

A hybrid neuro-fuzzy analytical approach to mode choice of global logistics management

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Abstract

This paper presents a hybrid neuro-fuzzy methodology to identify appropriate global logistics (GL) operational modes used for global supply chain management. The proposed methodological framework includes three main developmental phases: (1) establishment of a GL strategic hierarchy, (2) formulation of GL-mode identification rules, and (3) development of a GL-mode choice model. By integrating advanced multi-criteria decision-making (MCDM) techniques including fuzzy analytical hierarchy process (Fuzzy-AHP), Fuzzy-MCDM, and the technique for order preference by similarity to an ideal solution (TOPSIS), six types of global logistics and operational modes coupled with corresponding fuzzy-based multi-criteria decision-making rules are specified in the second phase. Using the specified fuzzy decision-making rules as the input database, an adaptive neuro-fuzzy inference system (ANFIS) is then developed in the third phase to identify proper GL modes for the implementation of global supply chain management. A numerical study with a questionnaire survey database aimed at the information technology (IT) industries of Taiwan is conducted to illustrate the applicability of the proposed method.

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1. Introduction

Selection and characterization of proper global logistics (GL) modes is vital to effective global supply chain management (G-SCM). It is extensively noticed that although remarkable advances in information technologies (IT) have contributed to the achievement of effective information flow in global supply chains; issues in coordinating physical flows in transnational distribution channels, including supplied raw materials, assemblies, and products, still remain in G-SCM. Furthermore, under conditions of global competition, forces oriented either upstream from global supply resources or downstream from global markets have made numerous international manufacturing enterprises perceive the urgent necessity of developing competitive GL modes.

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Despite the importance of GL mode selection and characterization in G-SCM, developing corresponding decision support systems for complex G-SCM issues is challenging and has received little discussion in previous literature. Most prior research has been limited to either simplified numerical studies using optimization models (Cohen and Lee, 1988; Arntzen et al., 1995; Cachon and Fisher, 1997; Nagurney et al., 2003) or exploring conceptual frameworks for system evaluation (Verter and Dincer, 1995; Motwani et al., 1998; Bowersox et al., 1999; Mollenkopf and Dapiran, 1999; Carranza et al., 2002; Morash and Lynch, 2002; Closs and Mollenkopf, 2004). Some typical models are illustrated in the following for reference.

Given that the number and locations of transnational facilities are fixed, a comprehensive framework which involves respective analytical procedures is proposed in Cohen and Lee (1988) to evaluate the corresponding performance of alternative manufacturing and material supply strategies in supply chains. Furthermore, a bi-objective optimization model is introduced in Arntzen et al. (1995) to minimize a weighted combination of total operational costs and activity days in a given global supply chain network. Specifically, Cachon and Fisher (1997) proposed simple inventory management rules and tested them with actual demand data for the operations of continuous replenishment (CR) strategies of a given international food corporations. Nagurney et al., (2003) developed a framework to analyze the dynamics of a simplified 3-layer global supply chain, which mainly considers the interactions among three distinct layers of decision makers, i.e., manufacturers, retailers, and end-customers.

In addition, there are many researchers who are devoted to exploring the influential factors and strategies for diverse international supply chain scenarios. For instance, factors of fluctuations in exchange rates and government policies are discussed in Kogut (1985), followed by a more detailed analysis by Carter and Vickery (1988). Comparisons between the decision-making process for locating facilities based on direct labor costs and the core competencies of the company are conducted in Bartmess and Cerny (1993). In MacCormack et al. (1994), a four-phase decision making process is further proposed for international location decisions, where several key factors, e.g., adequate infrastructure and managerial issues, are investigated. Furthermore, issues of global outsourcing strategies and corresponding channel relationship management in G-SCM are also drawing growing attentions from many researchers (Ohmae, 1989; Fagan, 1991; Monczka and Trent, 1991; Davis, 1992; Min et al., 1994; Tagaras and Lee, 1996; Talluri, 2002; Talluri and Narasimhan, 2003).

Clearly, developing sophisticated decision support systems in aid of selection and characterization of GL modes for G-SCM needs more research effort. As can be found in our literature review, the optimization programming methods remain used as a major solution technique to address related issues; however certain limitations may still exist. For instance, The published models may not be suitable for addressing the issues of uncertainties and complexities of GL strategic planning resulting from certain qualitative influence factors, e.g., transnational resource availability and foreign regulations. Furthermore, most of the published decision making approaches, e.g., analytic hierarchy process (AHP), appear incapable of dealing with the imprecise and vague comparisons of qualitative criteria.

Accordingly, this study presents a methodological framework, which serves not only to characterize GL modes but also to select appropriate GL operational modes for the use G-SCM of high-technology industries. The proposed methodology is established by integrating three major techniques, including (1) fuzzy multi-criteria decision-making (Fuzzy-MCDM), (2) fuzzy inference theories, and (3) neural networks. Relative to the existing GL strategic planning methods, such a process of embedding multiple techniques in a comprehensive framework can be quite sophisticated, but it is inevitably needed due to the complexities and uncertainties of global logistics and operational environments, as mentioned above. Furthermore, to our best knowledge, the utilization of such fuzzy-network techniques in GL strategic planning and management is rarely found in related areas. These may help to clarify the incremental contribution of this paper to the early literature.

2. Architecture of the proposed methodology

The corresponding architecture of the proposed methodology is composed mainly of three developmental phases, including (1) establishment of a GL strategic hierarchy, (2) formulation of GL-mode identification rules, and (3) development of a GL mode-choice model. They are detailed in the following.

2.1. Global logistics strategic hierarchy

In this phase, the GL hierarchical structure is specified, in which the number of layers embedded in the proposed structure and corresponding criteria that characterize the distinctive features of layers are defined. Then, the proposed GL strategic hierarchy is finalized through a questionnaire survey.

First, we analyzed existing GL strategies and operational models, then summarizing six typical types of GL modes used as the GL-mode choice candidates. Based on the G-SCM philosophy in terms of integration and sharing of transnational resources, six typical types of GL modes coded GL-modes A to F, illustrated in Fig. 1,

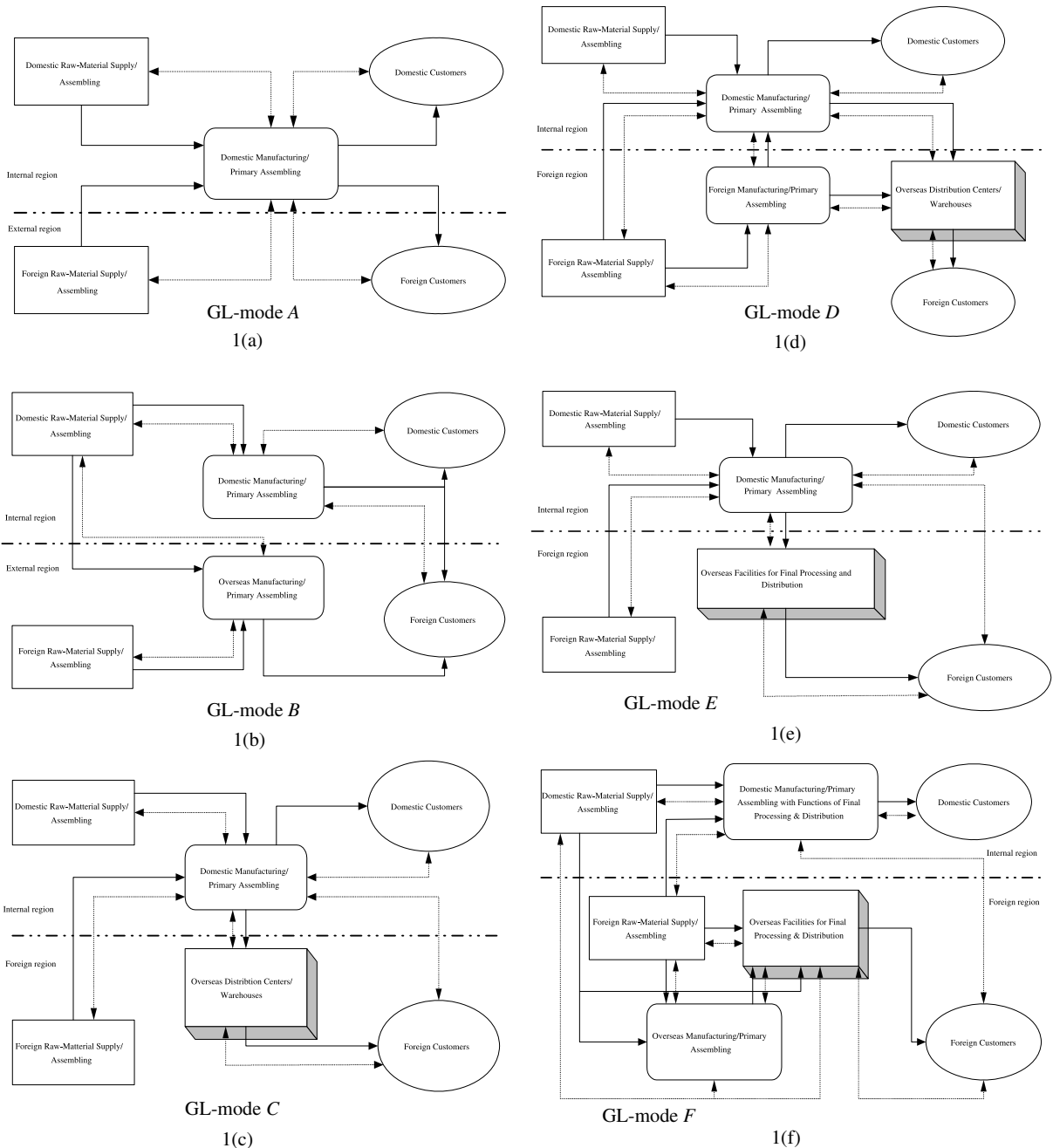


Fig. 1. Illustration of specified six types of global logistics modes.

are specified. Here each mode distinguishes itself from the others mainly in the degree of resource sharing and integration with foreign enterprises. The distinctive operational features of these modes, as well as corresponding enterprise representatives, are illustrated below.

GL-mode *A*, shown in Fig. 1a, represents a typical centralized GL mode which is dominated fully by the internal manufacturing/assembling center for global logistics management. Enterprises featuring GL-mode *A* tend to control the entire process of manufacturing, including primary assembling, and complete it internally. However, they may look for any potential in terms of availability of raw materials overseas and benefits oriented from global markets, and thus source raw materials and potential customers from abroad. In general, mode *A* is applicable particularly for those international enterprises which manufacture sophisticated assemblies or high-value products such as integrated circuit (IC) and laptop computers.

GL-mode *B*, as depicted in Fig. 1b, has almost the same function as GL-mode *A*, except for its manufacturing/primary assembling, which is partly outsourced abroad to either reduce production costs or meet the variety of overseas customer demands. Nevertheless, it is worth noting that given either GL-mode *A* or *B*, the aggregate product plan remains controlled by the domestic firm. In addition, the overseas logistics-related activities, e.g., product inventory and transportation, are dominated by local firms in GL-mode *B*.

In contrast, GL-mode *C* can be regarded as an extension of GL-mode *A* since it possesses the same features as GL-mode *A* in terms of internal centralization of manufacturing; however differing in the overseas logistics distribution function. In addition, GL-mode *C* permits external facilities, e.g., distribution centers and warehouses, in response to the variety of overseas customer demands. Overall, the firms with global brands may prefer GL-mode *C* to GL-mode *A* for the convenience of distributing finished products to local channel members overseas via these external logistics facilities.

GL-mode *D* represents a synthesized mode evolving from both GL-modes *B* and *C*, as shown in Fig. 1d. In addition to the outsourcing to foreign manufacturers/primary assembling firms, as exhibited in GL-mode *B*, GL-mode *D* also has the same property as GL-mode *C* in terms of utilizing the external distribution facilities to coordinate the logistics operations with overseas distribution channels. Correspondingly, GL-mode *D* must rely highly on the competence of foreign contracted logistics partners to implement GL strategies. Nevertheless, it is worth noting that GL-mode *D* may benefit those multinational enterprises by its mechanisms in transnational resource integration and sharing for managing global supply chains.

GL-Mode *E* refers to a specific GL mode suitable particularly for the operations of postponement strategies. As illustrated in Fig. 1e, almost-finished products can be manufactured internally, and then transported overseas for final processing which is not undertaken until the corresponding local orders are placed. As such, risks due to either the price appreciation of corresponding primary components or overproduction can be alleviated.

In contrast with all the other modes, GL-mode *F* shown in Fig. 1f represents a relatively sophisticated GL model because it covers almost all the value-added transnational logistics activities, including overseas assembling, final processing, inventory and distribution. In reality, such a mode has been greatly advanced in global logistical management, especially in terms of utilizing external sources for both final processing and assembling.

After the aforementioned GL-mode specification procedure, a 3-layer GL strategic hierarchy is proposed, where the top layer, termed the GL-mode alternative layer, includes the specified six GL-mode candidates; the second layer, termed the criteria layer, defines six respective criteria domains, including: (1) management control, (2) core competitiveness, (3) trans-organizational coordination, (4) marketing and service, (5) resource availability, and (6) environmental variability; and the third layer involves the corresponding factors associated with these criteria.

Then, the questionnaire survey aiming at international manufacturers of high-technology industries was executed to finalize the proposed GL hierarchical structure, including determination of the corresponding components embedded in layers 2 and 3. At this stage, we designed the contents of the questionnaire on the basis of the proposed GL hierarchic framework, and randomly sampled international high-technology manufacturers of Taiwan as well as researchers/professors in related areas. Here, our questionnaire aimed to request each survey respondent to identify the primary criteria and the corresponding influence factors considered in determining GL strategies. Aggregated from the survey data, those items agreed by more than 80% of the sampled respondents were then selected as the basis of the proposed 3-layer GL hierarchic framework.

Accordingly, a 3-layer GL hierarchic structure, as illustrated in Table 1, was finalized through the aforementioned survey data collection and test procedures, where the corresponding components associated with each layer and their relationships with the components of the corresponding upper layers are also summarized.

2.2. Global logistics identification rules

Our attempt in this phase is to develop fuzzy-based GL-mode identification rules used to characterize and assess GL modes with respect to their distinctive operational attributes. Here the identification of GL modes is formulated as a multi-criteria decision-making (MCDM) problem solved by the integration of Fuzzy-AHP, Fuzzy-MCDM, and TOPSIS techniques, respective fuzzy-based GL-mode identification rules. To achieve the aforementioned purpose, three developmental procedures are proposed in this phase: (1) estimation of pair-wise comparison matrices, (2) specification of fuzzy-weighted criteria, and (3) development of fuzzy logic rules.

First, two respective pair-wise comparison matrices associated with layers 2 and 3 of the specified 3-layer GL strategic hierarchy are estimated using the Fuzzy-AHP technique (Laarhoven and Pedrycz, 1983; Buckley, 1984; Lootsma, 1997). Here each element of a given pair-wise comparison matrix indicates the relative importance between a given pair of components associated with a given GL layer. In the process of matrix generation, the components of a given GL layer (k) are ranked in linear order, and associated with specific ordinal numbers based on survey respondents' judgments concerning the relative importance of these components measured on a 0-1 scale. Then, an element e_{ij}^k of the pair-wise comparison matrix is given by $e_{ij}^k = r_i^k / r_j^k$, where r_i^k and r_j^k represent the ordinal numbers associated with components i and j of layer k , respectively. Accordingly, we have a 6×6 pair-wise comparison matrix associated with layer 2 (M^2) and a 21×21 comparison matrix associated with layer 3 (M^3) of the proposed GL strategic.

Next, the fuzzy weights associated with the components in a given layer are approximated. Here, we employ a simple method to facilitate the approximation of the fuzzy weights. Given an $N_k \times N_k$ pair-wise comparison

Table 1
Proposed GL strategic hierarchy and components

Layer-1: GL-mode alternative	Layer-2: Criteria	Layer-3: Related influential factors
Six GL-mode candidates (GL-modes A to F)	1. Management control	1. Raw-material/assemblies purchasing process 2. Inventory management 3. Outbound logistics distribution and transportation
	2. Core competitiveness	4. Research and development (R&D) 5. Production scheduling 6. Production capacity 7. Ability to respond to changes of customer demands
	3. Trans-organizational coordination	8. Transnational strategic alliance 9. Communications with IT technologies
	4. Marketing and service	10. Marketing channels 11. Customer service 12. Market segmentation
	5. Overseas resource availability	13. Global raw-material/assemblies supply networks 14. Grouping with overseas industries 15. Availability of overseas human resources 16. Availability of overseas financial resources 17. Availability of overseas technology support
	6. Environmental variability	18. Foreign government policies 19. Foreign exchange 20. Modernization of infrastructure 21. Language and culture

matrix associated with a given layer k (\mathbf{M}^k), we then have the fuzzy weight associated with component i of layer k (f_i^k):

$$f_i^k = \frac{N_k \sqrt{\left(\prod_{j=1}^{N_k} e_{ij}^k\right)}}{\sum_{n=1}^{N_k} \left[N_k \sqrt{\left(\prod_{j=1}^{N_k} e_{nj}^k\right)} \right]} \tag{1}$$

Then, fuzzy-weighted criteria are generated. For this, we specify five linguistic terms, including “very high”, “high”, “medium”, “low”, and “very low”, indicating five qualitative degrees to describe the subjective importance associated with each component of a GL hierarchic layer. These qualitative criteria were then mapped into specific fuzzy membership functions to obtain raw fuzzy criteria via fuzzy-and-defuzzy transformation. Using the fuzzy weights obtained previously, the fuzzy-weighted criteria associated with the components of GL hierarchic layers were computed.

In addition, mapping the specified five qualitative criteria into specific fuzzy membership functions, referring to the process of fuzzy-and-defuzzy transformation, is a critical step. In this study, we associate the aforementioned five linguistic criteria with five specific fuzzy membership functions, respectively, including two trapezoidal and three triangular fuzzy membership functions, as shown in Fig. 2. Note that the parameters of these fuzzy membership functions can be approximated on the basis of survey respondents’ viewpoints through the proposed adaptive network-based fuzzy inference system (ANFIS).

After specifying fuzzy membership functions, the process of defuzzy transformation is then conducted. Here, we employ the right-and-left scoring method, which is also suggested in Chen and Hwang (1992) for its high efficiency in the process of quantifying linguistic variables. According to the fundamentals of the right-and-left score approach, the defuzzy value ($\mu_T(U_\sigma)$) associated with a specific fuzzy membership U_σ of a given linguistic criterion σ , termed the total score of the given fuzzy membership function, is computed by:

$$\mu_T(U_\sigma) = \frac{[\mu_R(U_\sigma) + 1 - \mu_L(U_\sigma)]}{2}, \tag{2}$$

where $\mu_R(U_\sigma)$ and $\mu_L(U_\sigma)$ represent the right and left score functions, given by:

$$\mu_R(U_\sigma) = \sup_x [U_\sigma(x) \wedge \mu_{\max}(x)], \tag{3}$$

$$\mu_L(U_\sigma) = \sup_x [\mu_{\min}(x) \wedge U_\sigma(x)]. \tag{4}$$

Herein, $\mu_{\max}(x)$ and $\mu_{\min}(x)$ are defined as the sets of maximization and minimization with respect to x , and their notations are given by:

$$\mu_{\max}(x) = \begin{cases} x, & 0 \leq x \leq 1, \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

$$\mu_{\min}(x) = \begin{cases} 1 - x, & 0 \leq x \leq 1, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Through the aforementioned fuzzy-and-defuzzy transformation process, the quantitative criterion associated with each GL component can then be determined. For instance, given GL-mode θ , the fuzzy-weighted crite-

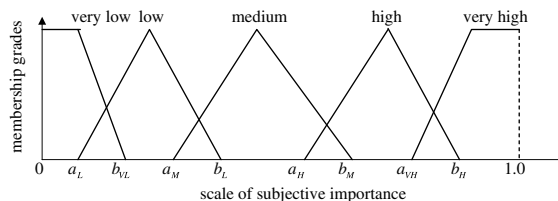


Fig. 2. Fuzzy membership functions for qualitative criteria scale of subjective importance.

tion associated with a specific component i of layer k in the GL-strategy hierarchic framework ($W_i^k(\theta)$) is estimated by

$$W_i^k(\theta) = f_i^k \times \left\{ \frac{\bar{w}_i^k(\theta)}{\sqrt{\sum_{\theta=1}^6 [\bar{w}_i^k(\theta)]^2}} \right\}, \tag{7}$$

where $\bar{w}_i^k(\theta)$ means the averaged raw fuzzy criterion associated with the component i of layer k of GL-mode θ , and its mathematical form is expressed as

$$\bar{w}_i^k(\theta) = \frac{\sum_{\sigma=1}^5 [\mu_T(U_\sigma)] \times n_{U_\sigma|i,k,\theta}}{S}, \tag{8}$$

where $n_{U_\sigma|i,k,\theta}$ represents the number of samples that rate the component i of layer k of GL-mode θ with the qualitative criterion σ , $n_{U_\sigma|i,k,\theta}$ is determined according to the data collected from a questionnaire survey to the high-technology enterprises; and S is the valid sample size of respondents in the survey.

The next step is to develop fuzzy logic rules using both TOPSIS and estimated fuzzy-weighted criteria. Given several alternatives considered in the multi-criteria decision-making process, the basic concept of TOPSIS is that the most preferred alternative should not only have the shortest distance from the ideal solution, but also have the longest distance from the anti-ideal solution (Chen and Hwang, 1992; Opricovic and Tzeng, 2004). Here, the specified six GL modes are regarded as the alternatives considered in the proposed GL strategic hierarchy. Accordingly, employing TOPSIS and the fuzzy-weighted criteria ($W_i^k(\theta)$) estimated in the previous procedure, we develop respective fuzzy logic rules to both identify these specified GL modes with their distinctive features and assess these modes by comparing the relative significance of their corresponding fuzzy-weighted criteria. The corresponding developmental steps involved in this procedure are summarized below.

Step 1. The corresponding ideal and anti-ideal solution sets (i.e., \bar{Z}^k and \underline{Z}^k) associated with all the components of each given layer k in the GL strategic hierarchy should be determined by

$$\bar{Z}^k = \{\bar{z}_i^k \mid i = 1, 2, 3, \dots, N_k\}, \tag{9}$$

$$\underline{Z}^k = \{\underline{z}_i^k \mid i = 1, 2, 3, \dots, N_k\}, \tag{10}$$

where \bar{z}_i^k and \underline{z}_i^k represent the ideal and anti-ideal solutions associated with a given component i of layer k , respectively, as given by

$$\bar{z}_i^k = \left(\max_{\theta} W_i^k(\theta) \mid i \in I' \right) \vee \left(\min_{\theta} W_i^k(\theta) \mid i \in I'' \right), \tag{11}$$

$$\underline{z}_i^k = \left(\min_{\theta} W_i^k(\theta) \mid i \in I' \right) \vee \left(\max_{\theta} W_i^k(\theta) \mid i \in I'' \right). \tag{12}$$

Here I' and I'' represent the benefit-oriented and cost-oriented criteria groups, respectively.

Step 2. Calculate the Euclidean distance-based separations of each given GL-mode alternative (θ) from both the ideal and anti-ideal solutions in the proposed GL strategic hierarchy. For each GL mode alternative (θ), there are two groups of separation measures defined: (1) the layer-based aggregate separations, and (2) the criterion-based disaggregate separations.

The layer-based aggregate separations (i.e., $\bar{Y}^k(\theta)$ and $\underline{Y}^k(\theta)$) refer to the aggregate separations of a given GL mode (θ) from both the ideal and anti-ideal solutions in a given layer k of the proposed GL strategic hierarchy. Here $\bar{Y}^k(\theta)$ and $\underline{Y}^k(\theta)$ are given by respectively by

$$\bar{Y}^k(\theta) = \sqrt{\sum_{\forall i \in I^k} [W_i^k(\theta) - \bar{z}_i^k]^2}, \quad \text{for } k = 2, 3, \tag{13}$$

$$\underline{Y}^k(\theta) = \sqrt{\sum_{\forall i \in I^k} [W_i^k(\theta) - \underline{z}_i^k]^2}, \quad \text{for } k = 2, 3, \tag{14}$$

where I^k represents the set of components associated with a given layer k in the proposed GL strategic hierarchy.

In contrast, the criterion-based disaggregate separations (i.e., $\bar{y}_i^k(\theta)$ and $\underline{y}_i^k(\theta)$) represent the respective separations of a given GL mode (θ) from both the ideal and anti-ideal solutions with respect to a given criterion i of a given layer k in the proposed GL strategic hierarchy. Similarly, $\bar{y}_i^k(\theta)$ and $\underline{y}_i^k(\theta)$ are given by

$$\bar{y}_i^k(\theta) = \sqrt{\sum_{\forall j \in I_i^{k+1}} [W_j^{k+1}(\theta) - \bar{z}_j^{k+1}]^2}, \quad \text{for } k = 2, \tag{15}$$

$$\underline{y}_i^k(\theta) = \sqrt{\sum_{\forall j \in I_i^{k+1}} [W_j^{k+1}(\theta) - \underline{z}_j^{k+1}]^2}, \quad \text{for } k = 2, \tag{16}$$

where I_i^{k+1} represents the set of the corresponding components of criterion i , which are embedded in the lower layer $k + 1$ of the proposed GL strategic hierarchy.

Step 3. Calculate both layer-based and criterion-based significance indexes (i.e., $P^k(\theta)$ and $p_i^k(\theta)$, respectively) associated with each given GL-mode alternative (θ) by

$$P^k(\theta) = \frac{\underline{Y}^k(\theta)}{\bar{Y}^k(\theta) + \underline{Y}^k(\theta)}, \quad \text{for } k = 2, 3, \tag{17}$$

$$p_i^k(\theta) = \frac{\underline{y}_i^k(\theta)}{\bar{y}_i^k(\theta) + \underline{y}_i^k(\theta)}, \quad \text{for } k = 2. \tag{18}$$

Step 4. Rank the GL-mode significance order for GL-mode characterization and assessment. Now, we can compare these GL-mode alternatives using the corresponding estimated significance indexes. Using the principles of TOPSIS (e.g., Opricovic and Tzeng, 2004), we further rank the corresponding GL-mode significance order by the following proposed rules.

Given any pair of GL-mode alternatives, θ^* and θ , for the comparison with respect to the relative significance of a given layer k , GL-mode θ^* can be perceived relatively significant than GL-mode θ if the following two conditions hold.

$$\text{Condition-1 : } P^k(\theta^*) > P^k(\theta), \tag{19}$$

$$\text{Condition-2 : } (\bar{Y}^k(\theta^*) < \bar{Y}^k(\theta)) \wedge (\underline{Y}^k(\theta^*) > \underline{Y}^k(\theta)); \text{ or} \tag{20}$$

$$(\bar{Y}^k(\theta^*) > \bar{Y}^k(\theta)) \wedge (\underline{Y}^k(\theta^*) > \underline{Y}^k(\theta)) \wedge \left(\bar{Y}^k(\theta^*) < \frac{\bar{Y}^k(\theta)\underline{Y}^k(\theta^*)}{\underline{Y}^k(\theta)} \right). \tag{21}$$

Otherwise, these two given GL-mode alternatives are ranked in the same order.

Similarly, given any pair of GL-mode alternatives θ^* and θ for the comparison with respect to the relative significance of a given criterion i , GL-mode θ^* can be perceived as relatively significant than GL-mode θ if the following two conditions hold:

$$\text{Condition-1 : } p_i^k(\theta^*) > p_i^k(\theta), \tag{22}$$

$$\text{Condition-2 : } (\bar{y}_i^k(\theta^*) < \bar{y}_i^k(\theta)) \wedge (\underline{y}_i^k(\theta^*) > \underline{y}_i^k(\theta)); \text{ or} \tag{23}$$

$$(\bar{y}_i^k(\theta^*) > \bar{y}_i^k(\theta)) \wedge (\underline{y}_i^k(\theta^*) > \underline{y}_i^k(\theta)) \wedge \left(\bar{y}_i^k(\theta^*) < \frac{\bar{y}_i^k(\theta)\underline{y}_i^k(\theta^*)}{\underline{y}_i^k(\theta)} \right). \tag{24}$$

Otherwise, these two given GL-mode alternatives are ranked with the same order in the given criterion-based assessment.

Step 5. Formulate fuzzy logic rules for GL-mode identification. For each given GL-mode θ , the respective fuzzy-based GL-mode identification rule is given by

$$\text{IF } [\max U_\sigma(\tilde{w}_i^k(\tilde{\theta})), \forall \sigma] > [\max U_\sigma(\tilde{w}_i^k(\theta)), \forall \sigma] > [\max U_\sigma(\tilde{w}_i^k(\tilde{\theta})), \forall \sigma], \quad \forall i, k, \tag{25}$$

then the given GL-mode θ can be identified readily by the respective linguistic criterion (σ) associated with each component of the given GL-mode θ embedded in the proposed GL strategic hierarchy. Here, $\tilde{\theta}$ and θ represent two neighboring GL-mode alternatives which are ranked with relatively higher and lower order, relative to the given GL-mode θ , based on the previous criterion-based assessment.

2.3. Global logistics mode choice forecasting

This phase develops a GL-mode choice forecasting model using the technique of an adaptive neural-based fuzzy inference system (ANFIS) which permits embedding the proposed fuzzy logic rules in an ANFIS framework to efficiently find one respective GL mode most suitable for the G-SCM operations. Descriptions in terms of the fundamentals of ANFIS techniques and related applications can be readily found elsewhere (Jang and Gulley, 1995; Jang et al., 1997; Tsoukalas and Uhrig, 1997), and thus are omitted in this paper in consideration of the space limit.

For simplicity, a 3-tier ANFIS architecture, shown in Fig. 3, is proposed, where each link in the ANFIS architecture represents the direction of information flow between a given pair of nodes. The square nodes represent respective data-processing functions possessing adaptive parameters which need to be determined by network training; and the circular nodes represent respective data-processing mechanisms without unknown parameters. Considering the different layers existing in the original 3-layer GL strategic hierarchy, these nodes are further classified into two groups, i.e., nodes of GL layers 2 and 3 of Fig. 3. The input data needed in this phase includes (1) the subjective measures of any given targeted enterprise with respect to the components embedded in layers 2 and 3 of the original GL strategic hierarchy; and (2) the data outputted from the proposed ANFIS framework is the forecasted GL mode that is identified as the most suitable GL mode for the targeted enterprise. In addition, each tier of the proposed ANFIS architecture performs a certain task, as described below.

Tier-1: Given the subjective input measure ($\sigma_{i,k}^l$) associated with a given GL component (i) of GL-layer k , obtained from a given targeted enterprise (l), the purpose of this tier is to generate the respective right and left scores ($\mu_R(U_{\sigma_{i,k}^l})$ and $\mu_L(U_{\sigma_{i,k}^l})$) associated with this given GL component using the pre-specified right and left score functions, i.e., $\mu_R(U_{\sigma})$ and $\mu_L(U_{\sigma})$ shown in Eqs. (3) and (4), respectively. Note that because there are unknown adaptive parameters involved in this tier, e.g., the shape-related parameters of those fuzzy membership functions, the corresponding nodes defined in this tier are represented by square nodes.

Tier 2: This tier involves respective circular nodes, which calculate the corresponding total score $\mu_T(U_{\sigma_{i,k}^l})$ associated with each subjective measure $\sigma_{i,k}^l$, where the total score function shown in Eq. (2) is employed.

Tier 3: This is the output tier with only one circular node which forecasts the corresponding GL-mode choice index (Φ_l) associated with the given targeted enterprise (l) by

$$\Phi_l = \sum_{\forall k} \sum_{\forall i} f_i^k \times \mu_T(U_{\sigma_{i,k}^l}). \tag{26}$$

Then, using the estimated Φ_l coupled with the identification criteria shown in the proposed fuzzy-based GL-mode identification rules, the most suitable GL mode (θ_l) for the given targeted enterprise (l) is determined if the following condition holds.

$$\min \left\{ \Phi_l - \left[\sum_{\forall k} \sum_{\forall i} f_i^k \times ([\max U_{\sigma}(\bar{w}_i^k(\theta_l)), \forall \sigma]] \right], \forall \theta \right\}. \tag{27}$$

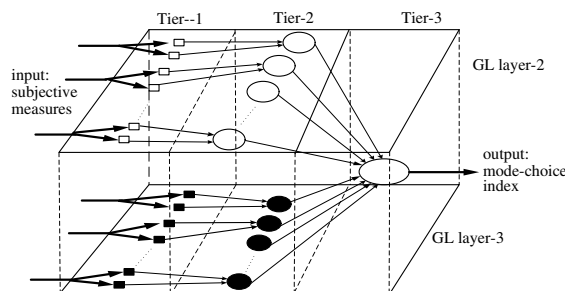


Fig. 3. Proposed ANFIS architecture for GL-mode choice.

3. Numerical examples

To demonstrate the applicability of the proposed method, particularly for GL mode-choice forecasting, a numerical study using the aforementioned questionnaire survey which aimed at the high-technology manufacturing industries of Taiwan was conducted. The survey was distributed randomly to 376 high-technology enterprises, and a total of 87 valid samples were obtained in this survey. The data gathered in the survey were used as the input for the proposed method. According to the proposed three developmental phases, the results output from the established fuzzy-based GL-mode identification rules and corresponding mode choice forecasting model are then discussed.

To generate the input data needed in the proposed method, survey respondents were asked to assess the importance degree associated with these criteria and factors on a 0–1 measurement scale, followed by the corresponding Cronbach's α tests to examine the reliability of the collected survey data. Furthermore, to approximate the unknown shape-related parameters of specified fuzzy membership functions, these survey respondents were also asked to quantify the upper and lower bounds associated with the specified five linguistic criteria (e.g., very important, and not important at all, etc.) on the same measurement scale.

To ensure data reliability, the survey data collected in the 1st stage were examined utilizing the Cronbach's α statistic, which has been widely used to assess the internal consistency based on the correlation between items, e.g., questions of the questionnaire. The results of the Cronbach's α tests associated with the components of GL layers 2 and 3 of the finalized GL strategic hierarchy are summarized in Table 2.

The numerical results shown in Table 2 indicate the acceptability of the specified criteria and corresponding influential factors embedded in the proposed GL strategic hierarchy. As can be seen in Table 2, all the 21 Cronbach's α measurements associated with GL-layer 3 are greater than 0.50, implying that the components of layer 3 are acceptable; noticeably, 15 of them are highly acceptable, with Cronbach's α measurements greater than 0.75. Similarly, the Cronbach's α statistics associated with the components of GL layer 2 also exhibit acceptability in terms of the criteria specified in GL-layer 2. Note that various thresholds for Cronbach's reliability tests have been utilized in previous literature (Cronbach and Meehl, 1955; Zaichkowsky, 1985); however, the thresholds 0.50 and 0.75 are generally suggested as loose and demanding thresholds, respectively, for determining the reliability of data, and are thus used in this study.

The next step is to generate the fuzzy-based GL-mode identification rules through three developmental procedures executed in the 2nd phase of the proposed methodology. First, using the collected survey data, we determined the ordinal numbers in terms of the comparative importance associated with the components in either layer 2 or 3; and then estimated the pair-wise comparison matrices associated with GL layers 2 and 3, as well as corresponding fuzzy weights (i.e., f_i^k shown in Eq. (1)) associated with the components of layers 2 and 3. Utilizing the aggregated data measured from collected survey data together with the estimated fuzzy weights, the fuzzy-weight criteria (i.e., $W_i^k(\theta)$ shown in Eq. (7)) associated with the components of GL layers 2 and 3 were estimated. Then, using the estimates of fuzzy-weighted criteria and TOPSIS approaches, the estimated linguistic criteria (σ) and corresponding significance ranking order were determined, as summarized in Tables 3 and 4, respectively. Given a GL-layer component, a lower ranking order number shown in Table 4 indicates higher significance of the given component exhibited in a given GL mode, relative to that exhibited in the other GL modes. Note that, as mentioned above, these estimated linguistic criteria and corresponding ranking order can be utilized to characterize the distinctive features of these GL modes. Corresponding generalizations obtained from Tables 3 and 4 are summarized.

Obtained from Tables 3 and 4, there are three major generalizations summarized below. First, despite the differences of operational features exhibited among these GL modes, the 1st, 3rd, 4th 5th and 7th factors, i.e., inbound and outbound logistics management, research and development (R&D), production scheduling, and ability to respond to changes of customer demands, remain vital to implementation of high-technology G-SCM. Second, GL-mode *A* and GL-mode *F* can be regarded as two extremely different operational modes for GL strategic planning and operations. According to their corresponding results shown in Tables 3 and 4, GL-mode *A* tends to execute the centralization-oriented GL strategies, and thus, the criterion of management control, and corresponding influential factors, as well as the R&D factor, are highly appropriate for GL strategic planning and management. In contrast, GL-mode *F* tends to implement G-SCM through decentralization-oriented GL strategies. Accordingly, factors relating to transnational channel coordination, overseas

Table 2
Summary of Cronbach's α test results

Component	Cronbach's α value	Result
<i>GL layer 2</i>		
1. Management control	0.71	Acceptable
2. Core competitiveness	0.92	Highly acceptable
3. Trans-organizational coordination	0.72	Acceptable
4. Marketing and service	0.67	Acceptable
5. Overseas resource availability	0.88	Highly acceptable
6. Environmental variability	0.89	Highly acceptable
<i>GL layer 3</i>		
1. Raw-material/assemblies purchasing process	0.65	Acceptable
2. Inventory management	0.58	Acceptable
3. Outbound logistics distribution and transportation	0.77	Highly acceptable
4. Research and development (R&D)	0.93	Highly acceptable
5. Production scheduling	0.86	Highly acceptable
6. Production capacity	0.87	Highly acceptable
7. Ability to respond to changes of customer demands	0.89	Highly acceptable
8. Transnational strategic alliance	0.82	Highly acceptable
9. Communications with IT technologies	0.64	Acceptable
10. Marketing channels	0.72	Acceptable
11. Customer service	0.45	Acceptable
12. Market segmentation	0.64	Acceptable
13. Global raw-material/assemblies supply networks	0.88	Highly acceptable
14. Grouping with overseas industries	0.81	Highly acceptable
15. Availability of overseas human resources	0.91	Highly acceptable
16. Availability of overseas financial resources	0.86	Highly acceptable
17. Availability of overseas technology support	0.85	Highly acceptable
18. Foreign government policies	0.90	Highly acceptable
19. Foreign exchange	0.82	Highly acceptable
20. Modernization of infrastructure	0.86	Highly acceptable
21. Language and culture	0.81	Highly acceptable

resource availability, and external environmental variability may highly influence the system performance of GL-mode *F*. Third, according to the corresponding G-SCM network, GL-mode *E* may tend to execute postponement strategies, and consequently the corresponding system performance may depend highly on the criterion of core competitiveness, and corresponding factors, e.g., production scheduling, R&D, and ability of responding to customers demands are distinctive features.

The following test scenario aims to demonstrate the capability of the proposed GL-mode choice forecasting model. To accomplish this goal, two stages are involved: (1) network training and (2) forecast demonstration.

In the first stage, the developed fuzzy-based GL-mode identification rules are embedded in the proposed ANFIS framework, and trained with collected survey data. Note that for convenience, the aforementioned network training tasks can be readily conducted using existing commercial neural networks packages, e.g., NeuroShell 2 and MATLAB produced by Ward Systems Groups, Inc. and Math Works, Inc., respectively, and thus are not detailed in this text. Herein, the aforementioned survey data collected from 87 samples were used for training the proposed ANFIS framework through 5000, 6000, and 7000 runs of training, respectively. The corresponding network training prerequisites, mainly including the rules for training termination and initial weight setting, as well as the resulting outputs are summarized in Table 5. Then, the respective thresholds with respect to the mode-choice index associated with the six GL mode candidates are determined.

The second stage is to test the validity of the trained GL-mode choice model in GL-mode forecasting. Here, a total of 20 Taiwanese high-technology manufacturing enterprises (*T*-1 to *T*-20) excluding the existing 87 valid samples were sampled. Here the corresponding survey respondents (e.g., managers of enterprises) were asked to linguistically measure the importance of the pre-specified GL criteria and corresponding influential factors with the pre-specified five linguistic terms (e.g., VERY LOW to VERY HIGH, etc.). In addition, information regarding the existing GL operational modes implemented by these targeted enterprises was also

Table 3
Estimates of linguistic criteria for characterization of GL strategic modes

Components (GL-mode identification criteria)	Linguistic criteria					
	Mode-A	Mode-B	Mode-C	Mode-D	Mode-E	Mode-F
<i>Layer 2</i>						
1. Management control	VH	VH	VH	VH	H	H
2. Core Competitiveness	VH	VH	VH	H	VH	H
3. Trans-organizational coordination	M	H	H	H	VH	VH
4. Marketing and service	H	M	VH	VH	H	VH
5. Overseas resource availability	M	H	H	H	VH	VH
6. Environmental variability	M	M	H	H	H	VH
<i>Components (influential factors)</i>						
<i>Layer 3</i>						
1. Raw-material/assemblies purchasing process	VH	VH	VH	VH	H	H
2. Inventory management	H	H	VH	VH	M	M
3. Outbound logistics distribution and transportation	VH	VH	VH	VH	VH	H
4. Research and development (R&D)	VH	VH	VH	H	VH	H
5. Production scheduling	H	VH	H	VH	VH	VH
6. Production capacity	VH	H	H	H	H	H
7. Ability to respond to changes of customer demands	H	H	VH	VH	VH	VH
8. Transnational strategic alliance	M	H	H	H	VH	VH
9. Communications with IT technologies	M	H	H	VH	H	VH
10. Marketing channels	H	H	VH	VH	VH	VH
11. Customer service	H	M	VH	VH	H	H
12. Market segmentation	H	H	H	H	VH	VH
13. Global raw-material/assemblies supply networks	H	H	H	H	H	VH
14. Grouping with overseas industries	M	H	H	H	VH	VH
15. Availability of overseas human resources	M	H	H	H	VH	VH
16. Availability of overseas financial resources	M	H	H	H	H	H
17. Availability of overseas technology support	H	M	M	H	H	VH
18. Foreign government policies	M	M	H	H	H	H
19. Foreign exchange	M	M	VH	VH	H	H
20. Modernization of infrastructure	M	M	H	H	H	VH
21. Language and culture	H	VH	M	H	VH	VH

VH: very high (importance degree).

H: high (importance degree).

M: medium (importance degree).

obtained through the survey. The aforementioned collected survey data were then input to the trained GL-mode choice forecasting model to forecast the respective GL-mode choice index (i.e., Φ_i shown in Eq. (26)). The forecast output of the proposed model and the corresponding GL operational modes executed by these targeted enterprises are summarized in Table 6. Findings and discussions are summarized in the following.

The numerical results of Table 6 imply the applicability of the proposed model used as a decision-making tool for GL-mode choice. As can be seen in Table 6, out of the sampled 20 Taiwanese high-technology enterprises, 14 (70%) are identified for using the GL modes consistent with those suggested by the proposed model. The remaining six sampled enterprises (termed *T-3*, *T-9*, *T-12*, *T-14*, *T-18*, and *T-20* shown in Table 6) presently execute GL modes differing from those predicted. Through our diagnosis of GL-mode choice, enterprises including *T-9*, *T-14*, *T-18*, and *T-20* tended to agree with the modes we suggested after our second-round interview survey. For instance, among these, enterprises *T-9*, *T-14*, and *T-18* highly accepted our suggestion that GL-mode *F* should be more suitable than *E* for their G-SCM operational cases, particularly considering the increasing difficulties and costs in gaining internal resources. In contrast, the other firms (*T-3* and *T-12*) declined our suggestion to replace GL-mode *A* with *B*. According to the resulting second-round interview survey, their two major concerns are: (1) the risks of product quality control in case of manufacturing outsourcing overseas, and (2) the difficulty of communications and practice coordination with transnational

Table 4
Relative significance ranking order of GL modes

Components (GL-mode identification criteria)	Significance ranking order					
	Mode-A	Mode-B	Mode-C	Mode-D	Mode-E	Mode-F
<i>Layer 2</i>						
1. Management control	1	2	4	3	5	6
2. Core competitiveness	2	3	5	4	1	6
3. Trans-organizational coordination	6	5	4	3	2	1
4. Marketing and service	5	6	1	2	4	3
5. Overseas resource availability	6	5	4	3	2	1
6. Environmental variability	6	5	4	3	2	1
Components (influential factors)						
<i>Layer 3</i>						
1. Raw-material/assemblies purchasing process	1	2	3	4	5	6
2. Inventory management	3	4	2	1	5	6
3. Outbound logistics distribution and transportation	2	1	3	4	5	6
4. Research and development (R&D)	1	3	4	5	2	6
5. Production scheduling	2	4	6	3	1	5
6. Production capacity	1	2	3	5	4	6
7. Ability to respond to changes of customer demands	6	5	4	3	2	1
8. Transnational strategic alliance	6	5	4	3	2	1
9. Communications with IT technologies	6	5	4	2	3	1
10. Marketing channels	5	6	1	2	4	3
11. Customer service	5	6	2	1	4	3
12. Market segmentation	5	6	3	4	2	1
13. Global raw-material/assemblies supply networks	6	5	4	3	2	1
14. Grouping with overseas industries	6	5	4	3	2	1
15. Availability of overseas human resources	6	5	4	3	1	2
16. Availability of overseas financial resources	6	5	3	4	2	1
17. Availability of overseas technology support	4	6	5	2	3	1
18. Foreign government policies	6	5	4	3	2	1
19. Foreign exchange	6	5	1	2	4	3
20. Modernization of infrastructure	5	6	3	2	4	1
21. Language and culture	6	3	4	5	2	1

Table 5
Network training prerequisites and outputs

<i>Training prerequisites</i>									
Sample size	87								
Termination rules	Average training error < 0.00005 Maximum training error < 0.0005								
Training iterations: 5000 runs									
Initial weight	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Output (total error)	0.75	0.667	0.625	0.625	0.583	0.5	0.375	0.333	0.333
Training iterations: 6000 runs									
Initial weight	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Output (total error)	0.333	0.458	0.5	0.417	0.417	0.042	0.375	0.333	0.333
Training iterations: 7000 runs									
Initial weight	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Output (total error)	0.417	0.208	0.458	0.375	0.208	0.042	0.375	0.333	0.333

organizations which did not share common language and organizational culture. Nevertheless, 18 out of our 20 suggestions were accepted in this test scenario, implying the applicability of the proposed method for practical uses.

Table 6
GL-mode choice forecast results

Target sample	GL mode (presently used)	GL mode (suggested by the proposed model)	Accepted/rejected (by the enterprise)	GL mode (finalized)
T-1	A	A	Accepted	A
T-2	A	A	Accepted	A
T-3	A	B	Rejected	A
T-4	C	C	Accepted	C
T-5	C	C	Accepted	C
T-6	C	C	Accepted	C
T-7	E	E	Accepted	E
T-8	E	E	Accepted	E
T-9	E	F	Accepted	F
T-10	F	F	Accepted	F
T-11	F	F	Accepted	F
T-12	A	B	Rejected	A
T-13	B	B	Accepted	B
T-14	E	F	Accepted	F
T-15	A	A	Accepted	A
T-16	C	C	Accepted	C
T-17	E	E	Accepted	E
T-18	E	F	Accepted	F
T-19	A	A	Accepted	A
T-20	C	D	Accepted	D

4. Concluding remarks

This paper has presented a hybrid neuro-fuzzy approach, which integrates Fuzzy-MCDM, TOPSIS, and ANFIS techniques to develop a decision support system used for analyzing and determining GL operational modes in the global supply chain environment. The architecture of the proposed methodology involves three main developmental phases, including (1) establishment of GL strategic hierarchy, (2) formulation of GL-mode identification rules, and (3) development of GL mode-choice model. After finalizing the proposed GL strategic hierarchy, which considers six typical types of GL operational modes as GL-mode choice candidates, the fuzzy-based GL-mode identification rules are specified using Fuzzy-AHP, Fuzzy-MCDM, and TOPSIS techniques. Then, a GL-mode choice forecasting model is developed employing the proposed ANFIS framework. Moreover, data collected from questionnaire surveys are used in the study case to demonstrate feasibility of the proposed method for real applications.

The corresponding analytical results have revealed the distinctive features of these GL operational modes and corresponding ranking order to explore the relative significance of these operational features among these GL modes. Particularly, factors including inbound and outbound logistics management, research and development (R&D), production scheduling, and ability to respond to changes of customer demands, appear to be generally important, no matter which GL mode is chosen for high-technology G-SCM. In addition, according to the corresponding analytical results presented in Tables 3 and 4, GL-modes *A*, *C*, *E* and *F* appear to have their own critical criteria significantly influencing system operations and performance. For instance, GL-mode *A* can be more suitable for those centralization-oriented high-technology enterprises, and thus, it may highly depend on the criterion of management control and corresponding influential factors. In contrast, GL-mode *F* may be more appropriate for the implementation of decentralization-oriented GL strategies. Therefore, factors such as transnational channel coordination, overseas resource availability, and external environmental variability appear to have relatively significant effects on the system performance of GL-mode *F*. In addition, the applicability of the proposed GL-mode choice forecasting model has been successfully demonstrated in the other test scenario using a different survey database.

In addition, the numerical results of Table 6 have implied the potential applicability of the proposed model used as a decision-making tool for GL-mode choice. Among 20 sampled enterprises, 18 (90%) agree with the GL-modes we suggested using the proposed method.

Despite the advantages of the proposed decision support system in characterizing and assessing such complicated GL strategic hierarchy for GL mode choice, it should be clarified that there still are various unknown factors, either supply-oriented or demand-oriented, that may significantly influence practical operations of global logistics and global supply chain management. Particularly, from a practical point of view, such sophisticated decision making maneuvers may also rely highly on marketing and financial objectives of the enterprises, as well as their organizational culture and decision-making mechanisms. This also explains our reasoning for limiting the proposed method to the extent of decision support tools.

Nevertheless, the methodology proposed in this study is expected to stimulate more research in the related fields of global supply chain management and corresponding strategic planning. In addition, we hope that this study may help developing logic rules and analytical skills for practical use in addressing issues regarding the uncertainty and complexity of global supply chain management of international high-technology industries. Extension and modification of the proposed model for other industries and operational cases may also warrant more research. Further effort in training the proposed neuro-fuzzy based model with more valid data is also needed for practical applications.

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