Expert Systems with Applications 38 (2011) 5428–5437

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Design and development of logistics workflow systems for demand management with RFID

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ARTICLE INFO

Keywords:
Logistics workflow
RFID
Artificial neural network
Backpropagation algorithm
Demand chain management
Supply chain management

ABSTRACT

This paper discusses demand and supply chain management and examines how artificial intelligence techniques and RFID technology can enhance the responsiveness of the logistics workflow. This proposed system is expected to have a significant impact on the performance of logistics networks by virtue of its capabilities to adapt unexpected supply and demand changes in the volatile marketplace with the unique feature of responsiveness with the advanced technology, Radio Frequency Identification (RFID). Recent studies have found that RFID and artificial intelligence techniques drive the development of total solution in logistics industry. Apart from tracking the movement of the goods, RFID is able to play an important role to reflect the inventory level of various distribution areas. In today's globalized industrial environment, the physical logistics operations and the associated flow of information are the essential elements for companies to realize an efficient logistics workflow scenario. Basically, a flexible logistics workflow, which is characterized by its fast responsiveness in dealing with customer requirements through the integration of various value chain activities, is fundamental to leverage business performance of enterprises. The significance of this research is the demonstration of the synergy of using a combination of advanced technologies to form an integrated system that helps achieve lean and agile logistics workflow.

1. Introduction

The logistics and supply chain environment is characterized by aggressive global competition, rapidly changing technologies and increasingly complex markets, all of which have prompted the development of information systems to facilitate the exchange and update of relevant data transactions. In general, decisions are made by logistics services providers, normally based on personal experience and knowledge. However, recent reviews on logistics systems indicate that inadequate attention has been given related to the development of a logistics workflow system which can respond rapidly to outside changes in an effective manner (Goutsos & Karacapilidis, 2004; Liu, Zhang, & Hu, 2005). With advert of RFID technology, information of moving objects can be obtained in a quick manner and easier way. Identification of demand pattern, market trend, and customer behaviour requires real time information and formulation of replenishment strategy needs both explicit and implicit knowledge. Since knowledge is captured by human experts and the turnover of the experienced staff may lead to loss of valuable corporate asset. This research aims to develop a responsive logistics workflow system featured with a combination of emerging technologies for capturing update information and deploying relevant knowledge, thus facilitating effective demand management (Lee, Lau, & Ho, 2005).

2. Related studies

To stay competitiveness in today's turbulent market, not only supply chain management but also demand chain management attracts the researchers' attention so as to respond to customers' needs quickly. Supply chain management is the integration of key business process for end users through original suppliers who add values on products, services, and information (Tan, 2001) while demand chain management is the whole manufacturing and distribution process may be seen as a sequence of events with one end in view; it exists to serve the ultimate consumers (Brace, 1989). If supply chain is regarded as a push strategy to the upstream operations driven by the downstream operations; demand chain is regarded as a pull strategy to meet customer needs with satisfactory quality in a profitable way. Demand chain management puts emphasis on the needs of the marketplace and

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0957-4174/$ - see front matter
doi:10.1016/j.eswa.2010.10.012

designing the chain to satisfy these needs of downstream operations which is triggered by the suppliers/manufacturers and working backward (Vollmann & Cordon, 1998). The main components of demand management are demand creation, communication, supply planning and order management which is in strategic, tactical and operational level (Thomas, 2004). To achieve effective demand chain management, the organizations need to consider the supply chain cost, product profitability, sales volume and customer value proposition. One of the prepositions of demand chain management model proposed by Heikkilä (2002) is reliable information flows which contribute to high efficiency in value chain. An integrated framework for the development of focused demand chains suggested by Childerhouse, Aitken, and Towill (2002) realized that information about the competitive situation can be interpreted; analyzed and represented in the form of key order winner and order qualifier. It cannot be denied that information plays a pivotal role in supply chain and demand chain to attain the goal of quick response.

With advent of new technology like Radio Frequency Identification (RFID), which is an automatic identification method, keeps track and trace of the moving objects within the logistics network. Both bar-code and RFID have its distinct strength in data collection and application areas. InLogic (2008) has done the comprehensive comparison between RFID and barcode in terms of line of sight, read range, read rate, identification, read/write operation, interference and automation and authors have include the data related to read rate, data capacity, communication protocol, cost, and summarized in Table 1. Bar codes has lower cost, easy tagging for different material and comparable accuracy rates due to the mature technology with large installed base. Comparing with bar-code, RFID has advantages of small tag size, longer lifespan, readable in harsh environments; support for nonstatic data, reprogrammable and traceable and those benefits are verified by the study of Jones, Wyld, and Totten (2005). RFID will gradually replace bar code based on condition of the dropping price of tag and hardware, international standard of common frequency of operation, advocates of large retailers and advance technical development of the tag and hardware. RFID is used for physical distribution and planning including inventory control (Jedermann, Behrens, Westphal, & Lang, 2006), warehousing (Chow, Choy, Lee, & Lau, 2006), material handling (Huang, Zhang, & Jiang, 2007) and order processing (Philips, 2004). RFID is advocated by Wal-Mart for promoting the use of electronic code to streamline the supply chain and Wal-Mart requests suppliers to attach tag to each pallet of goods in distribution center and warehouse. The invention of smart-shelf alerts practitioners to replenish the goods instantly when the goods are out of stock. This invention system can greatly reduce the error between the inventory record and physical record so as to reduce the number of cycle count and increase the effectiveness of inventory management. RFID, which is applied to manage the movement of material handling equipment such as fork-truck, results in increasing efficiency of picking processes by 15–20% (Chow et al., 2006). The application of RFID for point of sales can greatly reduce the processing time at cashiers and further reduce the queuing time. In short, RFID has been prompted to have strategic implementation with concerned of data management, system integration and security.

Cross-platform supply chain information system was proposed to enable data exchange among various data object over geographically isolated regions (Lau & Lee, 2000). Demand chain management solutions put much emphasis on collaborative forecasting processes between manufacturers, suppliers and customers to attain the goal of inventory optimization. However, it is difficult to have an accurate forecasting due to many uncertainty factors in the dynamic market. As a result, logistics information system is proposed to facilitate information exchange though the logistics workflow for just-in-time replenishment rather than putting too much emphasis on forecasting. In summary, this review of contemporary publications indicates that while many research studies have been conducted using various approaches to improve demand and supply chain, the research related to apply machine learning for demand pattern recognition has not received the attention it deserves. This issue is addressed in this paper with the introduction of a logistics workflow system for demand management, which is fully described in the following sections.

3. Proposed methodology

In order to keep inventory at reasonable level that is sufficient to provide supplies on demand continuously but avoid overstocking, distributors, manufacturers and retailers need effective information sharing among each other. The structural framework of responsive logistics workflow system (RLWS) is formulated and shown in Fig. 1. In particular, the focus of development is on

Table 1
Comparison of RFID and barcode.

	RFID	Barcode
Line of sight	Not required (in most cases)	Required
Data capacity	100's–1000's of characters	<20 characters with linear
Read range	Passive RFID: Up to 25 feet Active RFID: up to 100's of feet or more	Several inches up to 30 feet
Read rate	10's, 100's or 1000's simultaneously	Only one at a time
Read accuracy	90% depends on relative orientations of reader and tag antennas and their polarizations)	90% or higher
Identification	Can uniquely identify each item/asset tagged	Can typically only identify the type of item (UPC code) but not uniquely
Read/write	Many RFID tags are Read/Write	Read only
Technology	RF (Radio Frequency)	Optical (Laser)
Interference	Like the TSA (Transportation Security Administration), some RFID frequencies do not like metal and liquids They can cause interfere with certain RF frequencies	Obstructed barcodes cannot be read (dirt covering barcode, torn barcode, etc.)
Communication protocol	ISO 18000	RS232
Automation	Most "fixed" readers do not require human involvement to collect data (automated)	Most barcode scanners require a human to operate (labor intensive)
Cost	Tag 5¢ RFID startup kit with RFID reader, antennas, alien gateway software, startup kit tag and power supply/ power cable USD 2595	Barcode label near zero Barcode scanner USD 120–1500 Barcode printer USD 240–7500

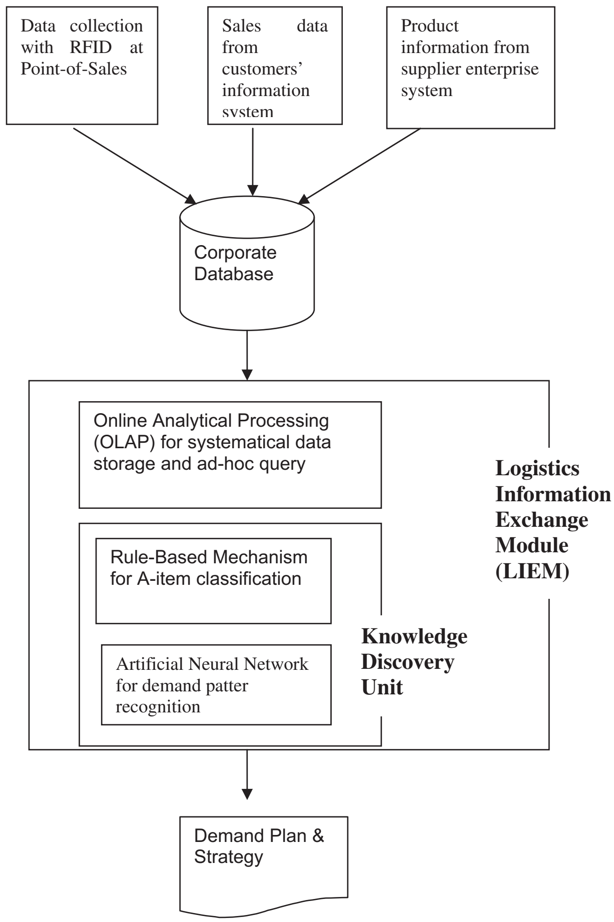

Fig. 1. Architecture and information flow of responsive logistics workflow system.

Knowledge Discovery Unit including rules based reasoning and artificial neural network for mining the knowledge among the data. Logistics Information Exchange Module (LIEM), which is an integral part of the RLWS, is used to model the logistics process and formulate the strategy for turbulent market. Instead of introducing specific information schema (Lee, Ho, Lau, & Yu, 2006), LIEM adopt the Electronic Product Code advocated by EPCGlobal to support RFID data exchange among industries and the encoding schemes is designed for Global Trade Item Number (GTIN), serial Shipping Container Code (SSCC), Global Location Number (GLN), Global Returnable Asset Identifier (GRAI), Global Individual Asset Identifier (GIAI) and General Identifier (GID). Electronic Product Code is used as coding schemes for RFID tag for data exchange to facilitate dynamic data conversion, ensuring data compatibility among various computer systems. It is indisputable that information system helps to analyze the data and transform those historical records to articulate replenishment strategy by studying the demand patterns. In particular, the proposed system supports the deployment of artificial neural network which plays an important role for leveraging knowledge in demand pattern recognition.

3.1. Collecting data with RFID

RFID makes use of radio wave to collect and retrieve data with devices called RFID tags or transponders. An RFID tag is a silicon chip with antenna for storing the electronic product code for product identification. RFID reader is installed at point-of-sales and distribution center to check the inventory level and provide nearly real time information of sales trend and demand patterns of various products. Real-time information management helps to achieve effective demand and supply management and minimize bullwhip effect (Frohlich & Westbrook, 2002; Min & Zhou, 2002). Practitioners get the update sales information and respond to the customer demand so as to co-ordinate the movement of goods for distribution planning. Nowadays, RFID reader can read 1500 tag in a second and collect terabyte of data in a few minutes (O'Connor and Roberti, 2005). Data management becomes a critical issue as it is a need to have quality data by removing redundant and noisy data. As enormous amount of data has been collected, it is a need to create a data warehouse to store and filter the data so as to extract the valuable information.

3.2. OLAP for data analysis

OLAP, which is a database application, supports data analysis and decision making. According to the definition provided by the OLAP Council, OLAP is a "*category of software technology that enables analysts, managers and executives to gain insight into data through fast, consistent, interactive access to a wide variety of possible views of information which has been transformed from raw data to reflect the real dimensionality of the enterprise as understood by the user* (Inmon, 1992)." The cube is typically displayed with three dimensions which are purchase category, time and geographical region. In the OLAP data cube, fact table and dimension table are used for manipulating the data in demand chain. The snow-flake scheme is deployed for exploiting the hierarchical structure. E.g. the single dimension "Product" in the star schema is normalized in the snowflake schema shown in Fig. 2 such that time dimension table now contains a new attribute product_class_id which further linked to the dimension table, product_class, containing information of product category.

OLAP allows complex analytical and ad hoc query with a short execution time. Analysts can obtain business report and interactive graphical presentation by OLAP operations which are roll-up, drill-down, rotate, slice and dice as shown in Fig. 3. The purpose of adopting OLAP in the proposed system is to extract recorded data sets from corporate database on the dispersed network, which allows decision-makers to view the data in different dimension and level. Making use of OLAP operation, decision makers can generate summarization, aggregations and hierarchies at each granularity level and at every dimension intersecting. E.g. The analyst would like to get the data from the cube "Sales Analysis" to find out the sales volume and tax amount in year 2005 and 2006 (time dimension) at southwest sales territory (location dimension). The sample code of MDX is shown as following.

```
SELECT
  {[Measures] · [Sales Volume],
    [Measures] · [Tax Amount]} ON COLUMNS,
  {[Date] · [Fiscal Time] · [Fiscal Year] · &[2005],
    [Date] · [Fiscal Time] · [Fiscal Year] · &[2006]} ON ROWS
FROM [Sales Analysis]
WHERE ([Sales Territory] · [Southwest])
```

The distinct features of OALP include computing a complex query, providing multi-dimensional view of data with flexible data modeling as well as time series analysis.

3.3. Rule based mechanism for product classification

During the replenishment cycle, practitioners need to handle all processes for inventory control and management. It is initiated when a retailer places an order to replenish inventories to meet future demand. The overall goal of the task allocation done by rule based mechanism is to replenish inventories at the retailer at

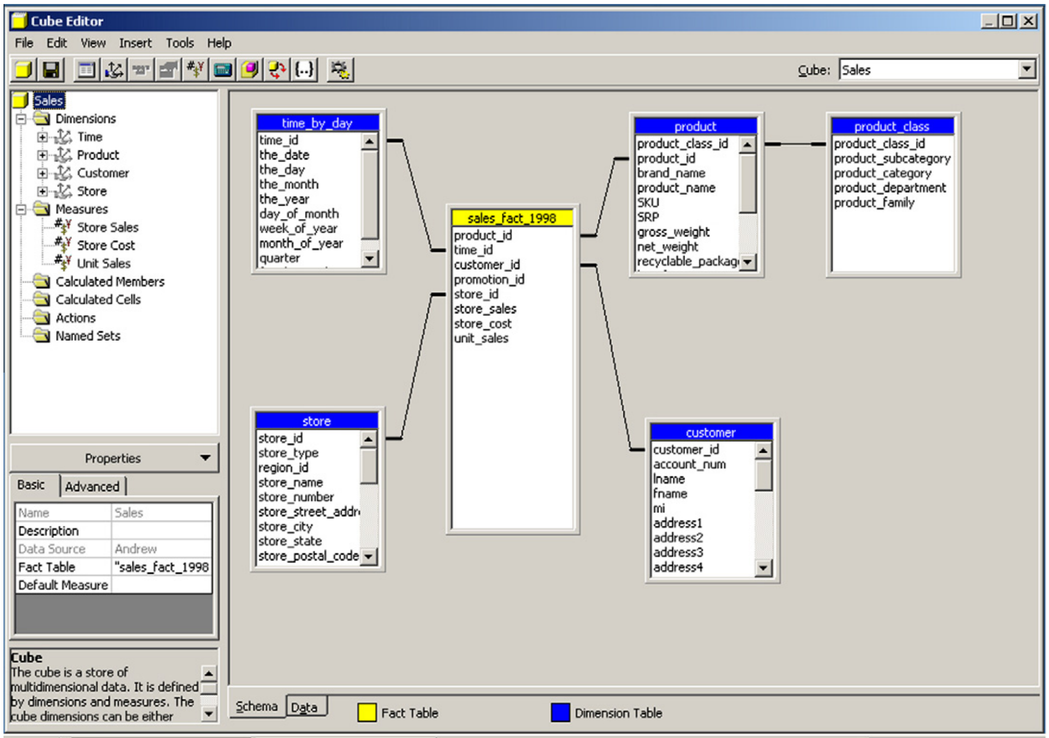

Fig. 2. Snowflake schema of a data warehouse.

minimum cost while providing high product availability. Demand management has four major elements including planning demand, communication demand, influencing demand and prioritizing demand (Crum & Palmatier, 2005). ABC analysis is used to prioritize the high valued orders from the customers such that enterprises can concentrate their resources on tracking the small group but high value orders or items. ABC analysis provides a means to prioritise the items/tasks of dealing with suppliers and tracking the materials at operational level. ABC classification can be used in purchase, production, and inventory management due to its generic applications. Having realized the class of the item, top management can formulate the strategy by considering the trade-off between high service level and low inventory level. According to the findings of Hautaniemi and Pirttila (1999), the following rules are constructed for product classification in rule based mechanism.

> ***If*** part X accounts for 80% or above value of the total amount, ***then*** part X is classified as Class A.
> ***If*** part X accounts for 80% or above value of the total amount and the supply lead time is shorter than FAS, ***then*** part X is classified as Class A GROUP (II) item.

For those items in Class A GROUP (II), further analysis and classification is needed and it requires Knowledge Discovery Unit to categorize the items. After classifying the item as singular, lumpy and continuous demand, related replenishment policy is suggested for multi-echelon inventory control.

3.4. Artificial neural network for demand pattern recognition

Artificial neural network (ANN) mimics the biological neural systems with the objective to "learn" patterns from data by finding out relationships, minimizing the errors and building the model to represent knowledge. ANN has widely applied for pattern recognition for speech, vision and senor fusion and recently more researchers start to apply ANN for demand pattern recognition and data analysis for market segmentation (Grønholdt & Martensen, 2005; Lee et al., 2006; Lee, Shih, & Chung, 2008). ANN is adopted in this research due to the good performance on large dataset and sigmoid function can smooth input data variation so as to provide accurate classification and prediction (Roiger and Geatz, 2003). ANN consists of an input layer, output layer and a hidden layer. Each layer has a number of nodes which interconnect with each other to form a complete network structure shown in Fig. 4. Each node acts as the processor and like neurones. The role of the node is to get the input received from connected nodes and adjust the weights with mathematical functions to calculate the output values. The back propagation algorithm is a supervised learning technique to calculate the gradient of the error of the network with respect to the network's modifiable weights. Through comparing the difference between the desired and actual output, the weight is adjusted to minimize the error.

Logistic function $f(x)$ is typically used as the activation function for backpropagation and the main criteria of selection activation function is that it can be differentiable. In this case, sigmoid function is adopted

$$f(y) = \frac{1}{(1 + e^{-\lambda \times y})}$$

where $y = \sum_{i=1}^{n} x_i w_i$ is an activation level determined by multiplying input signal x_i and connection weight w_i.

λ is the squashing parameter used to fine-tune the sigmoid curve.

The first-order derivate of sigmoid function is shown as following:

$$f'(y) = f'\left(\frac{1}{(1 + e^{-\lambda \times y})}\right) = \frac{1}{(1 + e^{-\lambda \times y})} \times \left(1 - \frac{1}{(1 + e^{-\lambda \times y})}\right)$$

According to Roiger and Geatz (2003), the output errors for hidden nodes at node i is computed as following.

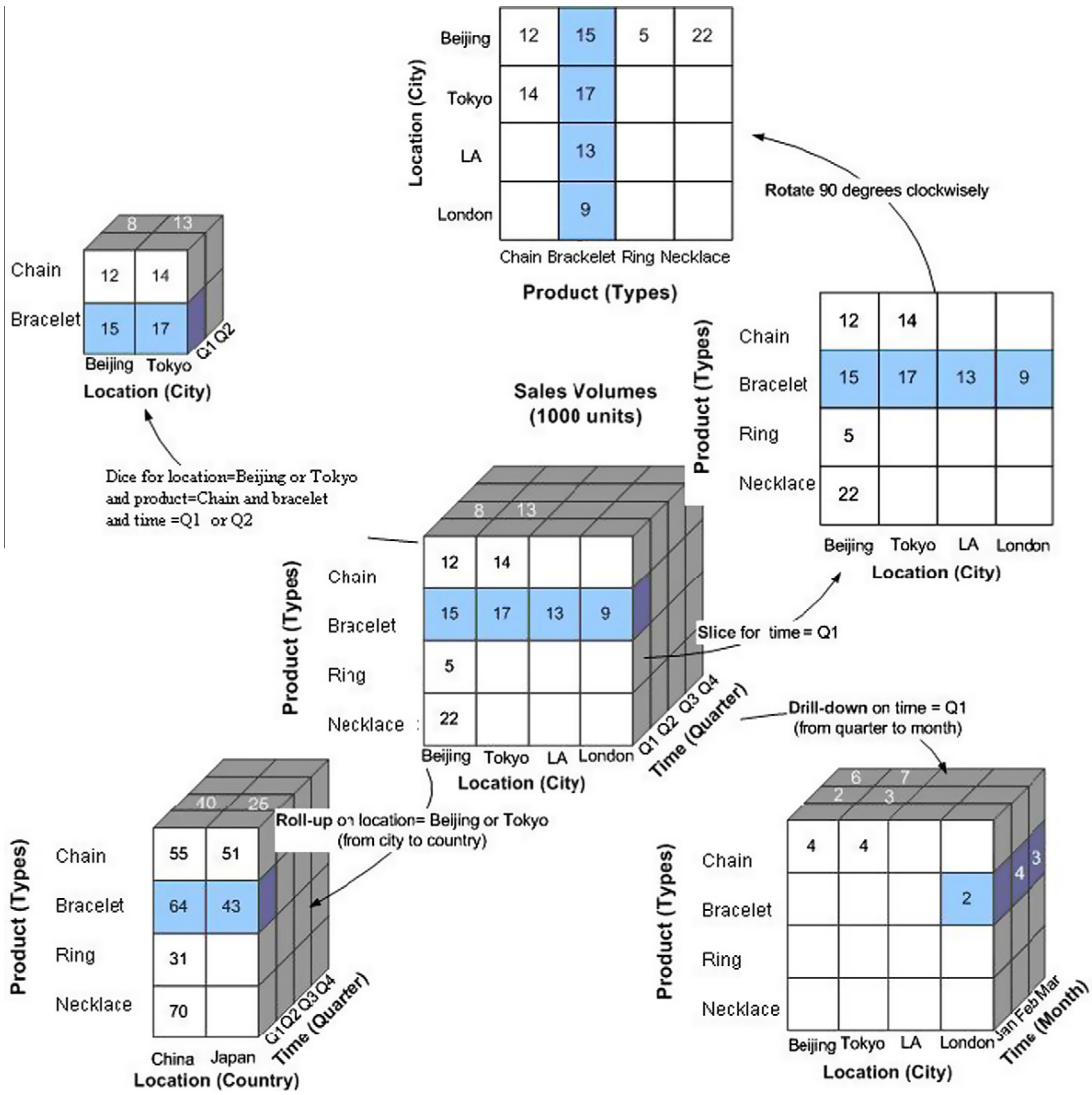

Fig. 3. OLAP operations on multidimensional data of product sales.

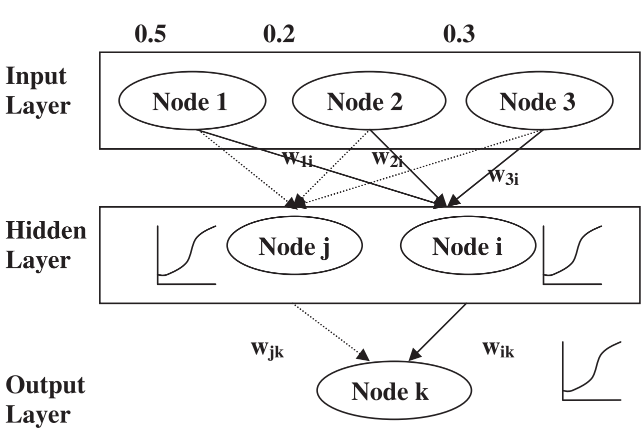

Fig. 4. A feed-forward neural network.

$$Error(i) = \sum_k Error(k) W_{ik} f'(x_i)$$

where $\sum_k Error(k)$ is the computed output error at node k. W_{ik} is the weight associated with the link between node i and output node k. $f'(x_i)$ is the first-order derivate of the sigmoid function. x_i is the input to the sigmoid function at node i.

The delta rule by Widrow and Hoff (1960) is shown below

$$w_{ik}(new) = w_{ik}(current) + \Delta w_{ik}$$
$$\Delta w_{ik} = -c[Error(k)]O_i$$

where c is the learning rate parameter between 0 and 1. *Error(k)* is the computed output error at node k. O_i is the actual output value of ith node.

Δw_{ik}, the weight adjustment between node i and node k, has been calculated as above and similar equation applied for calculating Δw_{1k}

$$\Delta w_{1i} = -c[Error(i)](I_1)$$

where c is the learning rate parameter between 0 and 1. *Error(i)* = the computed output error at node i. I_1 is the actual input value of node 1 (i.e. 0.5 shown in Fig. 4).

The final step of the backpropagation process is to update the weight associated with the individual node connections. Delta rules by Wedrow and Hoff (1960) are used to minimize the difference between desired output and actual output. As the network weight has been adjusted, the training process will be terminated when the network can achieve the Root Mean Squared (RMS). The accuracy of the network is tested based on a test data set so as to get the solution.

ANN is deployed for the recognition of distribution pattern of demand. Demand distribution of items, which is a multifactor problem involving how the parties in supply and demand chain to manage the replenishment time. The replenishment time is the summation of order lead time, production lead-time and transportation time while the supply lead time consists of production lead-time and order lead time. The purpose of ANN is to discover the key inputs for three types of distribution pattern of demand which is singular, lumpy and continuous demand (1999). A singular demand means that the unit per order is one and the item will be delivered when it is needed; lumpy demand is replenished in batches and the reorder quantity is in large amount; continuous demand means that the items are replenished continuously.

4. Exemplary case

In order to illustrate the proposed concept of RFID applications and artificial intelligence techniques, a case example of jewelry industry is used. Retailers and importers of jewelry industry now takes additional inventory by consignment, and they request suppliers for extended credits, exchange for unsold items, shorter delivery lead time, and trendy designs. An accurate demand analysis at distributed area is needed so as to provide a good mix of product and adequate service. On the contrary, excess stocks increase inventory and carrying cost and it in turn affects the cash flow. As shown in Fig. 5, the implementation steps are stated as follows.

4.1. Tracking sales volume and slow moving items with RFID equipments

Since the cost of jewelry is high, RFID equipments can be used to collect daily information in distributed location so as to keep track of the jewelry. Similar as the existing solution adopted by Damas Jewellery, the ISO 15693 compliant passive 13.56 tag can be tagged in a 16 mm long hard plastic case with both end of the cord attach to the case after it has been looped through jewelry so as to have complete and electric circuit and render the tag operable(Swedberg, 2006). TAGSYS and Solid provides special designed tags, ARIO70-SM 13.56 MHz, and RFID solution for jewelry industry while deployment of RFID system by de Grisogono shows the new milestone for jewelry IT system (O'Connor, 2006). Retail anti-theft in combination with Electronic Article Surveillance (EAS) tags helps to detect the product within the store by setting as 1 bit and set the bit value as 0 at the checkout counter. Reader detects the presences of the EAS tag in its read zone and trigger alarms to warn of a possible theft attempt (Lahiri, 2006).

The readers installed in distribution center or point-of-sales help to collect data to reflect the sales trend, distribution of goods and the inventory at various locations or consignees' counter. Apart from keep tracking the sold item, it can also help to track the slow movement items so as to alert suppliers about the supply of those items. The sold item or unsold item in the store is detected by RFID interrogator, the database store the data about the sales and inventory record. E.g. system administrator can set 100 days as slow movement item in the inventory management system and RFID system can detect the items which are in store or warehouse more than 100 days and report can be generated to shows the slow movement items. As RFID can be applied at the security gate, any items without proper check out and unable the tags will trigger the alarm system so as to avoid the products being stolen. Since each jewelry has unique identification number which is read by handheld interrogator for daily inventory checking, it can also disguise a theft to cut the cords to disable the tag (Swedberg, 2006).

4.2. Removing RFID reading error

As reading error can adversely affect the result of market analysis, RFID reading error should be eliminated before the data is imported to Knowledge Discovery Unit. Two main sources of RFID reading error are "miss" tag read and "ghost" tag read (i.e. reader reads an identifier that is not stored on any tag). Prior to storing the data in data warehouse, data pre-processing including data cleaning, data integration, data transformation and data reduction are needed. The "ghost" data are filtered and the "miss" data can be filled by using techniques such as identity association. Each sold items are scanned by RFID handheld interrogator and the records

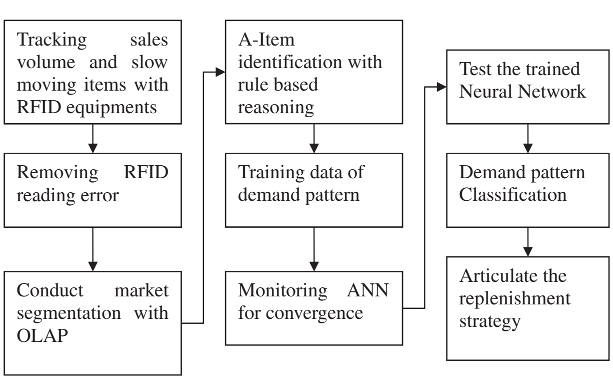

Fig. 5. Implementation steps of RLWS.

Table 2a
Item cost and class in Jan 2006.

Item No.	Cost	Class
JD001	6665	A
JD002	6561	A
JD003	264	C
JD004	845	C
JD005	456	C
JD006	732	C
JD007	1122	B
JD008	1321	B
JD009	2111	B
JD010	974	C
JD011	744	C

Table 2b
Item cost and class in Aug 2006.

Item No.	Cost	Class
JD001	4665	A
JD002	4561	A
JD003	264	C
JD004	845	C
JD005	456	C
JD006	732	C
JD007	1122	B (Sold)
JD008	1321	B
JD009	2111	B (Sold)
JD010	1121	B
JD011	744	C
JD012	234	C
JD013	1214	B

are displayed in the POS system. The sales person double checks the sold items; prints the receipt for the client and updates the inventory system so that the missing tag read can be avoided.

4.3. Conducting market segmentation with OLAP

OLAP is not only used to store the data systematically but also facilitates timely access and analysis of sales and inventory data of jewelry. The analyst can browse the information with drill down operation according to the dimension of time, place and product type. E.g. the sales data in 2005 is extracted by OLAP and those data can be further analysis by ANN. Segmentation metrics can be constructed to categorize the customers into various segments with different buying habits and preferences as those information is critical for sales promotion, targeted marketing and it helps to improve responsiveness for customers' needs.

4.4. A-item identification with rule based reasoning

"A-item" identification is complex in jewelry industry and rule-based mechanism is used to find out the most valuable items which are A-item of ABC analysis. In a jewelry shop, one article of jewelry includes different components such as jade, diamond, gold. Jade can be classified as grade A, B or C; the quality of diamond can be judged by color/cut/caret/clarity; Gold is categorized as 14K/18K/24K. Each finish products may have different combination of gold, diamond or jade and the fluctuation price of the precious metal leads to the changing price of the finished goods. Table 2a shows the cost of the items and the relative class by ABC analysis in January 2006. As most jewelry is handcraft and have unique design, the same item (JD010) may be classified as different category (from class C to class B) because different types of jewelry are produced and sold continuously. Table 2b shows the cost and the latest class of the items in Aug 2006. The classification of the same item may also change according to the cost of the product and on-hand inventory.

Table 3
Extracted neural network inputs for distribution pattern of demand diagnosis.

Uncertainty in demand during the replenishment time	Item's demand are fluctuate during the items' supply lead time
The demand per order distribution is known	No batch order
Demand forecast derived from the sales forecasts of end products	Known supply lead time
Fixed production lead time	Steady demand as the share of end products containing a specific item
Demand volumes are high	Uncertain transportation time
The distribution of the timing is know	

4.5. Training the data of demand pattern

The demand pattern is analyzed with ANN and the detailed procedure of applying ANN is listed as following.

The business analyst can load the training data (data of demand pattern) and initialize the neural network. The data file of distribution pattern for demand classification is loaded as training data. Demand patterns were loaded to QwikNet and the Network Topology section indicates that the network contains 11 inputs and 3 outputs. The extracted input attributes are shown in Table 3.

On the other hand, the typical output attributes are singular, lumpy and continuous demand. The demand pattern classification problem of six hidden neurons, and different topologies should be set. The training algorithm "MLP network" is selected as it has excellent pattern recognition problems property (Le Cerf, Ma, & Van Compernolle, 1994). As "Cross-Validate Training" check box in the training properties is checked, all errors are calculated only

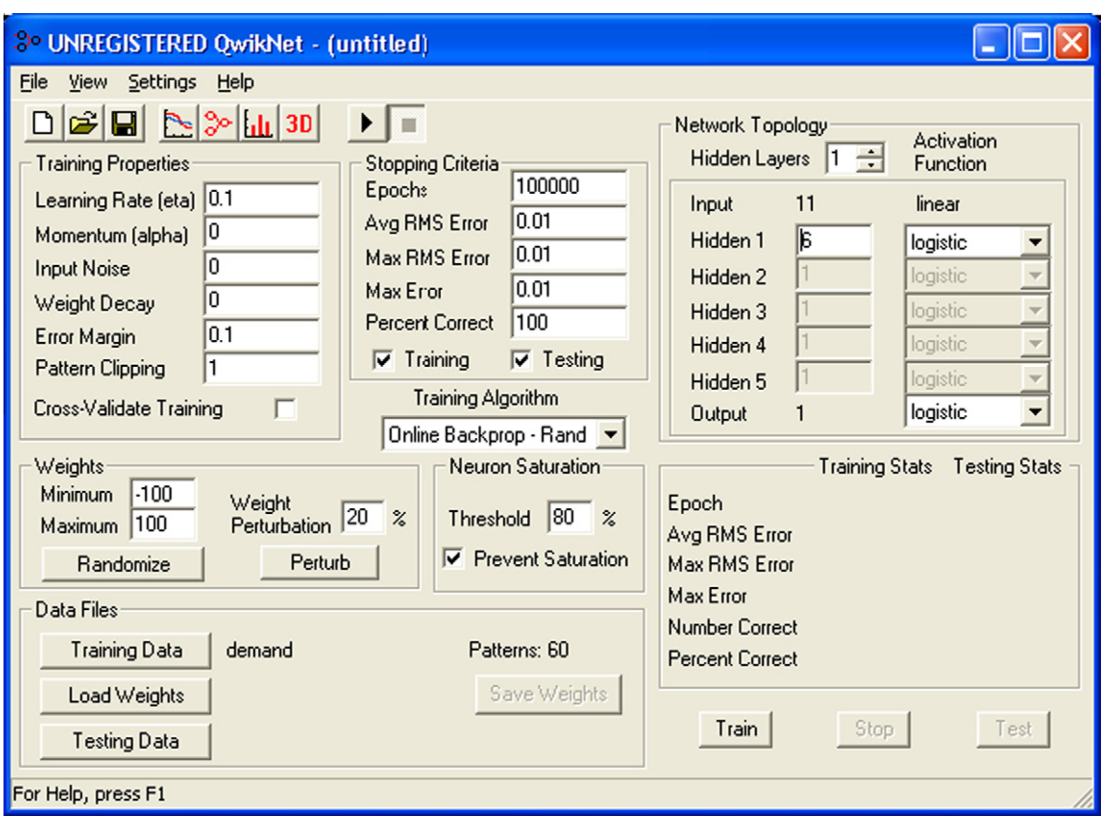

Fig. 6. Parameter settings in an artificial neural network.

on the portion of the training data file that is used for actual training and the partial data set are used in the training process. The parameter setting of ANN is shown in Fig. 6.

4.6. Monitoring ANN for convergence

A plot of the RMS training error versus the training epoch is used to examine the quality of trained network. Once the training process is completed, RMS error decreases as the epochs increase. The training will automatically stop provided that the error has been reduced to an appropriate level as specified in the fields of "Error Margin" or "Convergence Tolerance". However, if the training process gets stuck and the error stops decreasing or may even increase, the training should be first stopped and restarted by clicking the "Randomize" button. Different training algorithms and learning rates can be set to test how they affect the training process by stopping the training process, randomizing the weights and restarting training. The weight and the configuration are saved for further data retrieval.

4.7. Testing the final neural network

As ANN completes the training process, a solved network is loaded and contour plot is examined. The test data are loaded and the outputs are generated by adopting the network pattern. Transfer function is used to control the output signal strength for the nodes. The input to the transfer function is the dot product of all the nodes input signal and node's weight vector while the output signal strength is between 0.0 and 1.0. The typical functions include Logistics, Gaussian and Tanh.

Logistics function is regarded as the most widely used transfer function for back propagation neural network. Logistics function is similar to sigmoid S-curve with a continuous function which can have totally opened (1) or closed (0) and partially opened (between 0 and 1). Although it may take a longer time for training, sigmoid transfer function can improve accuracy by generalizing the learning characteristics (Vesta Servics Inc., 1999).

Gaussian transfer function is fully between 0 and 1 instead of fully opened and the shape is similar to a normal curve. Gaussian transfer function can sanitize the neural model to midrange values (Garson, 1998). Compared with sigmoid counterparts, Gaussian based network has a shorter learning time but it may prone to memorization (Vesta Servics Inc., 1999).

The hyperbolic tangent (Tanh), which has the output from −1 to +1, has different learning dynamics during training. The hyperbolic tangent has positive impact on predictive accuracy and learning speed as the activation of neuron is zero and there is not necessary to update the weight of neurons (Garson, 1998).

Three typical transfer functions including Gaussian, Tanh and Logistics are tested and the result is shown in Table 4. As adopting

Table 4
Comparison of transfer functions of ANN for demand pattern recognition.

Transfer function	Gaussian	Tanh	Logistics		
			Setting 1	Setting 2	Setting 3
Input	11	11	11	11	11
Hidden	6	6	4	6	10
Output	1	1	1	1	1
Epoch			100,000		
Avg. RMS error	1.0482	0.289	0.284	0.279	0.284
Max. RMS error	2	1.23001	1.15618	2.02186	1.15618
Max. error	−2	−1.23001	−1.15618	−1.02186	−1.15618
Number correct	11	45	46	47	47
Percent correct	18.33	75	76.67	78.33	78.33

Table 5a
Target and computed output of "Singular" class.

Instance	Uncertainty in demand during the replenishment time	Item's demand is fluctuate during the items' supply	The demand per order distribution is known	No batch order	Demand forecast derived from the sales forecasts of end products	Known supply lead time	Fixed production lead time	Steady demand as the share of end products containing a specific	Demand volumes is high	Uncertain transportation time	The distribution of the timing is known	Class	Output	Target
1	1	1	0	1	1	1	1	0	0	1	1	Singular	1.00103	1.000000
2	1	0	1	1	0	0	1	0	0	0	0	Singular	1.00546	1.000000
3	1	1	0	1	1	1	1	1	0	1	1	Singular	2.11247	1.000000
4	1	1	0	1	1	0	0	1	1	1	1	Singular	1.00742	1.000000
5	1	0	1	1	0	0	1	0	0	0	0	Singular	1.00546	1.000000
6	1	1	0	1	0	0	0	0	0	1	1	Singular	1.00703	1.000000
7	1	1	0	1	0	0	0	0	0	1	1	Singular	1.00703	1.000000
8	1	1	1	1	0	0	0	1	0	1	1	Singular	1.00193	1.000000
9	1	1	1	0	1	1	0	1	0	1	0	Singular	1.00046	1.000000
10	1	0	1	0	1	1	0	0	0	0	1	Singular	1.00105	1.000000
11	0	1	1	1	1	0	0	1	0	1	1	Singular	1.00458	1.000000
12	1	1	1	0	1	1	1	1	0	1	1	Singular	1.0114	1.000000
13	1	1	0	1	1	0	1	1	0	0	1	Singular	1.02084	1.000000
14	1	1	0	1	1	0	0	1	0	0	1	Singular	1.00233	1.000000
15	1	0	1	1	0	0	0	0	0	0	1	Singular	1.00616	1.000000
16	1	1	0	1	1	0	1	0	0	1	0	Singular	1.01731	1.000000
17	1	1	1	0	1	0	1	1	0	1	0	Singular	1.01228	1.000000
18	1	1	1	0	1	1	1	0	0	1	1	Singular	1.01241	1.000000
19	0	1	1	1	1	0	1	1	1	1	1	Singular	1.00915	1.000000
20	0	1	1	1	1	0	1	1	1	1	1	Singular	1.00915	1.000000
	17	16	12	15	14	6	11	11	3	14	15			

logistic setting 1 as baseline model to measure the performance of the transfer function, Table 4 shows that logistics transfer function has similar result as Tanh but better result than Gaussian. It is found that Logistic function has higher correct percentage. Authors used 4, 6 and 11 node for hidden layer; the optimal performance is achieved by setting 6 nodes for hidden layer. Sensitivity analysis is adopted to find out the best parameter setting so as to obtain a sophisticated network. Having tested the final neural network, the analyst can diagnose the demand distribution of items so as to have a quick response to the market trend and formulate the replenishment strategy.

4.8. Demand pattern classification

ANN, which adjusts the connection weight, determines the belonging category of items. Take singular class as example. Table 5a shows the class attributes, output computed by ANN and target value of singular class (i.e. 1.000000). Test set instance 1–20 (except test set instance 3) has a correct classification because the corresponding computed output closely matched the target value. The last row indicated that top two inputs with the highest frequency of "1" and "0". Table 5b shows two highest ranked positive and negated inputs for all training cases of singular item.

The rule related to demand pattern of singular item is generated by ANN as following.

IF demand is uncertain AND Item's demand are fluctuate during the items' supply lead time AND supply lead time is NOT know AND demand volume is NOT high
THEN class Singular

ANN in the proposed RWLS can derive the rules based on the training the data related to demand pattern.

4.9. Articulating the replenishment strategy

Having classified the demand distribution of items into three classes which are singular, lumpy and continuous demand, business analysts can formulate replenishment strategy including MRP/DRP, Kanban or reorder point for different types of demand distribution of items (Johnston, 2000). According to the analytical results of Jacobs and Whybard (1992), if forecast has great variation from the real situation, reorder point may give even better result than material requirement planning and the policy of reorder point should be adopted in the management of singular class. For lumpy orders, Collaborative, Planning, Forecasting and Replenishment (CPFR) is suggested so as to have better management of demand and supply CPFR involves exchanging forecast and sales information between partners in the supply chain in order to rectify any forecast problems before transaction of orders. For continuous orders, the vendor management inventory is adopted and inventory management rules are set between retailers and suppliers. Recent finding (Cachon & Fisher, 1997) shows that inventory can be reduced by maintaining or increasing average fill rates and it is claimed that the saving of retailers' cost cannot be achieved without vendor management inventory.

Table 5b
Positive and negated inputs of singular items.

Top 2 highest ranked positive inputs	Top 2 highest ranked negated inputs
Uncertainty in demand	Known in supply lead time
Item's demand is fluctuate during the items' supply lead time	Demand volume is high

5. Conclusion

The responsiveness of the logistics workflow system is expected to be significantly leveraged as OLAP and ANN are included to master the information efficiently. The benefits of the proposed system include power control over inventory so as to respond to customer's needs quickly. The improvement in efficiency will not simply come because the RFID devices can move data faster. The interlinking of the system, which will lead to better data transmission and recognize the demand pattern, has beneficial effect on the entire supply network. This paper proposes an infrastructural framework, involving various emerging technologies for the development of logistics workflow systems with distinct features of the ability to governing supply chain inventory through understanding the parameters of the distribution patterns. The major contribution of the proposed system is to determine the correct replenishment strategy by automatically classifying the distribution patterns within the complex demand and supply chain. It is recommended for the researchers to utilize the innovation information technologies to create values for distributors, manufacturers and retailers with vendor management inventory concept that can obtain a better quality of the ordering process and inventory management. Further research on the infrastructural framework, particularly relating to the synergetic combination of fuzzy logic is needed in order to leverage the uncertainties in the turbulent market.

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