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A fuzzy-based customer classification method for demand-responsive logistical distribution operations

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Abstract

In some cases, customer classification is important for the development of advanced logistical distribution strategies in response to the growing complexity in business logistical markets. This paper presents a new approach that can be employed to cluster customers before executing fleet routing in logistical operations. The proposed approach is developed on the basis of fuzzy clustering techniques, and involves three sequential mechanisms including: (1) binary transformation, (2) generation of a fuzzy correlation matrix, and (3) customer clustering. Such a customer clustering method should be performed prior to vehicle dispatching and routing in the process of goods distribution. The proposed methodology clusters customers on the basis of their demand attributes, rather than the static geographic property which is considered extensively in most published vehicle routing algorithms. In addition to methodology development, a case study was conducted to demonstrate the potential advantages of the proposed fuzzy clustering based method. It is expected that this study can stimulate more research on time-based logistics control and management.
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1. Introduction

The prominence of quick response (QR) strategies highlights the need for time-based logistical distribution strategies. Satisfying customers' time-based delivery needs is actually rooted in the concept of marketing, which advocates satisfying customer requirements as the first business objective.

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Furthermore, recent advances in information and communication technologies have significantly re-structured traditional logistics networks. As a consequence, there are increasing demand variants that influence demand fluctuation for logistical businesses and other related businesses, such as express delivery companies, retail-chain stores, and electronic business (e-business) enterprises.

Despite the importance of investigating customer demands in logistical distribution operations, there is a lack of studies addressing the issues related to pre-trip customer demand analyses, as well as the effects of customers' demand attributes on the performance of logistical distribution opera-tions. Herein pre-trip customer demands refer to the order entries of customers processed before the operations of vehicular dispatching. In other words, most researchers have concentrated their efforts on investigating en-route freight transportation issues [1,3,7,14,30,16,28,13], rather than problems of pre-trip customer demand analyses and classification. One common aspect of these typical vehicle routing algorithms is formulating vehicle routing problems (VRP) in order to minimize transportation costs. Recently there has been an increasing interest in developing sophisticated VRP algorithms to address issues on the utilization of advanced information and communication technologies and the limitations of distribution time windows [22–27]. Nevertheless, the effects of demand attributes from customers on logistical distribution operations have rarely been studied.

Clearly, customer classification conducted in advance of vehicle routing plays a key role in customer-oriented logistical operations, and warrants more research in the fields of logistical con-trol and management for the following reasons. First, minimizing transportation cost, as studied in the aforementioned VRP literature, does not mean to enhance the competitiveness of logistical operations cost, even though transportation cost represents a significant item in the logistical cost. It is also worth noting that physical distribution via transportation functionality is merely one of the activities in logistics. Other logistical activities, including inventory and order management, are also vital to determine the performance of logistical systems. In addition to minimum transportation cost, the operations of an integrated logistical system should also seek to achieve other objectives such as minimum inventory cost, continuous quality improvement, and life-cycle support (Bowerson et al., 1996). A growing number of researchers [17,9,2,10] have devoted themselves to integrating other core items of logistics such as inventory and customer demand satisfaction with freight trans-portation in optimizing the cost of logistical operations. And these methods are rooted on the basis of the concepts of supply chain management (SCM). Second, more effort is needed to exploit advanced transportation technologies, such as intelligent transportation systems-commercial vehicle operations (ITS-CVO), to improve logistical distribution performance, and to explore the effects of information and communication technologies on time-based logistical control strategies (e.g., just-in-time (JIT) and quick response (QR)) for providing customer-focused value-added logistical services.

In view of the significance of pre-trip customer classification on the real-world operations of logistical distribution, we propose a new method, which is based primarily on the fundamentals of fuzzy clustering technologies to address the issue of complexity in logistical markets, and which is in response to diverse customer demands on logistical services. This study can be the pioneering research to investigate the subject of pre-trip customer classification in logistical distribution, and to provide a linkage between the areas of customer classification and vehicle routing. It is also noted that in formulating vehicle routing problems, prior literature in relation to vehicle routing rarely takes account of pre-trip customer classification.

The remainder of this paper is organized as follows. The primary procedures for methodology development and the fundamentals of the proposed method are presented in Section 2. A real case

study together with numerical results generated via the proposed method is summarized in Section 3 to demonstrate the feasibility of the proposed method. Finally, Section 4 provides the conclusions.

2. Methodology development

The section is composed of three parts. In order to explicate the potential applicability of fuzzy clustering, the features of fuzzy clustering techniques are presented first. Following this, the decision variables employed in the proposed logistical distribution algorithm are specified, and then a brief description of the major steps executed in the proposed algorithm is provided.

2.1. Fuzzy clustering

Fuzzy clustering can be regarded as an improved clustering technique, which has been used successfully in diverse fields for both data compression but and data categorization [4,19,31,20,29]. As pointed out in Hoppner et al. [21], fuzzy clustering contains two very different areas: the analysis of fuzzy data and the analysis of crisp data with the help of fuzzy techniques. Although recent years have seen remarkable advances in developing diverse fuzzy clustering techniques, e.g., the fuzzy c-means algorithm, the fuzzy c-varieties algorithm, the adaptive fuzzy clustering algorithm, the fuzzy c-ellipsoidal shells algorithm, and the fuzzy hybrid hierarchical algorithm [4,5,11,12,15], for dealing with different complex levels of pattern recognition, the advantages offered by fuzzy clustering techniques for diverse real-world applications remain noteworthy.

In contrast with classical hard (crisp) clustering tools, fuzzy clustering techniques exhibit two distinctive features, which make their real-world applications relatively flexible. First, unlike the hard clustering techniques, which assign each data sample to one and only one cluster, fuzzy clustering utilizes fuzzy partitioning to group data such that any given data sample is allowed to belong to several groups with different degrees of similarity bounded within the range of 0 and 1. Such a feature permits the use of fuzzy clustering in cases where patterns of data attributes are relatively unclear. Second, fuzzy clustering techniques overall outperform conventional hard clustering techniques in multi-dimensional data analysis, particularly with data that consists of linguistic attributes.

Utilizing distinctive features of fuzzy clustering techniques, we propose a hybrid fuzzy-hierarchical clustering method to analyze the customer attributes, either qualitative or quantitative, and to group these customers in advance of the activity of vehicle routing. Correspondingly, each customer is conceptually regarded as a datum with multiple demand-oriented attributes, where some of these attributes are quantitative, e.g., the volume of the product ordered by a given customer, and others are qualitative, e.g., the customer's satisfaction with the delivery service. To provide group-based QR delivery service to those customers with mutually similar characteristics, the proposed fuzzy clustering based approach is used to analyze the attributes of customers, and to classify these customers into appropriate groups before vehicle dispatching. Such a two-stage logistical distribution strategy can make available the proposed logistical distribution method with benefits not only for efficient dynamic fleet management in the supply side, but also for rapidly responding to a variety of customer demands.

The proposed hybrid fuzzy-hierarchical clustering approach is referred to as an unsupervised fuzzy clustering technique, which uses the concepts of both fuzzy and hierarchical clustering in fuzzy data

analysis. Recently there has been the increasing use of similar techniques (Priber et al., 1997; Tao, 2002) [12,20], including our previous research which utilizes the integrated fuzzy-hierarchical clustering approach for real-time freeway incident detection and characterization [29]. In comparison with the fuzzy c-means algorithm, which is one of the most popular fuzzy clustering algorithms, the hybrid fuzzy-hierarchical clustering algorithm appears more applicable in cases where a great amount of multi-attribute data needs to be assigned to an unknown number of clusters, subject to limited computational time. Thus, such a fuzzy clustering technique is used in this study to address the pre-trip customer classification issue in the area of logistical distribution.

The following two subsections discuss the primary procedures conducted to specify the decision variables and to develop the proposed algorithm.

2.2. Determination of decision variables

Specification of decision variables used to explore the degree of customer satisfaction in distribution service is the first step in developing the proposed methodology. In this scenario, the customer attributes that potentially dominate the system performance of logistical distribution are analyzed, followed by the determination of decision variables.

For the analysis of demand attributes, we first investigated the relations between customer service on the supply side and customer satisfaction on the demand side. From a suppliers point of view, there seems to be a consensus that five major measures of effectiveness (MOE) can be used to examine, directly and indirectly, the capability of logistical distribution service: (1) safety, (2) transit time, (3) transportation cost, (4) accessibility, and (5) service quality. The implications of these supply-oriented MOE indexes associated with the customer satisfaction in the demand domain include primarily: (1) security, (2) reliability, (3) economic concern, (4) convenience, and (5) satisfaction in servers quality; and these are herein taken to be the major customer concerns. However, in real-world operations, the aforementioned customer concerns may not be perfectly consistent with the supply-driven MOE indexes, and to a certain extent, they may conflict, internally and externally, with each other. For instance, to provide a customer with high accessibility, the logistical supplier may need to invest heavily in restructuring distribution networks, and as a consequence, logistical costs including transportation cost must increase. Nevertheless, such conflicts are allowed in demand-oriented logistical control and management strategies because the benefits gained from the increased amount of new customers derived from the strategy of high convenience service may pay off the increased cost.

With the aforementioned postulations to determine the decision variables, two procedures were executed, including specification of variable candidates and a questionnaire survey. In the first stage, we tentatively proposed 15 candidates of decision variables derived from the aforementioned five major concerns of customers in a logistical distribution service. The candidates for these decision variables were presumed as the factors in segmenting customers for the proposed demand-responsive logistical distribution algorithm. A national questionnaire mail survey of the logistics-related community was then conducted in the second stage. Considering the comprehensiveness of the samples to be surveyed, we included three target groups, namely (1) related government representatives (the logistics-project funding supplier), (2) researchers/professors in the related fields, and (3) freight transportation/logistics business operators. In this survey, the total sample size was 108, collected randomly from the above three target groups. Among the 108 samples, 34 samples were valid,

meaning that their mail responses were received and assessable. Each survey respondent was asked to rate the 15 candidates of decision variables with a positive integer bounded by 1 and 10, corresponding to "not significant" and "most significant", respectively.

By factor analyses, we obtained a total of 9 variable candidates for the decision variables, with the generalization that they were classified into the group of significant factors. The denotations as well as explications of these finalized decision variables are summarized as follows.

(1) $x_i^1(k)$ represents the physical attribute of product distributed to customer i at time step k, and herein, the volume of product is considered most important. Practically, $x_i^1(k)$ is a key factor in determining the number of en-route vehicles, and herein it is used to replace the constraint of vehicular load capacity, which has been extensively formulated in the fields of classical vehicle routing problems.

(2) $x_i^2(k)$ represents the time lag between the deadline to customer i and the distribution time step k. In real-world operations, it is permissible to deliver products to those customers associated with close distribution deadlines, and thus, these customers can be categorized into a group that is served by the same vehicular fleet.

(3) $x_i^3(k)$ corresponds to the value of the product distributed to customer i at time step k, and to a certain extent it may depend on the market price of the product. In real-world distribution operations, high-value products may be segmented from other products, and handled with specific security measures for safe delivery.

(4) $x_i^4(k)$ represents the external similarity in terms of type of product ordered by customer i, relative to the products scheduled to be distributed to customers in a given group at time step k. This variable is specified for efficiency of providing bulk delivery service to customers in the same group. The higher the external similarities among the customers in a given group, the more efficient will be the bulk delivery service in distribution operations.

(5) $x_i^5(k)$ represents the server's quality anticipated by a given customer i at time step k. It is commonly agreed that the server's quality, including the time spent in responding to customers' demands, the server's personal attitude, and the server's confidence, determines the customer's satisfaction with the logistical distribution system. Herein, this variable serves to qualitatively indicate the customer's personal demand for the server's quality. From a practical point of view, logistical enterprises can group together those customers who demand similar server quality for providing specific delivery services.

(6) $x_i^6(k)$ represents the internal similarity in terms of the types of products associated with a given customer i at time step k. In contrast with the external similarity $x_i^4(k), x_i^6(k)$ indicates the similarity of the characteristics of products associated with customer i, and in this study, it can be used to determine if a given customer needs multiple deliveries.

(7) $x_i^7(k)$ corresponds to the geographical attribute associated with customer i at time step k. In this study, we generally characterize the geographical attribute of a customer with a two-dimensional variable in order to indicate the location of a given customer relative to the dispatcher, and thus those customers with similar geographical attributes can be served together in logistical distribution operations.

(8) $x_i^8(k)$ is defined as the satisfaction of customer i with respect to the security of the distributed product at time step k. This variable implies, to a great extent, a customer's personal demands in terms of condition of the product. In effect, a logistics company can group together

customers with similar measurements of $x_i^8(k)$ in response to their specific needs for delivery security.

(9) $x_i^9(k)$ represents the life cycle of the product distributed to customer i at time step k. This reflects the fact that products with similar life cycles tend to be delivered together in the process of distribution operations, in response to customers' concerns for either the expiration dates or the product values during their market lives.

All the aforementioned decision variables are measured with five linguistic terms, i.e., "very high", "high", "medium", "low", and "very low", using daily transaction data of customers' order entries, and they are then transformed into binary-type variables for fuzzy clustering analysis. The related procedures are detailed in the following subsection. In addition, variables $x_i^5(k)$ and $x_i^8(k)$ may need supplementary means, such as interviews or mail questionnaires, to be estimated in real-world operations. In addition, a time step is defined in the study as a given time period in which a specific logistical distribution mission is implemented in order to serve given groups of customers that are pre-clustered via the proposed algorithm.

2.3. Algorithm development

The architecture of the proposed fuzzy clustering-based algorithm, as illustrated in Fig. 1, is composed of three major mechanisms including: (1) binary transformation, (2) generation of fuzzy correlation matrix, and (3) customer grouping. The primary steps executed in the aforementioned mechanisms are detailed in the following.

2.3.1. Binary transformation

The mechanism of binary transformation serves mainly to transform the measurements of customers' decision variables collected from order entries into binary data. Herein, three sequential steps are involved in this mechanism. First, we specified five linguistic terms, including "very high", "high", "medium", "low", and "very low", which represent five levels of qualitative criteria to associate customers' attributes with specific demand patterns. Second, according to the real data that characterize customers' demands, the decision variables associated with each customer were measured with the aforementioned five linguistic terms. In reality, these measurements can be collected from order entries, and updated at each time step. Third, according to the mapping relationships presented in Table 1, the measured decision variables with linguistic items were transformed into binary codes. Herein, each linguistic item is represented by a specific set of four bits such as "0000" for the linguistic item "very low", and "1111" for "very high." Thereby, each given linguistic decision variable p measured from customer i ($x_i^p(k)$) can be transformed into binary codes with four bits ($\sigma_{i,j}^p(k)$), and expressed as

$$x_i^p(k) = [\sigma_{i,1}^p(k), \sigma_{i,2}^p(k), \sigma_{i,3}^p(k), \sigma_{i,4}^p(k)]. \tag{1}$$

A numerical example is illustrated as follows. Given that the order entry of a given customer i is processed in a given time step k, the decision variable of external similarity associated with the given customer i ($x_i^4(k)$) is linguistically identified to be "high", indicating that the corresponding product is highly related to other products scheduled to be delivered to the given customer group at time step k. Thereby, $x_i^4(k)$ is coded with $(1, 1, 1, 0)$, according to Table 1.
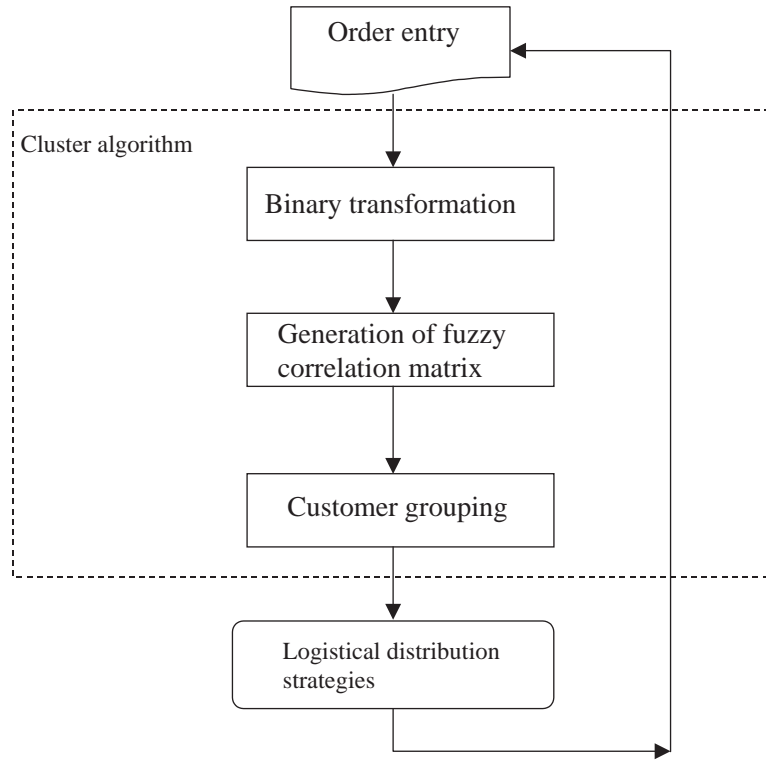
Fig. 1. Conceptual framework for the proposed fuzzy clustering-based algorithm.

Table 1
Binary transformation of the specified five linguistic terms (given customer i and the pth decision variable)

Binary code linguistic measure	$\sigma_{i,1}^p(k)$	$\sigma_{i,2}^p(k)$	$\sigma_{i,3}^p(k)$	$\sigma_{i,4}^p(k)$
Very high	1	1	1	1
High	1	1	1	0
Medium	1	1	0	0
Low	1	0	0	0
Very low	0	0	0	0

To facilitate processing the heterogeneity of decision variables, the procedure of standardization with respect to $\sigma_{i,j}^p(k)$ is conducted, and herein, the standardized value of $\sigma_{i,j}^p(k)$ ($\tilde{\sigma}_{i,j}^p(k)$) is given by

$$\tilde{\sigma}_{i,j}^p(k) = \frac{\sigma_{i,j}^p(k) - \bar{\sigma}_j^p(k)}{S_j^p(k)}, \tag{2}$$

where $\bar{\sigma}_j^p(k)$ and $S_j^p(k)$ correspond to the values of the mean and standard deviation with respect to $\sigma_{i,j}^p(k)$, respectively, as denoted by

$$\bar{\sigma}_j^p(k) = \frac{\sum_{i=1}^M \sigma_{i,j}^p(k)}{M}, \tag{3}$$

$$S_j^p(k) = \left[\frac{\sum_{i=1}^M (\sigma_{i,j}^p(k) - \bar{\sigma}_j^p(k))^2}{M-1}\right]^{1/2}. \tag{4}$$

Herein, M represents the number of customers that are served at the current time step, so we have the standardized decision variable ($\tilde{x}_i^p(k)$):

$$\tilde{x}_i^p(k) = [\tilde{\sigma}_{i,1}^p(k), \tilde{\sigma}_{i,2}^p(k), \tilde{\sigma}_{i,3}^p(k), \tilde{\sigma}_{i,4}^p(k)]. \tag{5}$$

2.3.2. Generation of fuzzy correlation matrix

At this stage, a time-varying $M \times M$ fuzzy correlation matrix ($\Psi(k)$) is constructed in which each element ($\omega_{r,s}(k)$) represents the correlation between a given pair of customers r and s. Herein, we have $\Psi(k)$ and $\omega_{r,s}(k)$ expressed as

$$\Psi(k) = [\psi_1(k)|\psi_1(k)|\ldots\ldots|\psi_M(k)]_{M\times M}$$

$$= \begin{bmatrix} \omega_{11}(k) & \omega_{12}(k) & \omega_{13}(k) & \cdots & \omega_{1M}(k) \\ \omega_{21}(k) & \omega_{22}(k) & \cdots & \cdots & \vdots \\ \omega_{31}(k) & \cdots & \ddots & & \vdots \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ \omega_{M1}(k) & \cdots & \cdots & \cdots & \omega_{MM}(k) \end{bmatrix}_{M\times M}, \tag{6}$$

$$\omega_{r,s}(k) = 1 - \frac{1}{\lambda_1}\sqrt{\sum_{p=1}^\Omega \sum_{\theta=1}^\Theta [\tilde{\sigma}_{r\theta}^p(k) - \tilde{\sigma}_{s\theta}^p(k)]^2}, \tag{7}$$

where Ω and Θ correspond to the number of decision variables and the number of bits used to specify a given decision variable, and as noted above, in this study they are 9 and 4; λ_1 is a parameter set mainly for the upper and lower boundaries of $\omega_{r,s}(k)$, i.e., 1 and 0, respectively, and herein predetermined via using the historical data of customer demand. It should also be noted that according to Eqs. (6) and (7), $\Psi(k)$ turns out to be a symmetric matrix.

2.3.3. Customer grouping

This mechanism is triggered to execute the functionality of clustering customers into several groups with the objective that customers assigned to the same group are characterized by relatively high similarity in terms of their attributes, compared to the members in any other groups. Fig. 2 presents the proposed customer grouping logic, and the major computational steps are summarized as follows.

Step 0: Initialize the computational iteration. Set the iteration index $\pi = 1$; input the estimated fuzzy correlation matrix, i.e., Eq. (6) measured in the previous procedure; start the iteration from the first column of the fuzzy correlation matrix ($\psi_1(k)$), as shown in Fig. 3, letting $s := 1$.
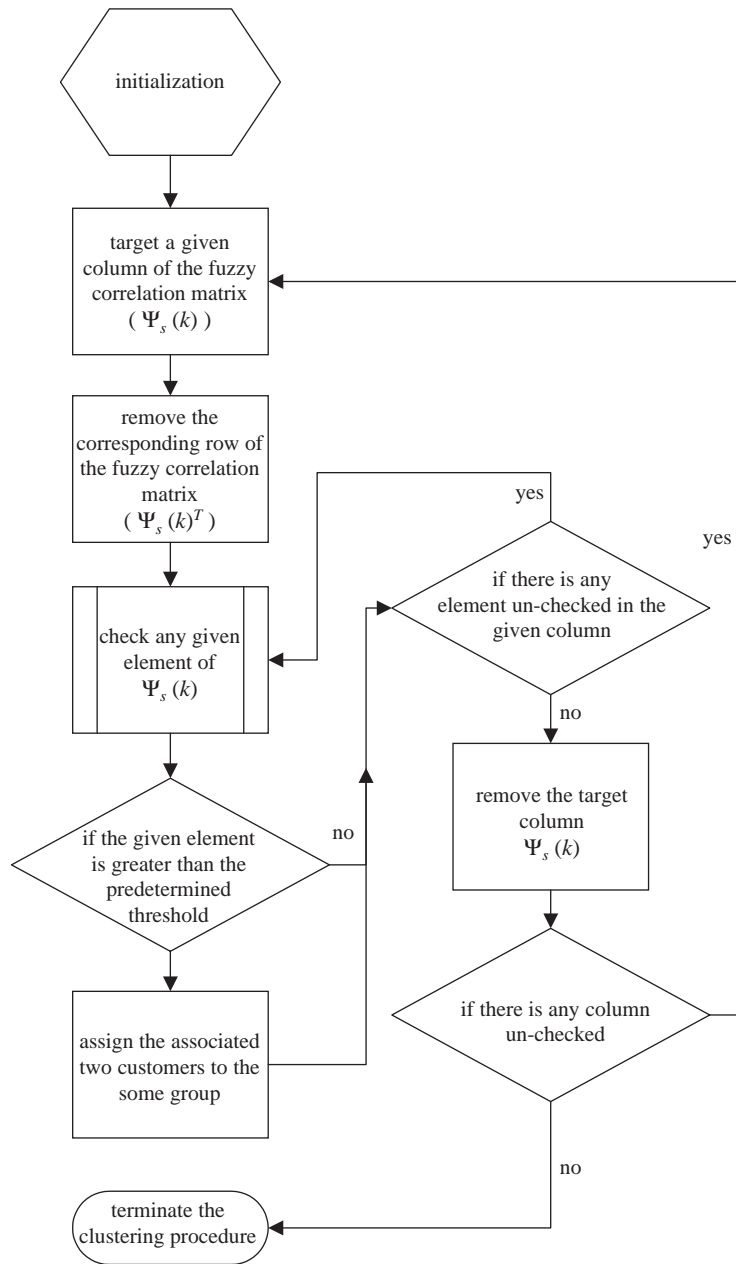
Fig. 2. Proposed customer grouping logic.

Step 1: Given a target customer s, remove the row of $\Psi(k)$ associated with customer s ($\psi_s(k)^{\mathrm{T}}$). The corresponding illustration is presented in Fig. 4, given $s := 1$. Note that herein, the column of the fuzzy correlation matrix associated with the given customer s ($\psi_s(k)$) is targeted for the purpose of clustering other possible customers with the given customer s in the same group using the elements

The estimated fuzzy correlation matrix $\Psi(k)$

Column of $\Psi(k)$ Row of $\Psi(k)$	$\psi_1(k)$	$\psi_2(k)$	………	$\psi_M(k)$
$\psi_1(k)^T$	$\omega_{11}(k)$	$\omega_{12}(k)$	………	$\omega_{1M}(k)$
$\psi_2(k)^T$	$\omega_{21}(k)$	$\omega_{22}(k)$	………	$\omega_{2M}(k)$
⋮	⋮	⋮	⋱	⋮
$\psi_M(k)^T$	$\omega_{M1}(k)$	$\omega_{M2}(k)$	………	$\omega_{MM}(k)$

Start out from column 1

Fig. 3. Illustration (1) of the proposed customer grouping algorithm.

Column of $\Psi(k)$ Row of $\Psi(k)$	$\psi_1(k)$	$\psi_2(k)$	………	$\psi_M(k)$
$\psi_1(k)^T$	$\omega_{11}(k)$	$\omega_{12}(k)$	………	$\omega_{1M}(k)$
$\psi_2(k)^T$	$\omega_{21}(k)$	$\omega_{22}(k)$	………	$\omega_{2M}(k)$
⋮	⋮	⋮	⋱	⋮
$\psi_M(k)^T$	$\omega_{M1}(k)$	$\omega_{M2}(k)$	………	$\omega_{MM}(k)$

Remove the row $\psi_1(k)^T$

Fig. 4. Illustration (2) of the proposed customer grouping algorithm.

of $\psi_s(k)$ in the following procedures. The elements of the row associated with the given customer s ($\psi_s(k)^T$) are redundant in the following clustering process, and thus they are removed in this step.

Step 2: Find the maximum element in $\psi_s(k)$, denoted by $\omega_{rs}(k)$, and then conduct the following cluster procedures in sequence:

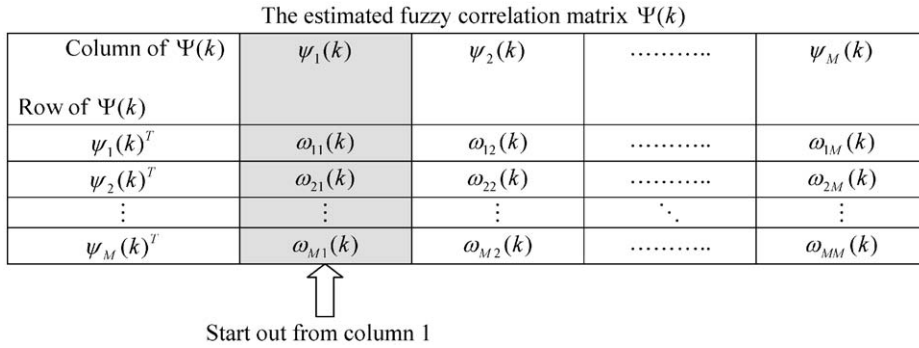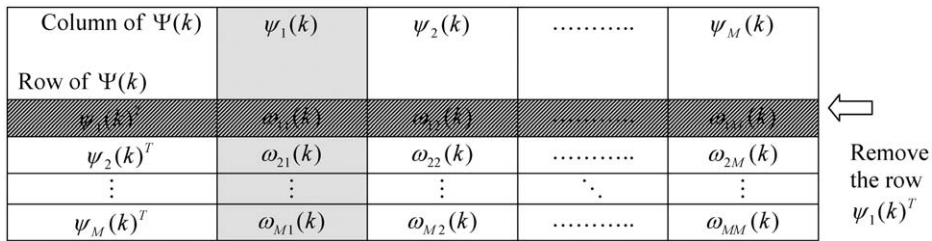- If the condition $\omega_{rs} > \lambda_2$ holds, then assign customer r to the same group as customer s, and remove the row of $\Psi(k)$ associated with customer r($\psi_r(k)^T$). The corresponding illustration is shown in Fig. 5, where $r := 2$ is given.
- Go back to *Step* 2 to continue checking the other elements of $\psi_s(k)$ until there is no element that meets the aforementioned clustering condition.
- Remove $\psi_s(k)$ from $\Psi(k)$.
- If there are any customers assigned at this stage, then, let all the assigned customers be the target customers (i.e., let $s := r$), and go back to *Step* 1 to process the elements of $\Psi(k)$ associated with these target customers.
- Let $\pi = \pi + 1$, and then, $s := \pi$.

Step 3: Conduct the following termination rules to stop the mechanism of customer grouping:

- if no column remains, then stop the cluster procedure,
- else, go back to *Step* 1 for the next iteration,

Column of $\Psi(k)$ Row of $\Psi(k)$	$\psi_1(k)$	$\psi_2(k)$	………..	$\psi_M(k)$
$\psi_2(k)^T$	$\omega_{21}(k)$	$\omega_{22}(k)$	………..	$\omega_{2M}(k)$
⋮	⋮	⋮	⋱	⋮
$\psi_M(k)^T$	$\omega_{M1}(k)$	$\omega_{M2}(k)$	………..	$\omega_{MM}(k)$

Given $r = 2$, and $\omega_{21}(k) > \lambda_2$

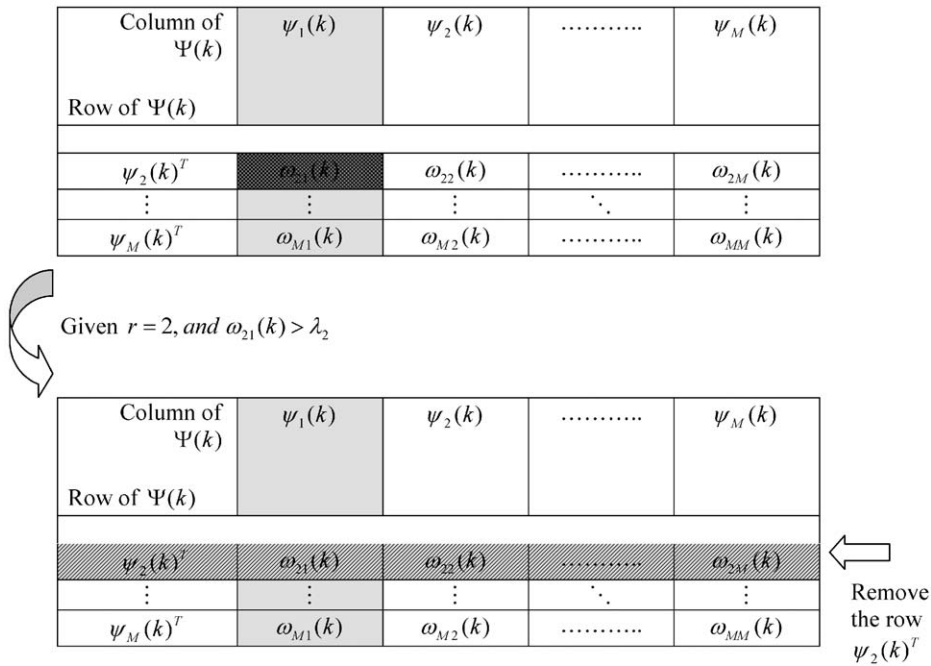| Column of $\Psi(k)$ Row of $\Psi(k)$	$\psi_1(k)$	$\psi_2(k)$	………..	$\psi_M(k)$
$\psi_2(k)^T$	$\omega_{21}(k)$	$\omega_{22}(k)$	………..	$\omega_{2M}(k)$
⋮	⋮	⋮	⋱	⋮
$\psi_M(k)^T$	$\omega_{M1}(k)$	$\omega_{M2}(k)$	………..	$\omega_{MM}(k)$

Remove the row $\psi_2(k)^T$

Fig. 5. Illustration (3) of the proposed customer grouping algorithm.

where λ_2 is a threshold for identifying the relative similarity between a given pair of customers, and set to be 0.7 using trial-and-error tests in this study. In practice, in the proposed clustering algorithm, λ_2 determines the number of iteration steps and the number of clusters, both of which exhibit a trade-off relationship in the clustering procedure. For instance, a lower value of λ_2 may speed up the clustering procedure as indicated by the reduced number of iteration steps; and meanwhile, it may cause a reduced number of customer groups, which loosens the requirement for identifying the mutual similarity of intra-group customers. Furthermore, λ_2 also depends on the availability of the servers and freight transportation vehicles in the logistical distribution procedure. Accordingly, it is suggested that subject to the constraints in terms of available servers and shipping vehicles in real-world application cases, λ_2 greater than 0.5 be specified by the decision-makers of the logistical operations to control the overall system performance of logistical distribution.

3. Numerical results

To demonstrate the applicability of the proposed method for demand-responsive logistical distribution operations, a case study was conducted in Taiwan during the spring of 2001. In this study scenario, a private department store in the city of Kaohsiung, Taiwan was contracted to collect customers' order entries. A random sample of customers was drawn from the order entries to generate a database used for measuring customers' characteristics. The proposed fuzzy clustering method was

then utilized to classify customers according to the measured customers' decision variables, and the delivery was arranged according to the clustering results. In addition, a telephone questionnaire survey was conducted immediately after the delivery to determine the sampled customers' perceptions of the new delivery service, and the survey responses were used as the basis for evaluating the performance of the proposed demand-responsive distribution strategy.

In addition to traditional customer shopping, this department store also provided internet-shopping together with home-delivery services for the customers' convenience. The original delivery strategies conducted by the targeted department store were derived mainly from the first-in-first-out (FIFO) service principle, subject to the policy that any internet-shopping customers would get delivery within one week. The frequency of vehicle dispatch of the targeted department store was two times per day, and the dispatching headway was 4 h. The dispatched fleet size in each delivery mission depended primarily on the volume of the ordered goods, but was subject to the maximum fleet size available. During the 1-week test period, the targeted department store tentatively adjusted their vehicle dispatching strategies to employ the pre-trip customer classification results, and the constraint of the maximum fleet size remained.

In order to evaluate the performance of the proposed method, a database including order entries and survey responses was generated. Two major procedures were involved in this scenario. First, the customers of this department store were randomly sampled from the database of order entries, and a total of 24 order entries were collected from diverse customers. The processed spatial and temporal attributes of the sampled order data are summarized in Table 2. In addition, the targeted customers were asked via telephone survey about their perceptions on the server's quality and the security of the distributed product to measure the relevant decision variables $x_i^5(k)$ and $x_i^8(k)$, respectively. Note that the other decision variables can be quantified according to the information contained on the order entries. Second, a telephone questionnaire survey was conducted after the targeted customers received the ordered goods. The questionnaire consisted of two parts: (1) customer's perception on the new delivery service, and (2) relative satisfaction in comparison with the original delivery service. All the items shown in the questionnaire were measured on a 5-point scale, with 1 indicating that a given item was not important and 5 indicating that the item was very important.

Utilizing the proposed fuzzy clustering method, we re-processed the collected order entries, and classified the customers into specific groups via the aforementioned computational procedures of the proposed customer classification algorithm. In order to show the superiority of the proposed method, we plotted the clustering results graphically in Fig. 7 in contrast with Fig. 6, which illustrates the original delivery strategy (i.e., FIFO service) with the customers being served in sequence. In the original delivery operations, the customers should be classified into seven groups, and the associated routes represented by the customer code and the delivery depot α are:

- route-1 α-1-2-3-4-5-6-α
- route-2 α-7-α
- route-3 α-8-9-10-11-12-13-14-15-α
- route-4 α-16-17-α
- route-5 α-18-19-20-α
- route-6 α-21-22-23-α
- route-7 α-24-α

Table 2
Summary of the spatial and temporal features of the collected order data feature

Feature order entry	Time of order arrival (day/h/min)	Delivery deadline requested by customer (day)	Relative location of customer to the department in km (x-axis, y-axis)
Customer 1	00/00/17	2	−10.3, 9.7
Customer 2	00/03/44	3	−4.4, −6.6
Customer 3	00/04/28	3	−8.5, 6.3
Customer 4	00/06/33	1	2.7, 9.3
Customer 5	00/08/49	3	−5.3, −4.5
Customer 6	00/10/57	3	−0.6, 5.2
Customer 7	00/12/21	3	18.6, −13.2
Customer 8	01/01/48	2	−11.9, 3.7
Customer 9	01/03/37	1	3.3, 7.8
Customer 10	01/04/06	2.5	−1.8, −11.1
Customer 11	01/05/29	2	8.6, 2.5
Customer 12	01/08/45	3	−6.9, 1.6
Customer 13	01/08/56	2	7.8, −7.0
Customer 14	01/09/27	2	16.8, −18.4
Customer 15	01/11/38	1.5	12.7, −1.8
Customer 16	02/01/43	2	14.3, −21.3
Customer 17	02/03/07	2	8.2, −15.8
Customer 18	02/03/46	1	11.5, 10.4
Customer 19	02/04/44	2	1.1, −8.5
Customer 20	02/07/49	2	20.7, −22.7
Customer 21	02/08/52	1	6.4, −0.9
Customer 22	02/10/07	2	−7.3, 11.6
Customer 23	02/11/21	1	−12.2, −2.4
Customer 24	03/01/30	1	10.4, 21.7

In contrast with the original delivery, the 24 customers are classified into five distinctive groups according to the demand attributes of the customers via the proposed fuzzy-clustering method, and the associated vehicle routing planning can be designed, effectively and efficiently, as

- route-1 α-12-8-1-22-3-6-α
- route-2 α-9-18-24-4-α
- route-3 α-5-23-2-10-19-α
- route-4 α-11-15-17-13-21-α
- route-5 α-16-20-14-7-α

Once the pre-trip customer classification procedure is completed, the en-route transportation operations shown above can be easily determined according to the geographical relations of the customers in a given group. In practice, this can be readily accomplished merely by drivers' experience or by conducting the existing vehicle routing algorithms, which attempt to efficiently and effectively determine optimal solutions of vehicle routing. To reveal the distinctive features of the proposed pre-trip customer classification method, we maintained the original vehicle routing strategies executed by the contracted department store. That is, once the customers were clustered, the route associated with
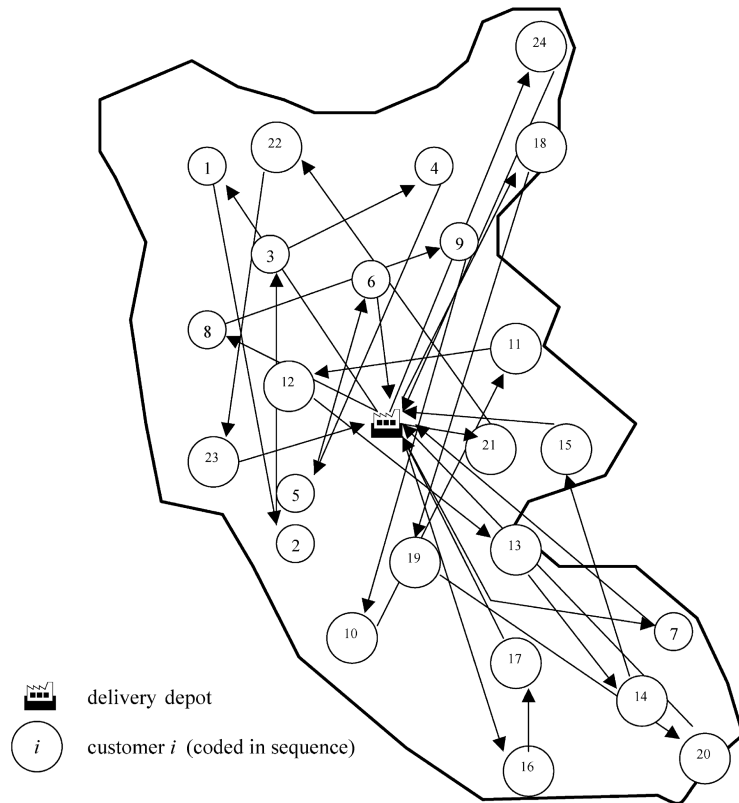
Fig. 6. Geographical distribution of customers.

any given group of customers would be determined merely on the basis of the contracted drivers' experiences. Clearly, such a treatment for en-route transportation operations is adjustable. In reality, there are other alternatives, including the integration of pre-trip customer classification strategies with elaborate vehicle routing and dispatching strategies. Moreover, it is worth mentioning that the relative advantages of such two-stage logistical distribution operations may turn out to be increasingly significant in implementing time-based logistical control and management under conditions of complicated logistical service networks.

   To quantitatively assess the system performance of the proposed method with respect to the improvements in logistical distribution operations, we compared the operational results obtained from the proposed distribution strategy and the original strategy utilizing four criteria defined as follows:

(1) the total transportation cost given a set of the shortest paths $TC(k)$,
(2) the average service time $ST(k)$ which is the average time spent in delivery service with respect
    to the sampled customers and can be obtained by averaging the time differences between when
    an order is received and when the delivery service is completed for all the sampled customers,
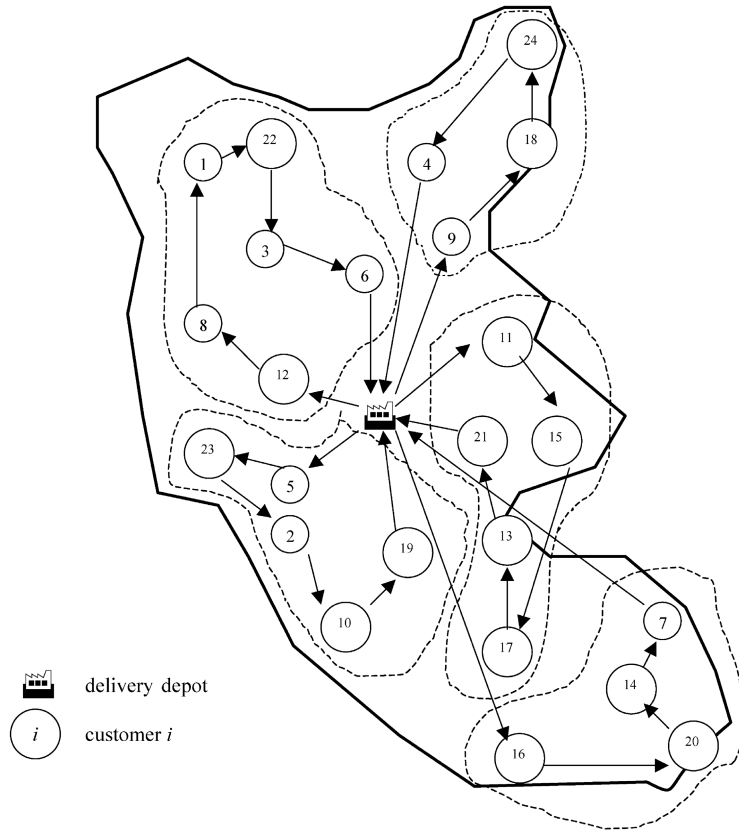(3) the aggregated customer satisfaction on service quality $CS(k)$, and

Fig. 7. Customer classification results obtained by the proposed method.

(4) the competence in completing express delivery service $ED(k)$, which is herein defined as the ratio of the customers being served with express delivery to all sampled customers.

The notations of $TC(k)$, $ST(k)$, $CS(k)$, and $ED(k)$ are given by

$$TC(k) = \sum_{\forall g} \sum_{\forall o \in \tilde{\delta}} \sum_{\forall d \in \tilde{\delta}} c_{od}^{g}(k), \tag{8}$$

$$ST(k) = \frac{\sum_{\forall g} \sum_{\forall i_g} [k - k_0^{i_g}]}{M}, \tag{9}$$

$$CS(k) = \frac{\sum_{\forall g} \sum_{\forall i_g} \varsigma_{i_g}}{M}, \tag{10}$$

$$ED(k) = \frac{M_{\exp}}{M}, \tag{11}$$

where $c_{od}^{g}(k)$ denotes the transportation cost in a given link with the origin o and the destination d on the shortest path $\tilde{\delta}$ to serve the customer group g; i_g represents a given customer i

Table 3
Comparative results of system performance

Criteria Strategy	$TC(k)$ ($)	$ST(k)$ (h)	$CS(k)$ (5-point scale)	$ED(k)$ (%)
Proposed	3,279.7	28.5	3.8	75.0
Original	6,631.5	76.3	2.1	29.1
Relative improvement (%)	50.6	62.6	44.7	61.2

who belongs to the customer group g; $k_0^{i_g}$ corresponds to the time when the delivery service is completed for a given customer i_g; M, as defined previously, is the sample size in the study, herein equal to 24; ς_{i_g} represents the customer satisfaction associated with a given customer i_g, as measured on a 5-point scale by the customer; and $M_{\exp}$ is defined as the number of customers who are served with express delivery by which the ordered product is delivered within 2 days. The comparison results according to the aforementioned criteria are summarized in Table 3. As can be seen, the performance of the original delivery strategy was estimated mainly on the basis of historical data as well as the experiences of the contracted department store in their business operations.

Overall, the comparison results shown in Table 3 reveal that there are significant improvements in logistical distribution operations by implementing the proposed pre-trip customer classification strategy. Two observations from the analysis are provided to elaborate on this generalization. First, the improvements with respect to these criteria are evenly high. As depicted in Table 3, the measurements of relative improvement associated with these criteria are for the most part greater than 50%, and as a consequence, the average improvement is greater than 50%. Clearly, these measurements may also imply that there is an urgent necessity to improve the original delivery strategy of the contracted department store to meet the requirements for the operations of time-based logistical distribution management and control.

Second, it is impressive that not only the demand-based criteria, including $CS(k)$, and $ED(k)$, but also the supply-based criteria, $TC(k)$ and $ST(k)$, indicated the considerably positive signal in the evaluation scenario. This implies that the proposed distribution strategy may provide benefits to both the supply and demand sides.

According to the observations from the numerical results, there are several findings worth mentioning, as follows:

(1) Although the sampled customers were to a certain extent satisfied with the improved delivery service, timeliness remains a major factor in determining the customers' satisfaction. This is reflected by the distribution of the ratings of customers' satisfaction collected from the respondents. Out of the 24 respondents, three respondents rated this item with the point less than 3: one respondent rating this item with 1 point on the pre-specified 5-point scale, and two rating it with 2 points. Therefore, the measurement of $CS(k)$ was not as universally high as originally expected. We should note that the aforementioned three respondents are the customers whose goods were delayed in the proposed delivery operations.

(2) Compared with the original delivery strategy that could serve only seven customers with express delivery, the proposed distribution strategy appears to possess the relative potential advantage in

Table 4
Results of comparisons with other fuzzy clustering algorithms

Clustering algorithms criteria	Proposed	FCM	GK
$TC(k)$	3279.7	4,962.5	4,771.5
t	2.4	5.8	11.4
c	5	13	10
ι	9	41	36

providing QR service to customers because out of 24 samples, 18 customers were served with express delivery by the proposed strategy. This can be proven with the measurements associated with $ED(k)$ shown in Table 2.

(3) Despite the measurements of $TC(k)$ and $ST(k)$, which both indicate high improvements in transportation cost and service time, respectively, there still remains a high potential for improving the operations performance in terms of logistical distribution by means of integrating advanced vehicle routing technologies with the proposed pre-trip customer classification methodology. As mentioned previously, in order to highlight the potential advantages as well as the significance of the functionality of pre-trip customer classification in the demand-responsive logistical distribution operations, a simple heuristic vehicle routing approach that is derived mainly from driver's experiences in searching the static shortest path was utilized in the proposed delivery strategy. Employing the same vehicle routing principle, the performance of the proposed delivery strategy was then compared with that of the original delivery strategy. Such a treatment, however, has stimulated our interest in further investigating more advanced demand-responsive logistical distribution approaches which may involve dynamic pre-trip customer classification and real-time en-route freight transportation algorithms.

To demonstrate the relative effectiveness of the proposed fuzzy clustering algorithm when used for pre-trip customer classification in the operations of logistical distribution, a simple comparison with other well-know fuzzy clustering algorithms, including fuzzy c-means (FCM) Gustafson-Kessel (GK) algorithms [4,18], was further conducted. Herein, we coded the aforementioned two fuzzy clustering algorithms in the Turbo C language. Given the same attributes of the collected customer demand data, as shown previously in Fig. 2, and fairly selected parameters associated with each algorithm, the three fuzzy clustering based algorithms including the proposed approach were executed. According to the clustering result obtained from each selected algorithm, the corresponding transportation cost ($TC(k)$) was calculated. In addition, the other computational properties associated with these algorithms, including the computation time (t), the number of customer groups (c), and the number of iteration steps executed for the convergence of the clustering process (ι) were recorded for comparison. The numerical results of comparison are presented in Table 4.

The comparison results summarized in Table 4 indicate that the proposed fuzzy clustering method remains competitive for the application of QR demand-responsive logistical distribution in comparison with other published fuzzy clustering techniques. It is observed that using the proposed algorithm, the transportation cost is 33.9% and 31.3% lower than FCM and GK algorithms, respectively. Similarly, the proposed method also appears to outperform the other two algorithms with respect to the computational properties, i.e., t, c, and ι. This is not surprising since, as illustrated in the

description of the proposed algorithm, the decision variables are transformed into binary codes, which may facilitate data processing and generating the fuzzy correlation matrix. Moreover, as mentioned previously, the proposed hybrid fuzzy-hierarchical clustering is particularly applicable for the cases of multi-attribute fuzzy data analysis without knowing the number of clusters. As a consequence, the procedure of customer grouping can be readily executed employing the properties of hierarchical clustering analysis.

4. Concluding remarks

This paper has presented a fuzzy clustering based approach to pre-trip customer classification used for demand-responsive logistical distribution operations. Through analyzing customers' demand attributes and a nation-wide questionnaire survey, nine decision variables were determined. Utilizing the measured decision variables collected from customers, the proposed method executes three sequential mechanisms including: (1) binary transformation, (2) generation of fuzzy correlation matrix, and (3) customer clustering to accomplish the purpose of grouping customers. In addition to describing the primary procedures of methodology development, this study presents a case study demonstrating the potential advantages of the proposed method in comparison with traditional vehicle routing strategies employed by a department store in the city of Kaoshiung, Taiwan. With four specified criteria, including two supply-based and two demand-based criteria, the operations performance of the proposed logistical distribution strategy is measured, and compared to that of the original strategy. Findings as well as generalizations yielded from the comparisons are discussed.

Overall, the comparison results suggest the relative advantages as well as the importance of the proposed customer classification method in the development of demand-responsive logistical distribution strategies. It is found that remarkable improvements can be made via the proposed logistical distribution strategy for both the supply and demand sides.

Nevertheless, there remains a high potential to improve the efficiency and effectiveness of the operations performance of logistical distribution by means of integrating elaborate vehicle routing algorithms with the proposed pre-trip customer classification method. Such two-stage logistical distribution operations appear considerably important in implementing time-based logistical control and management strategies under conditions of complicated logistical service networks as well as a variety of customers' demands. This argument seems to hold under the condition that customers are considerably sensitive to the degree of timeliness for the delivery service.

It is expected that this study can make available the proposed pre-trip customer classification method with benefits not only for the development of demand-responsive logistical distribution strategies, but also for clarifying the importance of dynamic customer grouping in the operations of time-based logistics control and management. The express delivery-to-home service which is being increasingly implemented for e-business can be a striking example to illustrate the potential applications of the advocated logistical distribution methodology. It is also worth noting that this study has provided a striking demonstration of using fuzzy clustering based technologies in research related to both freight transportation and logistics management. On the basis of the present results, our further research will aim at developing advanced time-based demand-responsive logistical distribution technologies which involve two-stage distribution strategies including pre-trip customer grouping and en-route fleet management algorithms. Moreover, the applicability of the proposed method for QR

logistical operations in the e-business environment is also part of our interest, and warrants further research.

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