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Genetic algorithm dynamic performance evaluation for RFID reverse logistic management

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ABSTRACT

Environmental awareness, green directives, liberal return policies, and recycling of materials are globally accepted by industry and the general public as an integral part of the product life cycle. Reverse logistics reflects the acceptance of new policies by analyzing the processes associated with the flow of products, components and materials from end users to re-users consisting of second markets and remanufacturing. The components may be widely dispersed during reverse logistics. Radio frequency identification (RFID) complying with the EPCglobal (2004) Network architecture, i.e., a hardware- and software-integrated cross-platform IT framework, is adopted to better enable data collection and transmission in reverse logistic management. This research develops a hybrid qualitative and quantitative approach, using fuzzy cognitive maps and genetic algorithms, to model and evaluate the performance of RFID-enabled reverse logistic operations (The framework revisited here was published as "Using fuzzy cognitive map for evaluation of RFID-based reverse logistics services", *Proceedings of the 2009 international conference on systems, man, and cybernetics* (Paper No. 741), October 11–14, 2009, San Antonio, Texas, USA). Fuzzy cognitive maps provide an advantage to linguistically express the causal relationships between reverse logistic parameters. Inference analysis using genetic algorithms contributes to the performance forecasting and decision support for improving reverse logistic efficiency.

1. Introduction

Enterprises are applying reverse logistics as a means for fulfilling different market regions' recycling requirements. The European Union has a waste electrical and electronics equipment (WEEE) directive and the United States uses state and federal laws for enforcing recycling programs. Reverse logistic processes help enterprises fulfill their social responsibility and build their reputation by providing systems and processes for customers to return products and components either for repair, reuse, or disposal. Traditionally, supply chains without return and recycling processes are modeled as linear structures with a one way flow of goods from suppliers, manufacturers, wholesalers, retailers, and finally to consumers. Modern distribution channels that include repair, recycling, and responsible waste disposal must accommodate bi-directional flows or reverse logistics flows.

Reverse distribution channels include direct returns to manufacturers, indirect returns to repair facilities, individualized returns with small quantities, extended order cycles associated with product exchanges, and a variety of disposition options (e.g., repair versus exchange). The complexity of processes makes the modeling and implementation of reverse logistics a challenging task. In addition, it is difficult to measure the impact of product return and recycling on profitability and customer loyalty. An underlying cause for the measurement difficulties is that most enterprises are unable to trace the reverse logistics processes in real-time.

Radio frequency identification (RFID) technology enables enterprises to gather and track reverse logistics process data in real-time. RFID uses tags that can be automatically detected by readers without manual scanning, a major advantage over bar code readers. RFID uses radio frequency as a means to transmit data from tags affixed to physical objects such as products, boxes, or shipping containers. Data related to physical objects can be identified, stored, traced and monitored during transportation through the entire product life cycle. RFID also makes it possible to simultaneously detect and identify multiple items. For example, a list of goods packed in a sealed box can be automatically identified using a RFID reader without opening the box. Tags with memory can also be dynamically modified, inventory modifications can be batch processed, and stock keeping unit (SKU) data are readily transferred across enterprise systems. As a result, RFID technology enables precise tracking and real-time monitoring of each tagged item with minimal effort.

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In this research, fuzzy cognitive maps (FCM) are used to construct a reverse logistics network decision model. RFID technology provides the mechanism for real-time monitoring of the reverse logistics processes. The FCM decision model, using data collected by RFID technology, provides two critical functions, i.e., inference analysis and decision analysis. Inference analysis is applied to forecast future states of the reverse logistic operations. If sudden changes occur, the information system sends a warning message to alert the manager. The manager also receives decision support to improve logistic performance. In this research, a case is used to demonstrate and evaluate the implementation of fuzzy cognitive maps and genetic algorithms for managing the RFID-enabled reverse logistics of a cold storage chain.

2. Related research

In this section, fuzzy cognitive map, reverse logistics, and RFID technology are reviewed. A fuzzy cognitive map is used to represent causal relationships between the logistic process parameters. RFID technology provides the basis for collecting and transmitting the process data for real-time performance analysis and evaluation.

2.1. Fuzzy cognitive map

Fuzzy cognitive maps (FCMs) are an extension of cognitive maps (Axelrod, 1976). The elements used for building the graphs include the concepts and the relationships between concepts. Cognitive maps (CMs) represent concepts as nodes which contain the key knowledge fact of a specific domain (Dickerson & Kosko, 1993). As shown in Fig. 1, the use of positive (+) and negative (−) signs on arcs between nodes represents the positive or negative effect of one node on another. Thus, a positive sign between nodes represents a stimulating relationship and a negative sign represents an inhibiting relationship. CMs can be represented as a symmetric weight adjacency matrix (consisting of only +1 or −1 elements) to mathematically describe the relationships between nodes. The direction of the arrow reveals the cause-effect relationship between nodes (Kardaras & Karakostas, 1999). For instance, if the condition of node C1 is satisfied, then C2 and C4 will be positively stimulated as depicted in Fig. 1. CMs define links as causal relationships without specifying the strength of the relationship between nodes. FCMs, on the other hand, use fuzzy logic to quantify the strength of the relationships between nodes (Fig. 1). The values range from −1 to 1 where the value 0 stands for no effect and 1 represents the strongest relationship between nodes.

Fuzzy cognitive maps model causal relationships between concepts using directed arcs and logical inference networks (Kosko, 1987). An FCM links the events, values, objects, and tendencies with a feedback dynamic system (Dickerson & Kosko, 1993). The map is a graph with nodes, weights, and directed arcs that represent specific behaviors belonging to a real world system. The FCM defines the relations between causes and their effects using a link and a weight. FCMs are often compared to neural networks or expert systems to emphasize the following benefits (Miao, Liu, Siew, & Miao, 1999). First, the modeling of causal relationships with FCM is less difficult than modeling neural networks since the concepts of a system can be represented as different nodes. Then, the weight associated with the link represents the strength and cause-effect relationships and how a concept will react to causal inputs. Second, in comparison to expert systems, FCM uses matrix operations instead of if–then rules to infer possible outcomes. As a result, FCM offers greater flexibility in computing inference outcomes.

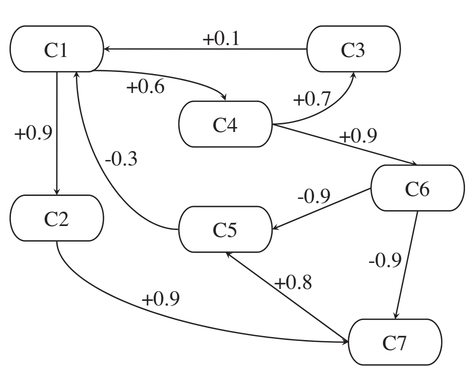

Fig. 1. A fuzzy cognitive map with directed and quantified relationships.

FCM facilitates collaboration between model builders. Different maps from different experts can be integrated into a larger map. An individual FCM represents the domain knowledge or opinion of an expert (i.e., different weighted coefficients represent different beliefs) and maps of several experts can be combined by merging their adjacency matrices (Hagiwara, 1992). Compared to Bayesian networks, FCMs are also relatively easy to use for inferring future state transitions through simple matrix operations (Kim, Kim, Hong, & Kwon, 2008). Thus, the FCM approach has been applied to simulation (Fu, 1991), modeling of organizational strategies (Paradice, 1992), investment analysis (Lee & Kim, 1997), political decision making (Tsadiras, Kouskouvelis, & Margaritis, 2003), and modeling critical success factors (Luis, Rossitza, & Jose, 2007).

2.2. Reverse logistics

The scope of reverse logistics throughout the 1980s was limited to the movement of materials from customers back to producers (Rogers & Tibben-Lembke, 2001). Other definitions for reverse logistics cover activities such as product returns, recycling, materials substitution, reuse of materials, waste disposal, repair, and remanufacturing (Stock, 1998). The goal of reverse logistics is to extract tangible and intangible values from the processes of disposal, recycling, and reuse. For example, if an enterprise has a sound reverse logistics system, then an intangible benefit is a more positive corporate image (Carter & Ellram, 1998). Moreover, reverse logistics includes processes for the return of damaged goods, the disposal of out of date inventory, and the restocking or salvaging of these goods. Also, a better reverse logistics process improves hazardous material control, obsolete equipment disposition, and asset recovery (Rogers & Tibben-Lembke, 2001).

Reverse logistics covers a broad range of activities. When a product return process is triggered, enterprises use different reverse logistics processes depending on the situation and the roles played by the supply chain intermediaries and owners. Rogers and Tibben-Lembke (2001) categorized reverse logistics activities according to products and their packages. The activities for products include reselling, selling through outlets, salvaging, reconditioning, returning to suppliers, refurbishing, remanufacturing, recycling, and disposal. Packaging includes fewer activities such as reusing, salvaging, refurbishing, recycling, and disposal.

A number of authors discuss the reasons for product returns. For example, De Brito, Flapper, and Dekker (2002) categorized three types of supply chain returns, i.e., manufacturing returns, wholesaler/retailer returns, and customer returns. Rogers and Tibben-Lembke (2001) extend the list of returns categories to include customer returns, market returns, asset returns, product recalls, and environmental returns. Product returns are the result of product damage and defects, return policies and warranties, customer dissatisfaction, and incorrect product placement. Market returns are the results of business failures, out of season goods, and excessive inventories. Asset returns include packaging reuse and return of shipping containers and pallets. Finally, if there is a product safety issue, products are recalled according to the governing rules and regulations. Obviously, the improper or inefficient implementation of reverse logistics processes will dramatically impact operations costs and lower profits.

2.3. Application of RFID technology

RFID technology is defined as the wireless and automatic identification and capture of product identification data. Other types of product identification technologies include barcodes, optical character recognition, biometrics, card technology, and contact memory technology (Wamba, Lefebvre, Bendavid, & Lefebvre, 2008). Several standards have been developed for RFID technology. The electronic product code (EPC) global network, developed by Auto-ID Center at MIT (Kin, Mun, & Daniel, 2005), is a standard used for automatic product identification in retail stores. The EPC network consists of six components including the RFID tags, RFID readers, the savant, the EPC information service, the object naming service, and the EPC discovery service. The EPC network is considered a standard infrastructure that assures the efficient information sharing and exchanges of the supply chain across heterogeneous systems (Wamba et al., 2008).

3. Methodology

In this section, the methodology for constructing the nodes of the reverse logistics FCM model is defined. After the FCM model is created, a genetic algorithm is used to assign weights to the arcs between model nodes. Finally, RFID technology is applied to the reverse logistics processes for real-time data tracking and collection.

3.1. Constructing the fuzzy cognitive map

Fuzzy cognitive map analysis is divided into three steps. The first step is the definition of each node based on expert observations. The second step is the acquisition of data to represent each node from the target network. The third step is the evaluation of causality and assigning the degree of weight for the arcs between nodes. Reverse logistics activities involves many intermediaries working collaboratively. Fig. 2 shows a simplified supply chain consisting of suppliers, manufacturers, distributors, retailers, and customers include using a landfill for product disposal, a recycling center, and a reverse logistics center.

The FCM nodes represent operational factors and performance factors. The details of the reverse logistics processes depend on the key activities of the participants, e.g., manufacturers, logistic centers and retailers. For example, the retailer's reverse logistics cognitive map can be shown as Fig. 3, which illustrates relationships between levels of customer satisfaction, reverse logistic services, and service times and costs.

3.2. Weight training algorithm

After constructing the FCM, the weight (i.e., the relationship strength) training algorithm is used to derive the strength of causal relationships between nodes. The weights are empirically derived based on historical data gathered from the reverse logistics network. In this paper, a genetic algorithm (GA) is used for weight training since it is widely regarded as an affective approach (Stach, Kurgan, Pedrycz, & Reformat, 2005). The algorithm uses four elements including the chromosome structure, the fitness function, the selection mechanism, and the genetic operation. Each element is described in this section. A chromosome is a vector which contains elements called genes. In the proposed weight training algorithm, genes are encoded as floating point numbers ranging from -1 to 1. According to Herrera, Lozano, and Verdegay (1998), floating point numbers provide better efficiency and precision than binary numbers. In this research, each gene represents the weight between two nodes. If there are N nodes in an FCM, then there are $N(N-1)$ genes in the chromosome.

After defining the chromosome, the next step is to define the fitness function for evaluating whether the chromosome is appropriate or not. In this paper, $S(t)$ is defined as an input vector and $S(t+1)$ is the system response. If the iteration number is assumed to be K, then the error E is derived by calculating the sum of difference for all input and system response pairs. The error is expressed in Eq. (2):

$$S(t) \rightarrow S(t+1), \quad \forall t = 0, \ldots, K-1, \tag{1}$$

$$E = \sum_{t=1}^{K} \sum_{i=1}^{N} \left(S_i(t) - \widehat{S}_i(t) \right), \tag{2}$$

where $S_i(t)$ is the known system response vector for $S_i(t-1)$, $\widehat{S}_i(t)$ is the simulation result of FCM for $S_i(t-1)$, and N is the total number of vectors. In Eq. (3), a is a constant and the calculated error E from the previous equation is used as input:

$$\text{Fitness function} = f(E), f(x) = \frac{1}{ax+1}. \tag{3}$$

The value of the fitness function is normalized between 0 and 1 with 1 representing an ideal chromosome. A selection mechanism is used to choose suitable chromosomes. The selected chromosomes act as the initial values for evolution into the next generation. There are different methods for selection such as random

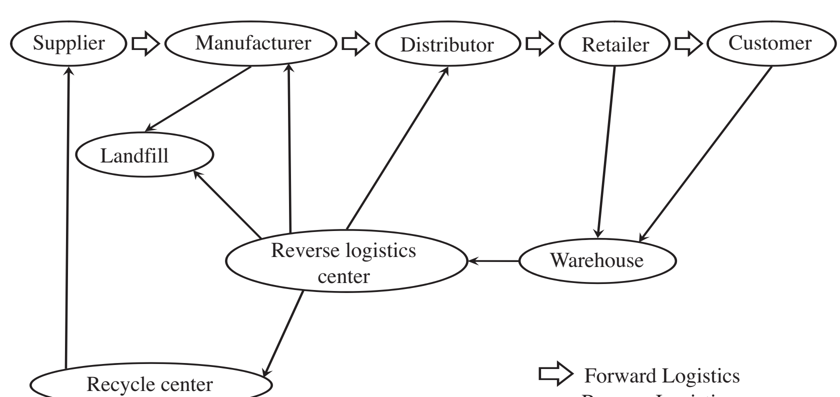

Fig. 2. The supply chain reverse logistics activities.

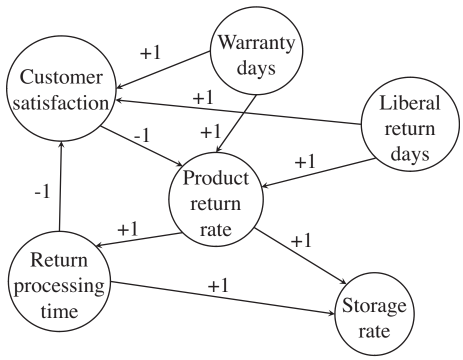

Fig. 3. Retailer's reverse logistics cognitive map.

sampling, directive sampling, and mixed sampling. In this research, directive sampling was used to improve fitness value performance (Gen & Cheng, 1997). The genetic operations such as crossover or mutation are performed based on the selected chromosomes. Three methods for the crossover operation are considered. These methods are single point, two point, and uniform crossover. For reducing computational costs and to ensure a desirable evolution speed, a two point crossover is used in this research. Finally, random mutation is used to minimize violent changes during mutation.

3.3. Reverse logistics FCM

The initial step of constructing an FCM for reverse logistics is to define the data transformation function and transfer the input values to a range between 0 and 1 as shown in Eq. (4) (Kim et al., 2008). The fuzzification mapping for the crisp transformation values are shown in Table 1:

$$g(s_i^t) = \begin{cases} 0 & \text{if} \quad s_i^t < a_i \\ (s_i^t - a_i)/2(m - a_i) & \text{if} \quad a_i < s_i^t < m_i \\ 0.5 + (s_i^t - b_i)/2(b_i - m) & \text{if} \quad m_i < s_i^t < b_i \\ 1 & \text{if} \quad s_i^t > b_i \end{cases} \tag{4}$$

where $g(x)$ is the transform function, s_i^t is the observed value of ith state at time t

$$\begin{aligned} a_i &= \min\{s_i^t\}, t \in T \\ b_i &= \max\{s_i^t\}, t \in T \\ m_i &= \text{average}\{s_i^t\}, t \in T \end{aligned}$$

After mapping all input values, the state vectors $S(t)$ for different times t can be derived. An input state vector can be represented as $S(t) = [s_1^t, s_2^t, s_3^t, \ldots, s_n^t]$. The input state vector is multiplied by the weight matrix to derive the system response vector, $s_i(t+1)$. Afterward, the result vector value is filtered using a threshold function. Finally, the stable state is derived after several iterations. There are many threshold functions that can be used for node value filtering. In this research, the sigmoid function in Eq. (6) is used because of its reported effectiveness (Salvador & Jose, 2009):

Table 1
State vector fuzzification.

Symbolic variable	Value
Very high	(0.8, 1]
High	(0.6, 0.8]
Normal	(0.4, 0.6]
Low	(0.2, 0.4]
Very low	(0, 0.2]

$$s_i(t+1) = f\left(\sum_{j=1}^{n} w_{ji} s_i(t)\right), \tag{5}$$

$$W = \begin{pmatrix} w_{11} & w_{12} & w_{13} & \cdots & w_{1n} \\ w_{11} & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & w_{ij} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ w_{n1} & \cdots & \cdots & \cdots & w_{nn} \end{pmatrix}, \tag{6}$$

and

$$f(x) = \frac{1}{1 + e^{-x}}, \tag{7}$$

where $s_i(t)$ is the state of node i at time t, W is the weight matrix of FCM, and $f(x)$ is the threshold function.

3.4. Decision analysis

After training the weight matrix, it is used to forecast the future states for decision support. As shown in Fig. 4, S^E is the expected vector at time $t+1$. S^I is the real cause vector of S^E and S^D is the predicted cause vector of S^E derived using decision analysis. $\widehat{S}^E$ is the inference vector derived using the inference analysis from S^D where S^D is computed using the genetic algorithm.

Unlike the inference analysis, the population for the genetic algorithm decision analysis is composed of state vectors. The difference in the Euclidean space between the inference vector computed from the predicted decision vector and the expected vector becomes the fitness value of the state vector. The predicted decision vector with the minimum fitness value is selected using the genetic algorithm (Eq. (8)):

$$S^D = \arg\min\left\{\text{distance } \left(\widehat{S}^E, S^E\right)\right\}. \tag{8}$$

4. Cold food container reverse logistics

The proposed methodology is demonstrated using a reverse logistics case for cold food container recycle management. The case company manages the cold storage logistics chain and monitors the temperature using RFID technology. A cold storage logistics chain provides the services for maintaining cold food temperature throughout transportation, delivery and storage. Fig. 5 depicts the information architecture for the RFID system used for collecting data in this reverse logistic chain.

The container recycling experts in the food logistic companies identify twenty-eight key parameters (Fig. 6). Twelve parameters are for manufacturers (S1–S12), twelve for logistics centers (S13–S24), and 4 for retailers (S25–S28), to form the fuzzy cognitive map for performance evaluation. Among the 28 parameters, experts further identify five parameters (S3, S14, S18, S25 and S26 in Table 2) as the key factors influencing the logistic performance. Ten parameters (S4, S5, S7, S9, S10, S13, S16, S19, S21 and S22 in Table 3) are the direct performance indicators of the logistic system. Thus, there are 15 critical parameters of the FCM used for forecasting and decision analysis. In our case study, data from 12 months operations are gathered. The parameters for the FCM

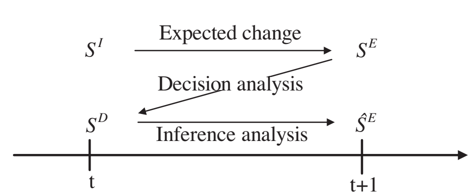

Fig. 4. Decision analysis derived state vector relationships.

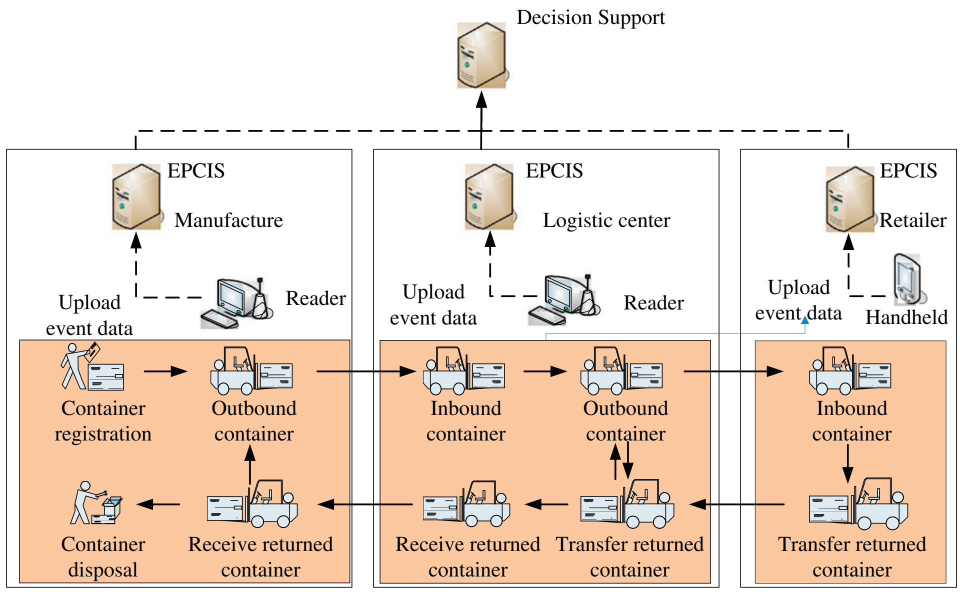

Fig. 5. RFID-based system information architecture.

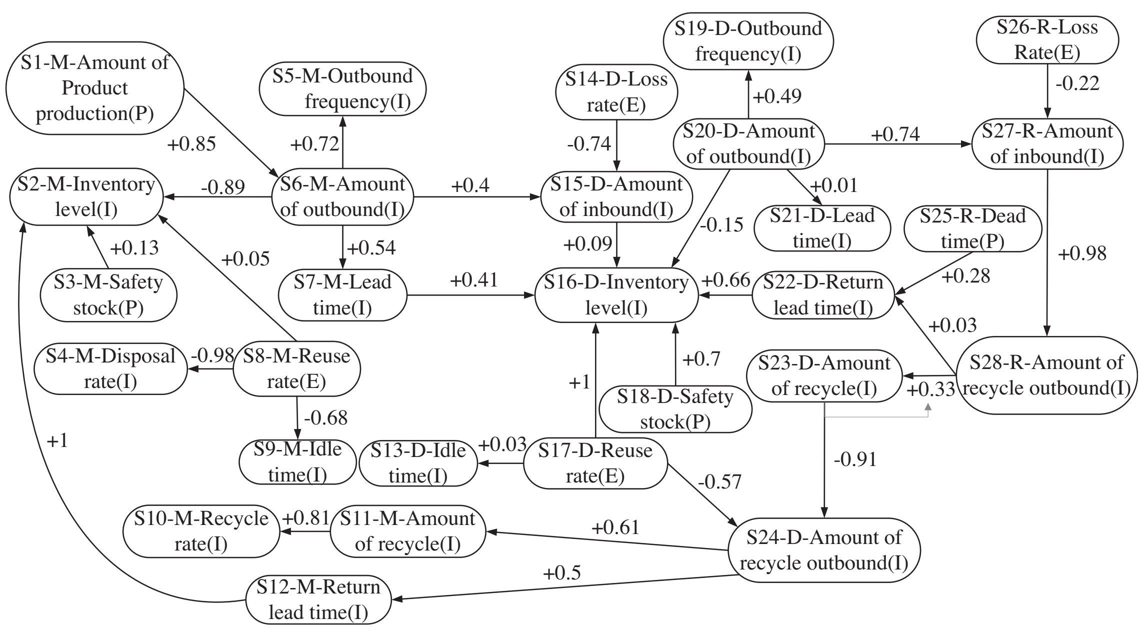

Fig. 6. FCM for a cold storage reverse logistics chain.

Table 2
Five key factors influencing supply chain performance.

Role	Node
Manufacturer (M)	S3: M-The safety stock
Logistics center (D)	S14: D-Loss rate S18: D-The safety stock
Retail site (R)	S25: R-Dead-time S26: R-Loss rate

are derived using the genetic algorithm given a population size of 100, a maximum training time of 1000, and a mutation rate of 0.1. After setting the initial parameter values, the iterative processes train the model. With weight training, the FCM model for container reverse logistic management was defined with adjusted relationship strengths as shown in Fig. 6. The mean square error (0.44) shows that the training outcome is consistent. The decision support process is shown in Fig. 7.

Table 3
Manufacturer and logistics center performance indicators.

Role	Node
Manufacturer (M)	S4: M-Disposal rate S5: M-Outbound frequency S7: M-Lead time S9: M-Idle time S10: M-Recycle rate
Logistics center (D)	S13: D-Idle time S16: D-Inventory level S19: D-Outbound frequency S21: D-Lead time S22: D-Return lead time

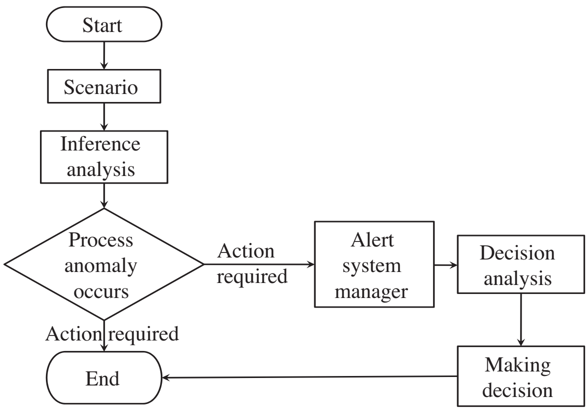

Fig. 7. Decision support flow for performance improvement.

When a process anomaly occurs, the inference analysis module forecasts the future states of the system. If action is required, the information system alerts the manager who uses the decision analysis module to stabilize the system. The following process simulates the decision support flow.

4.1. Node definition

Table 2 lists the roles and nodes in the container reverse logistics FCM, which are the five key factors influencing the performance of the reverse logistic operation. The ten performance indicators that directly impact the reverse logistic chain's efficiency are listed in Table 3. The vector values representing the scenario in the initial stage are given in Table 4.

4.2. Case analysis

After making inferences using the FCM model, the results are shown in Fig. 8. The manager receives a list of performance values and is alerted that there are inefficiencies with the manufacturer's outbound frequency, the manufacturer's lead time, the manufacturer's recycle rate and the logistic center's return lead time.

Based on these data, the manager defines the expected future state and inputs the expected vector into the decision analysis module. Table 5 provides the new vector values and Fig. 9 shows the results derived from the decision analysis.

Fig. 9 indicates that the manager should maintain the same safety stock for the manufacturer, the same loss rate for the logistic center, and the same lead time for the retailer. Further, increasing the safety stock of the logistic center and controlling the loss rate of the retailer will improve performance. The average error of 0.021 is computed by finding the difference between the expected and the inference vectors. Fig. 10 demonstrates the matching of ten performance indicators against expectation followed by the model derived decisions.

4.3. Case verification

This section analyzes the accuracy of the proposed decision support model. Given the historical data for validation, S^T is the real vector, S^C is the cause vector of S^T, and $\widehat{S}^C$ is the predicted cause vector of S^T derived through decision analysis. The error function $e = |\widehat{S}^C - S^C|$ is the accuracy indicator of the decision model. For the container reverse logistics case, the average error for nine historical data sets is 0.046 (with errors ranging from 0 to 0.08), an acceptable value for improving logistic performance.

Table 4
The initial values of fifteen key performance parameters for the scenario.

M-Safety stock	D-Loss rate	D-The safety stock	R-Lead time	R-Loss rate
0.51 (N)*	0.5 (N)	0.29 (L)	0.5 (N)	0.33 (L)
M-Disposal rate	M-Outbound frequency	M-Lead time	M-Idle time	M-Recycle rate
0.13 (VL)	0.05 (VL)	0.35 (L)	0.5 (N)	0.5 (N)
D-Idle time	D-Inventory level	D-Outbound frequency	D-Lead time	D-Return lead time
0.5 (N)	0.52 (N)	0.49 (N)	0.05 (VL)	0.48 (N)

* VL, very low; L, low; N, normal; H, high; VH, very high.

Table 5
Expected vector values for the future state.

M-Disposal rate	M-Outbound frequency	M-Lead time	M-Idle time	M-Recycle rate
0.2–0.4 (L)*	0.4–0.6 (N)	0.2–0.4 (L)	0.2–0.4 (L)	0.6–0.8 (H)
D-Idle time	D-Inventory level	D-Outbound frequency	D-Lead time	D-Return lead time
0.2–0.4 (L)	0.4–0.6 (N)	0.5 (N)	0.2–0.4 (L)	0.2–0.4 (L)

* VL, very low; L, low; N, normal; H, high; VH, very high.

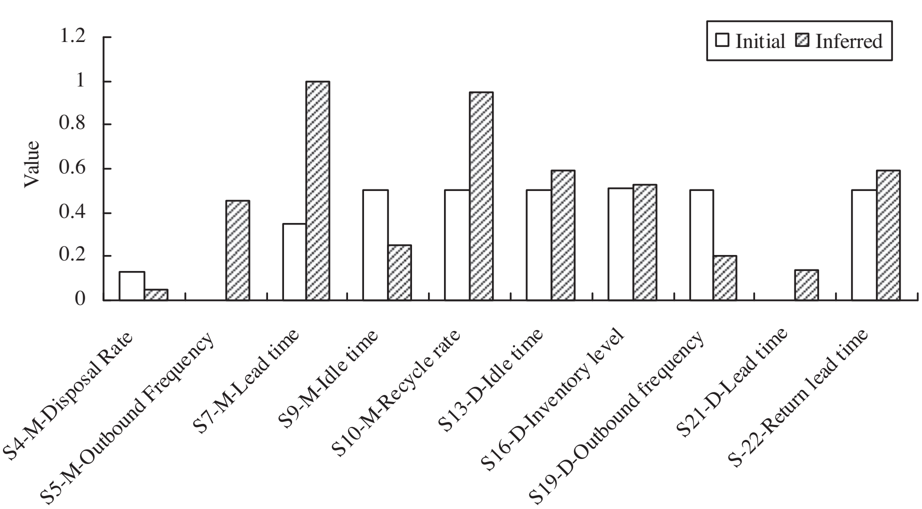

Fig. 8. The performance indices of the inference analysis.

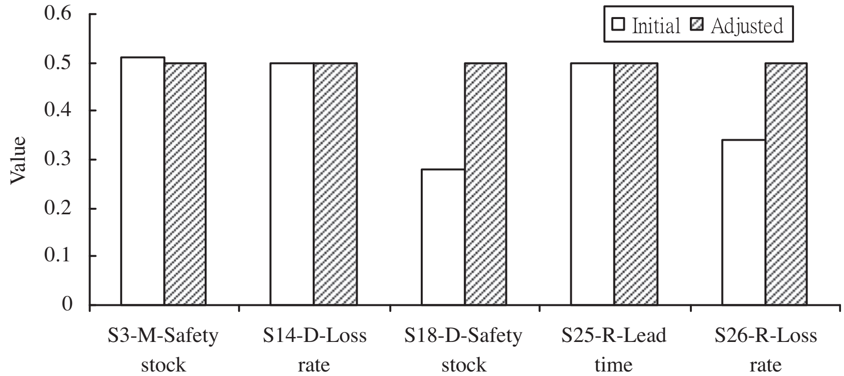

Fig. 9. Suggested decisions based on the expected future state.

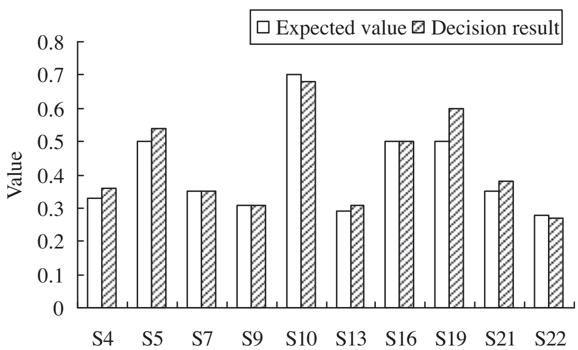

Fig. 10. Decision performance for the ten indicators.

5. Conclusion

This paper proposes a fuzzy cognitive map model for improving reverse logistic process decision support. Given the dynamic and complex features of the reverse logistics network, the FCM is used to construct a reverse logistics network that incorporates RFID technology to collect real-time data from daily operations. The model is integrated with the RFID module to provide data for network performance forecasting and decision support. Finally, a cold storage container management case is presented. The inference analysis and decision analysis is used to forecast the container logistics chain response and adjust the operation parameters to better control the system performance according to managements established operating processes.

The management of uncertainty is a critical task for forward and reverse logistic operations. This study provides a method to predict future logistic operation states and to constructs a decision support model to manage system performance based on the forecast. The results show the potential of the proposed methodology for enhancing competitiveness and efficiency of complex and dynamic reverse logistic chains.

Acknowledgements

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