply chain operations and production decision-making activities.
(2) On the basis of this architecture, a significant amount of real-time production data can be collected from distributed plants. The application of these data in other decision-making activities and existing information systems in the company were not examined. Future data analysis and processing may be conducted according to actual decision-making requirements, thereby maximizing the usefulness of the collected data for production operations.
(3) Although the RISD model includes a general optimum-seeking process for real-world production scheduling problems, effective optimization models must be further developed based on this mechanism for specific production scheduling problems in labor-intensive manufacturing. The reason is that no optimization technique can be applied to all real-world scheduling problems.

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