

A hybrid fuzzy-optimization approach to customer grouping-based logistics distribution operations

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Received 1 June 2005; received in revised form 1 December 2005; accepted 9 March 2006
Available online 12 June 2006

Abstract

This paper presents an integrated fuzzy-optimization customer grouping based logistics distribution methodology for quickly responding to a variety of customer demands. The proposed methodology involves three main mechanisms: (1) pre-route customer classification using fuzzy clustering techniques, (2) determination of customer group-based delivery service priority and (3) en-route goods delivery using multi-objective optimization programming methods. In the process of pre-route customer classification, the proposed method groups customers' orders primarily based on the multiple attributes of customer demands, rather than by static geographic attributes, which are mainly considered in classical vehicle routing algorithms. Numerical studies including a real-world application are conducted to illustrate the applicability of the proposed method and its potential advantages over existing operational strategies. Using the proposed method, it is shown that the overall performance of a logistics distribution system can be improved by more than 20%, according to the numerical results from the case studied.

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Keywords: Logistical distribution; Pre-route customer classification; Fuzzy clustering; Multi-objective optimization; En-route goods delivery

1. Introduction

Integrating both the operations of pre-route customer grouping and en-route goods delivery to customers is key to the effectiveness and efficiency of logistics distribution. According to the practical procedures of logistics distribution, processing customer orders and delivering them via suitable freight vehicles are regarded as two key elements for efficient logistics service. Furthermore, quick response to a variety of customer demands for goods delivery service appears to be a basic requirement for a successful third-party logistics enterprise in today's competitive business environment. Herein, the three sequential tasks of customer group-based vehicle loading, dispatching and routing should be well coordinated so as to enhance the effectiveness and efficiency of

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such demand-responsive logistics distribution. In previous literature [1–3], it has also been pointed out that both customer-based order clustering and vehicle routing strategies should be integrated in formulating comprehensive vehicle routing problems.

Despite the urgent need of an integrated vehicle dispatching strategy for logistics distribution, there are few studies on mathematically formulating the corresponding problems. Correspondingly, most of previous literature appears to aim at either the pre-route planning phase (e.g., logistics resource allocation) or the en-route operational phase (e.g., vehicle routing operations). Some typical models are exemplified below.

According to Bramel and Simchi-Levi [2], the deterministic vehicle routing problems (DVRP) are classified into four groups, depending on the separability of customer demands and time window constraints. Given customer demands and corresponding geographical attributes, the typical DVRP algorithms intend to find a set of routes with minimal routing costs and penalties so as to satisfy the given customer demands subject to corresponding resource constraints. Relative to DVRP, stochastic vehicle routing problems (SVRP) cope particularly with the uncertain patterns of customer demands by assuming that they follow specific probability distributions. Such a postulation arises particularly when logistics servers deliver goods to a given set of local warehouses in response to the uncertainty of local customer demands. Nevertheless, the effects of the variety of demand attributes on the performance of the existing VRP models are rarely investigated in previous research, either in the deterministic domain [4–7] or the stochastic domain ([8–12]). Recent years have also seen growing interest in fleet management to address the issues of assigning given loads to given sets of vehicles and determining vehicle routes, subject to corresponding resource constraints [13–23]. Further sophisticated solution techniques can be seen elsewhere [24,25,14,18,26]. Nevertheless, research effort in terms of clustering customer orders, and the corresponding effects of these order attributes on the performance of either vehicle loading or vehicle routing in the ITS-induced dynamic traffic environment appear inadequate in the previous literature.

In essence, the logistical distribution problem investigated in this study may differ from typical VRP-related issues from the following two viewpoints. First, logistics refers to an integrated procedure aiming at providing value-added logistics services driven by customer needs. Therefore, all the related operational tasks including customer order processing, logistics resource allocation, and vehicle dispatching and routing should be coordinated to fulfill customer needs, effectively and efficiently. Second, minimizing transportation cost, as pursued in most previous VRP-related literature, does not necessarily lead to enhancing the competitiveness of logistical operations because the transportation functionality is merely one of the activities in logistics. Other logistical activities, including inventory and order management, are also vital in determining the performance of logistics systems. More specifically, there is a trade-off relationship between the performances of transportation and of inventory in logistics, thus leading to plausible solutions as existing VRP methods are directly employed. Similar arguments can also be found elsewhere [27]. Therefore, a certain number of researchers [28–31] have devoted themselves to integrating other core items of logistics such as inventory and customer demand satisfaction with freight transportation in searching for optimal solutions for logistics management.

Accordingly, the major purpose of this study is to demonstrate the necessity of grouping customer orders conducted previous to vehicle routing, and the resulting advantages of integrating these operational phases in logistics distribution. Here, we insist on the idea that the identification of customer groups should be executed prior to freight fleet management and vehicle routing in a comprehensive logistics distribution operational procedure. Such a pre-route planning phase appears to be important particularly in the daily large-scale logistics distribution cases, where there are a great number of diverse goods delivery demands dispersing in urban areas. Furthermore, the resulting customer demands coupled with the corresponding demand attributes may vary significantly with each short time period of vehicle dispatching.

In this study, we may shed light on the tasks undertaken to integrate the phases of pre-route customer classification and the resulting group-based goods delivery, rather than on the development of specific VRP algorithms. Here, we propose an integrated customer group-based logistics distribution methodology which integrates three operational phases, including (1) pre-route customer classification, (2) determination of customer group-based delivery service priority, and (3) en-route goods delivery. In the phase of route customer classification, the principles of fuzzy clustering technologies are employed to develop the corresponding algorithm aiming at grouping customers under the condition that the attributes of customer demands are time-varying, and hard to quantify completely. Then, using multi-objective programming approaches, the service priority associated with each clustered customer group and corresponding vehicle routing strategies are

determined in the second and third phases, respectively, where each vehicle route is specified to serve the customers assigned to a given customer group.

The rest of the paper is organized as follows. The methodology development, including the architecture of the proposed logistics distribution system and corresponding models used in the aforementioned three sequential phases, is described in Section 2. Section 3 depicts numerical results generated using the proposed method. Finally, concluding remarks are summarized in Section 4.

2. Methodology development

The architecture of the proposed logistics distribution system is composed of three sequential operational phases: (1) pre-route customer classification, (2) determination of customer group-based delivery service priority, and (3) en-route goods delivery. Fig. 1 illustrates the proposed system architecture. Here, the corresponding computational algorithms embedded in these three phases will be resumed each time when a new logistics distribution mission is undertaken. Corresponding models executed in these phases are detailed in the following subsections.

2.1. Phase-I: pre-route customer classification

This phase aims to dynamically group multi-attribute customer orders using fuzzy-clustering techniques. Considering the existence of qualitative and quantitative attributes of customer demands for logistics service,

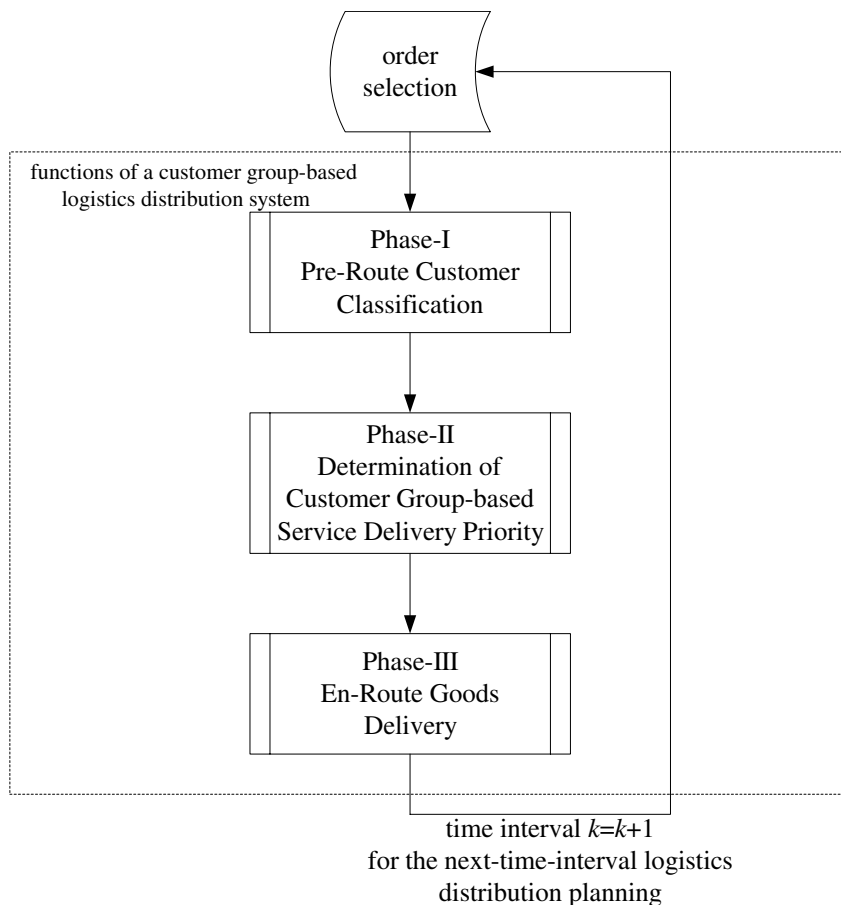


Fig. 1. Architecture of methodology.

Table 1
Definitions of order-oriented customer attributes

Notation	Definition	Explanation
$\psi_i^1(k)$	The perceived volume of goods scheduled to be delivered to a given customer i in a given time interval k	Here, $\psi_i^1(k)$ is regarded as a key factor in determining types of vehicles needed to serve given customer groups
$\psi_i^2(k)$	The perceived value of goods scheduled to be delivered to a given customer i in a given time interval k , which to a certain extent may depend on the market price of the product	In real-world logistics distribution operations, high-value products might be segmented from other products, and handled with specific security measures for safe delivery
$\psi_i^3(k)$	The external compatibility of the goods ordered by a given customer i , relative to the goods scheduled to be delivered to a given customer group in a given time interval k	This attribute is specified for the efficiency of providing bulk delivery service to customers in the same group. The higher the external compatibility is among the goods of a given customer group, the more efficient the bulk delivery service is in logistics distribution operations
$\psi_i^4(k)$	The internal compatibility among the goods scheduled to be delivered to a given customer i in a given time interval k	In contrast with $\psi_i^3(k)$, $\psi_i^4(k)$ indicates the compatibility of goods associated with customer i , and here it can be used to determine if multiple deliveries are needed to serve a given customer
$\psi_i^5(k)$	The geographical vicinity associated with a given customer i , relative to a given customer group in a given time interval k	Here, the location associated with any given customer is characterized with a two-dimensional variable. Then, those neighboring customers can be served together in logistical distribution operations
$\psi_i^6(k)$	The temporal proximity in terms of the delivery deadline associated with a given customer i , relative to the date of the present vehicle dispatching	In real-world operations, customers associated with close delivery deadlines can be assigned to given groups, and served express by specific vehicular fleet in the process of logistical distribution
$\psi_i^7(k)$	The temporal proximity in terms of the daily delivery time window associated with a given customer i , relative to a given time interval k	In real-world logistics distribution operations, customers with close time windows tend to be served together for convenience. Compared to $\psi_i^2(k)$, this variable aims to group customers based on their similarity in delivery time of day

a hybrid fuzzy-hierarchical clustering method¹ is proposed to perform the corresponding pre-route customer classification mechanism in this phase. Correspondingly, each customer order is regarded as a datum with multiple order-oriented attributes, where some of these attributes are quantitative (e.g., the volume of goods and delivery deadline), and others are qualitative (e.g., type of delivery service). To provide efficient group-based goods delivery service to those customers with similar demand attributes, a fuzzy clustering based approach is proposed to dynamically classify customer orders into appropriate groups before vehicle dispatching. The clustered customer groups identified in this phase is then used as the input of the second phase for the determination of their service priority.

In this phase, seven order-oriented customer attributes are specified as determinants of grouping customers, according to the analytical results from our previous research [37]. The notations and corresponding descriptions of these specified attributes are summarized in Table 1. Herein, the length of a given time interval k shown in Table 1 is defined as the temporal headway between two logistics distribution missions in the business hours of one day.

Based on the specified customer order attributes, we can specify a (7×1) attribute vector associated with each given customer i ($\Psi_i(k)$) as

$$\Psi_i(k) = [\psi_i^1(k), \psi_i^2(k), \psi_i^3(k), \psi_i^4(k), \psi_i^5(k), \psi_i^6(k), \psi_i^7(k)]^T. \tag{1}$$

¹ 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 [32–36,3]. 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.

Then, a fuzzy clustering-based algorithm, which includes the procedures of (1) binary transformation, (2) generation of fuzzy correlation matrix, and (3) multi-attribute customer grouping, is proposed to perform the function of pre-route customer classification. Details about these procedures are described in the following.

2.1.1. Binary transformation

The function of binary transformation executes the transformation of the measurements of order-oriented customers' demand attributes into binary data to facilitate fuzzy clustering. As mentioned previously, these demand attributes are either quantitative (e.g., $\psi_i^1(k)$ and $\psi_i^2(k)$) or qualitative (e.g., $\psi_i^3(k)$, $\psi_i^4(k)$, $\psi_i^5(k)$, $\psi_i^6(k)$, and $\psi_i^7(k)$). To efficiently cluster these multi-attribute customer order data sets, such a data-processing procedure is needed. Here, two transitional steps are involved. First, for each given customer order datum, the corresponding order-oriented customer attributes are measured with five linguistic terms, including “very high”, “high”, “medium”, “low”, and “very low”, which represent five levels of qualitative criteria. These measured attributes are then transformed into binary codes, where each linguistic criterion is represented by a 4-bit binary code, e.g., “0000” for the linguistic term “very low” and “1111” for “very high”, as illustrated in Table 2.

Accordingly, any given p th order-oriented attribute associated with customer i ($\psi_i^p(k)$) can then be transformed into a binary code with four bits (i.e., $\sigma_{i,j}^p(k)$ for $j = 1, 2, 3$, and 4), and is given by

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

A numerical example is illustrated as follows. Given that the order of a given customer i is served in a given time interval k , and the order-oriented customer attribute associated with the given customer i in terms of the external compatibility of goods (i.e., $\psi_i^3(k)$) is linguistically measured as “high”, then $\psi_i^3(k)$ is coded (1, 1, 1, 0), according to Table 2.

To facilitate data processing, the standardization procedure of $\sigma_{i,j}^p(k)$ is proposed, and the corresponding standardized value of $\sigma_{i,j}^p(k)$ ($\bar{\sigma}_{i,j}^p(k)$) is given by

$$\bar{\sigma}_{i,j}^p(k) = \frac{\sigma_{i,j}^p(k) - \bar{\sigma}_j^p(k)}{S_j^p(k)}, \tag{3}$$

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

$$\bar{\sigma}_j^p(k) = \frac{\sum_{i=1}^M \sigma_{i,j}^p(k)}{M}, \tag{4}$$

$$S_j^p(k) = \left[\frac{\sum_{i=1}^M (\sigma_{i,j}^p(k) - \bar{\sigma}_j^p(k))^2}{M - 1} \right]^{\frac{1}{2}}. \tag{5}$$

Here, M represents the total number of order entries scheduled to be processed in the given time interval k . Accordingly, we have the standardized binary demand attribute ($\tilde{\chi}_i^p(k)$), which is given by

$$\tilde{\chi}_i^p(k) = [\bar{\sigma}_{i,1}^p(k), \bar{\sigma}_{i,2}^p(k), \bar{\sigma}_{i,3}^p(k), \bar{\sigma}_{i,4}^p(k)]. \tag{6}$$

Table 2
Definitions of 4-bit binary codes for linguistic criteria

Linguistic criterion	4-Bit binary code			
	1st bit	2nd bit	3rd bit	4th bit
“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

2.1.2. Generation of fuzzy correlation matrix

In this procedure, a time-varying $M \times M$ fuzzy correlation matrix ($\mathbf{W}(k)$) is estimated employing the standardized demand attributes measured in the previous procedure, where each element ($\omega_{r,s}(k)$) of $\mathbf{W}(k)$ represents the correlation² between a given pair of customers r and s . The mathematical forms of $\mathbf{W}(k)$ and $\omega_{r,s}(k)$ are given by

$$\mathbf{W}(k) = \begin{bmatrix} \omega_{11}(k) & \omega_{12}(k) & \omega_{13}(k) & \dots & \omega_{1M}(k) \\ \omega_{21}(k) & \omega_{22}(k) & \dots & \dots & \vdots \\ \omega_{31}(k) & \dots & \ddots & & \vdots \\ \vdots & \dots & \dots & \ddots & \vdots \\ \omega_{M1}(k) & \dots & \dots & \dots & \omega_{MM}(k) \end{bmatrix}_{M \times M}, \tag{7}$$

$$\omega_{r,s}(k) = 1 - \frac{1}{\alpha} \sqrt{\sum_{p=1}^P \sum_{\theta=1}^{\Theta} [\tilde{\sigma}_{r\theta}^p(k) - \tilde{\sigma}_{s\theta}^p(k)]^2}, \tag{8}$$

where α represents a parameter pre-determined for the upper and lower boundaries of $\omega_{r,s}(k)$, i.e., 1 and 0, respectively; P and Θ represent the number of order-oriented customer attributes and the number of bits pre-specified, and as noted above, they are 7 and 4, respectively. It is also worth noting that according to Eqs. (7) and (8), $\mathbf{W}(k)$ turns out to be a symmetric matrix.

However, according to the fundamentals of fuzzy clustering technologies, the estimated fuzzy correlation matrix $\mathbf{W}(k)$ should be further processed through the proposed max–min composition operation (i.e., $\mathbf{W}^{(\vartheta)}(k) \circ \mathbf{W}^{(\vartheta)}(k)$, where \circ represents a composition symbol) to ensure the consistence of the estimated fuzzy correlations. Here, in the proposed max–min composition routine, each element ($\omega_{r,s}^{(\vartheta)}(k)$) of $\mathbf{W}(k)$ should be processed at each given iteration (ϑ) by

$$\omega_{r,s}^{(\vartheta)}(k) = \max_{t=1}^M \left\{ \min_{t=1}^M [\omega_{r,t}^{(\vartheta-1)}(k), \omega_{t,s}^{(\vartheta-1)}(k)] \right\}, \quad \forall (r, s). \tag{9}$$

Such a routine should be continued until the following condition holds:

$$\text{IF } \widetilde{\mathbf{W}}^{(\vartheta)}(k) \circ \widetilde{\mathbf{W}}^{(\vartheta)}(k) = \widetilde{\mathbf{W}}^{(\vartheta)}(k), \quad \text{THEN } \widetilde{\mathbf{W}}^{(\vartheta)}(k) \text{ is the finalized matrix,} \tag{10}$$

where $\widetilde{\mathbf{W}}^{(\vartheta)}(k)$ represents the resulting composite fuzzy correlation matrix of $\mathbf{W}(k)$ obtained at a given iteration ϑ .

2.1.3. Customer grouping

This procedure clusters customer orders into several groups so that those customer orders with relatively high similarity are assigned to the same group. Correspondingly, after conducting the customer grouping procedure, the demand attributes of customers in a given group are highly mutually similar, and however, can be significantly different from those of any other groups. To execute this mechanism, five major computational steps are involved in the proposed algorithm, and they are summarized as follows:

Step 0: Initialize the computational iteration. For this, set the iteration index $\pi = 1$; input the estimated fuzzy correlation matrix ($\widetilde{\mathbf{W}}(k)$) measured in the previous procedure; start the iteration from the first column of the processed fuzzy correlation matrix ($\widetilde{\mathbf{w}}_1(k)$), and let $s = 1$. Herein, we target the first customer to trigger the customer grouping procedure. It is also noteworthy that any selected target customer is regarded as the representative of a given customer group in the following cluster process.

² According to the theories of fuzzy clustering [38], here $\omega_{r,s}(k)$ can be interpreted as the degree of the similarity between the demand datum of customer r and that of customer s , thus bounded between the values 0 and 1.

Step 1: Given a target customer s , remove the row of $\widetilde{\mathbf{W}}(k)$ associated with customer s ($\widetilde{\mathbf{w}}(k)^T$). Once a customer is selected as the target customer denoted by $\widetilde{\mathbf{w}}_s(k)$, it is not necessary to re-cluster the target customer in this algorithm. Accordingly, the corresponding row $\widetilde{\mathbf{w}}_s(k)^T$ is redundant, and should be ignored to facilitate the following clustering process.

Step 2: Find the maximum element in $\widetilde{\mathbf{w}}_s(k)$, denoted by $\hat{\omega}_{rs}(k)$, and then conduct the following cluster procedures in sequence:

- If the condition $\hat{\omega}_{rs}(k) > \lambda_1$ holds, then assign customer r to the same group as the target customer s , and remove the row of $\widetilde{\mathbf{W}}(k)$ associated with customer r ($\widetilde{\mathbf{w}}_r(k)^T$). This represents that the given customer r is assigned to the same group as that of the target customer s .
- Go back to Step 2 to continue checking the other elements of $\widetilde{\mathbf{w}}_s(k)$ until there does not exist any element that meets the aforementioned clustering condition. If so, remove $\widetilde{\mathbf{w}}_s(k)$ from $\widetilde{\mathbf{W}}(k)$, representing that all the elements of $\widetilde{\mathbf{w}}_s(k)$ have been considered, and thus the corresponding clustering process based on the demand attributes of the target customer s can be ended.
- If there are 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 $\widetilde{\mathbf{W}}(k)$ 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.

Herein, λ_1 is a pre-determined threshold for identifying the relative similarity between a given pair of customers, and in practice it can be specified by the decision-makers of logistics operations. Suppose that N customer groups are identified in a given time interval k through the aforementioned customer classification procedure. Then, we have the processed demand attribute matrix associated with a given customer group n ($\Gamma_n(k)$) given by

$$\Gamma_n(k) = [\Psi_{i_1^n}(k) | \Psi_{i_2^n}(k) | \dots | \Psi_{i_{\ell_n}^n}(k)]_{P \times \ell_n}, \tag{11}$$

where $\Gamma_n(k)$ is referred to as a $\Omega \times \ell_n$ group-based demand attribute matrix which is composed of the demand attribute vectors of ℓ_n customers (i.e., $\Psi_{i_1^n}(k), \Psi_{i_2^n}(k), \dots, \Psi_{i_{\ell_n}^n}(k)$); and ℓ_n represents the total number of customers involved in a given group n . Note that herein each attribute vector has the same dimension as the raw customer demand attribute vector $\Psi_i(k)$ shown in Eq. (1).

In addition, detailed rationales of fuzzy clustering methodology and related applications can also be found elsewhere [39–41,35,3], and thus they are omitted in this paper.

2.2. Phase-II: determination of customer group-based delivery service priority

In this phase, a respective algorithm is proposed to determine the service priority associated with the clustered customers groups subject to the availability of the present fleet size. The following summarizes the major steps executed in this algorithm:

Step 1: Given a customer group n , select a target customer i_*^n which is geographically closest to the distribution depot compared to other customers in the same group.

Step 2: Calculate the corresponding delivery service priority determinant associated with the customer group n ($v_n(k)$) using

$$v_n(k) = \frac{\sum_{i^n=1}^{\ell_n} \{ \tilde{\omega}_{i^n, i_*^n}(k) \times [\psi_{i^n}^2(k) + \psi_{i^n}^3(k) + \psi_{i^n}^5(k) + \psi_{i^n}^7(k)] \}}{\sum_{i^n=1}^{\ell_n} \tilde{\omega}_{i^n, i_*^n}(k)}, \tag{12}$$

where i^n represents a customer index associated with the customer group n ; and $\tilde{\omega}_{i^n, i_*^n}(k)$ denotes the processed fuzzy correlation between a given customer i^n and the target customer i_*^n . Here, the 2nd, 3rd, 5th, and 7th types of demand attributes represented by $\psi_{i^n}^2(k), \psi_{i^n}^3(k), \psi_{i^n}^5(k)$, and $\psi_{i^n}^7(k)$, respec-

tively, are viewed as the primary demand-driven factors that determine the group-based distribution priority at this stage.

Step 3: Determine the group-based service priority subject to the availability of the fleet size. This step starts by examining the customer group (\hat{n}) associated with the highest value of $v_{\hat{n}}(k)$ according to the following rules:

- *IF* the current fleet size satisfies the basic distribution requirement, as shown in Eq. (13), for delivering goods of the target customer group (\hat{n}) in the present time interval,
- *THEN* include the given target customer group in the distribution mission in this time interval, associate the targeted customer group with a given priority³ $\varphi_{\hat{n}}(k)$ in order, remove it from the group candidates, and then go back to Step 3 to continue to check the remaining customer groups with this rule;
- *OTHERWISE* exclude the target customer group together with the remaining groups from the service list in the present time interval, and terminate the execution of this phase.

Herein, the order-oriented demand attribute $\psi_{\hat{n}}^1(k)$ can be employed to determine if the aforementioned requirement condition meets the following constraint:

$$\sum_{\forall \hat{n}} \psi_{\hat{n}}^1(k) \leq \sum_{\forall c \in C} N_c(k) \times \alpha_c^{\hat{n}}(k) \times L_c, \tag{13}$$

where subscript c is a given type of vehicle; $\alpha_c^{\hat{n}}(k)$ corresponds to the loading factor associated with vehicle type c for the goods types of customer group \hat{n} , and is bounded within the values 0 and 1; $N_c(k)$ represents the number of type c vehicles which are available in a given time interval k ; C is the set of vehicle types that can provide the delivery service for customer group \hat{n} ; and L_c represents the loading capacity associated with vehicle type c .

Herein, only those customer groups involved in the service list of the present time interval are considered in the following execution phase (i.e., Phase-III); the other groups are decomposed, then being re-clustered with new customer order entries in the next time interval.

2.3. Phase-III: en-route customer group-based goods delivery

In this phase, a composite multi-objective optimization approach is proposed to formulate the problem of en-route goods delivery for multiple customer groups. Here, each given customer group, planned to be served in the present time interval, is associated with two respective objective functions, including (1) demand-oriented penalties for violating customers' time-of-day windows and (2) supply-oriented operating costs of vehicle routing. Accordingly, the generalized form of the multi-objective functions ($\min \mathbf{F}(k)$) is given by

$$\min \mathbf{F}(k) = [\mathbf{F}_{\tilde{n}}(k), \tilde{n} = 1, 2, \dots, \tilde{N}], \tag{14}$$

where $\mathbf{F}(k)$ represents the $(2\tilde{N} \times 1)$ aggregate multi-objective vector which involves all the corresponding multi-objective vectors ($\mathbf{F}_{\tilde{n}}(k)$) associated with the customer groups planned to be served in a given time interval k ; and \tilde{N} represents the total number of customer groups identified in the previous phase. Herein, the corresponding multi-objective vector ($\mathbf{F}_{\tilde{n}}(k)$) associated with a given customer group \tilde{n} can be further expressed by

$$\mathbf{F}_{\tilde{n}}(k) = \begin{bmatrix} f_1^{\tilde{n}}(k) \\ f_2^{\tilde{n}}(k) \end{bmatrix}, \tag{15}$$

where $f_1^{\tilde{n}}(k)$ and $f_2^{\tilde{n}}(k)$ refer to the corresponding demand-oriented and supply-oriented objective functions associated with a given customer group \tilde{n} , and are given respectively by

$$f_1^{\tilde{n}}(k) = \sum_{\forall j^{\tilde{n}} \in \tilde{n}} \left\{ CL_{j^{\tilde{n}}} \times \max \left[0, \left(TL_{j^{\tilde{n}}} - \sum_{\forall c \in C} \sum_{\forall i^{\tilde{n}} \in \tilde{n}} X_{i^{\tilde{n}}, j^{\tilde{n}}}^c(k) \times t_{j^{\tilde{n}}}^{\text{arr}}(k) \right) \right] \right. \\ \left. + CU_{j^{\tilde{n}}} \times \max \left[0, \left(\sum_{\forall c \in C} \sum_{\forall i^{\tilde{n}} \in \tilde{n}} X_{i^{\tilde{n}}, j^{\tilde{n}}}^c(k) \times t_{j^{\tilde{n}}}^{\text{arr}}(k) - TU_{j^{\tilde{n}}} \right) \right] \right\}, \tag{16}$$

³ Here, a lower value of $\varphi_{\hat{n}}(k)$ indicates a higher service priority associated with a given customer group \hat{n} .

$$f_2^{\tilde{n}}(k) = \sum_{\forall c \in C} a_c \times \left\{ \left[\sum_{\forall i^{\tilde{n}}} \sum_{\forall j^{\tilde{n}}} t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k) \times X_{i^{\tilde{n}},j^{\tilde{n}}}^c(k) \right] + \sum_{\forall j^{\tilde{n}}} t_{j^{\tilde{n}}}^{\text{ser}}(k) \times \left[\sum_{\forall i^{\tilde{n}}} X_{i^{\tilde{n}},j^{\tilde{n}}}^c(k) \right] \right\}. \tag{17}$$

In Eq. (16), $f_1^{\tilde{n}}(k)$ indicates the group-based delivery penalties caused by both early and late arrivals of vehicles, relative to the pre-determined lower and upper bounds (i.e., $TL_{j^{\tilde{n}}}$ and $TU_{j^{\tilde{n}}}$) of the time-of-day window associated with each given customer ($j^{\tilde{n}}$) of a given group \tilde{n} , where $CL_{j^{\tilde{n}}}$ and $CU_{j^{\tilde{n}}}$ represent the penalties per time unit due to early and late arrivals at the given customer $j^{\tilde{n}}$ in any given day; $t_{j^{\tilde{n}}}^{\text{arr}}(k)$ represents the time of a given vehicle arriving at the given customer $j^{\tilde{n}}$ in a given time interval k . In contrast, $f_2^{\tilde{n}}(k)$ shown in Eq. (17) indicates the group-based vehicular routing costs spent to provide the delivery service for a given customer group \tilde{n} , where a_c represents the unit transportation cost per given time unit associated with a given type of vehicle c ; $t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k)$ represents the path travel time departing from a given customer $i^{\tilde{n}}$ to the corresponding next customer $j^{\tilde{n}}$ in a given time interval k ; $t_{j^{\tilde{n}}}^{\text{ser}}(k)$ represents the service time, including unloading time, associated with a given customer $j^{\tilde{n}}$ in a given time interval k ; and $X_{i^{\tilde{n}},j^{\tilde{n}}}^c(k)$ represents a binary decision variable in a given time interval k with either the value 1 indicating that the link between any given pair of customers $i^{\tilde{n}}$ and $j^{\tilde{n}}$ is served by a given type of vehicle c , or the value 0 indicating that the aforementioned condition does not hold.

Considering the potential conflicting effects of $f_1^{\tilde{n}}(k)$ and $f_2^{\tilde{n}}(k)$ on $\mathbf{F}_{\tilde{n}}(k)$ and those of respective group-based multi-objective vectors ($\mathbf{F}_{\tilde{n}}(k)$) on the aggregate multi-objective vector ($\mathbf{F}(k)$), the aforementioned aggregate multi-objective vector ($\mathbf{F}(k)$) can be reformulated as a composite form ($\tilde{\mathbf{F}}(k)$) by summing them with respective weights, as given by

$$\tilde{\mathbf{F}}(k) = \sum_{\tilde{n}=1}^{\tilde{N}} \{ \rho_{\tilde{n}}(k) \times [\varepsilon_1^{\tilde{n}} \times f_1^{\tilde{n}}(k) + \varepsilon_2^{\tilde{n}} \times f_2^{\tilde{n}}(k)] \}, \tag{18}$$

where $\varepsilon_1^{\tilde{n}}$ and $\varepsilon_2^{\tilde{n}}$ represent the corresponding weights associated with $f_1^{\tilde{n}}(k)$ and $f_2^{\tilde{n}}(k)$, indicating the relative effects of $f_1^{\tilde{n}}(k)$ and $f_2^{\tilde{n}}(k)$ on a given group-based multi-objective function ($\mathbf{F}_{\tilde{n}}(k)$); and $\rho_{\tilde{n}}(k)$ refers to the time-varying weight associated with the given group-based multi-objective function ($\mathbf{F}_{\tilde{n}}(k)$), indicating the relative effect of $\mathbf{F}_{\tilde{n}}(k)$ on $\tilde{\mathbf{F}}(k)$, compared to the other group-based multi-objective functions. Herein, $\varepsilon_1^{\tilde{n}}$ and $\varepsilon_2^{\tilde{n}}$ can be pre-determined by the corresponding logistics decision makers, according to their perception in terms of the relative significance of corresponding demand-oriented and supply-oriented objective functions. In contrast, $\rho_{\tilde{n}}(k)$ is a time-varying weight given by

$$\rho_{\tilde{n}}(k) = \frac{\tilde{N}}{\varphi_{\tilde{n}}(k)}. \tag{19}$$

In addition, the limitations in terms of either operational conditions or resource availability for vehicle routing should also be considered, and thus the corresponding constraints, as shown in Eqs. (20)–(26), are considered in the proposed model.

Eqs. (20) and (21) represent the corresponding limitations in terms of the aggregate and disaggregate number of vehicles available in the given time interval k :

$$\sum_{\forall c \in C} \sum_{\forall \tilde{n}} \sum_{\forall j^{\tilde{n}}} X_{0,j^{\tilde{n}}}^c(k) \leq \sum_{\forall c \in C} N_c(k), \quad \forall k, \tag{20}$$

$$\sum_{\forall \tilde{n}} \sum_{\forall j^{\tilde{n}}} X_{0,j^{\tilde{n}}}^c(k) \leq N_c(k), \quad \forall \{c, k\}, \tag{21}$$

where $X_{0,j^{\tilde{n}}}^c(k)$ represents the respective binary decision variable indicating whether or not a given type of vehicle c dispatches from a given logistics distribution center (0) to serve the corresponding next customer $j^{\tilde{n}}$ in a given time interval k .

Eqs. (22) and (23) represent the constraints ensuring that each given customer of a given customer group \tilde{n} is served one and only one time in any given time interval k :

$$\sum_{\forall c \in C} \sum_{\forall j^{\tilde{n}}} X_{i^{\tilde{n}},j^{\tilde{n}}}^c(k) = 1, \quad \forall \{j^{\tilde{n}}, k, \tilde{n}\}, \tag{22}$$

$$\sum_{\forall c \in C} \sum_{\forall j^{\tilde{n}}} X_{i^{\tilde{n}},j^{\tilde{n}}}^c(k) = 1, \quad \forall \{i^{\tilde{n}}, k, \tilde{n}\}. \tag{23}$$

Eq. (24) represents the link flow equilibrium condition ensuring that any given type of vehicle (c) arriving to serve a given customer ($s^{\tilde{n}}$) in a given time interval k must depart in the same time interval. Correspondingly, any given en-routing vehicle is not allowed to stay at a given customer for more than one time interval:

$$\sum_{\forall i^{\tilde{n}}} X_{i^{\tilde{n}},s^{\tilde{n}}}^c(k) = \sum_{\forall j^{\tilde{n}}} X_{s^{\tilde{n}},j^{\tilde{n}}}^c(k), \quad \forall \{c, k, \tilde{n}\}. \tag{24}$$

Eq. (25) represents a set of inequalities which are sub-route elimination constraints to ensure that the group-based route visits each customer exactly once and continuously, i.e., the Hamiltonian circuit; and similar formulations can also be found elsewhere [42–44]:

$$\sum_{\forall i^{\tilde{n}}} \sum_{\forall j^{\tilde{n}}} X_{i^{\tilde{n}},j^{\tilde{n}}}^c(k) \leq |\delta^{\tilde{n}}| - 1, \quad \forall \delta^{\tilde{n}} \subset \tilde{n} (\delta \neq \phi, \delta \neq \tilde{n}), \text{ and } 2 \leq |\delta^{\tilde{n}}| \leq \ell_{\tilde{n}}, \tag{25}$$

where $\delta^{\tilde{n}}$ is a nonempty subset of \tilde{n} , and is not equal to \tilde{n} ; and $\ell_{\tilde{n}}$ represents the total number of customers involved in a given customer group \tilde{n} .

Furthermore, Eq. (26) should be involved to characterize the binary feature associated with these decision variables:

$$X_{i^{\tilde{n}},j^{\tilde{n}}}^c(k) \vee X_{0,j^{\tilde{n}}}^c(k) \vee X_{i^{\tilde{n}},0}^c(k) = 0 \text{ or } 1, \quad \forall (i^{\tilde{n}}, j^{\tilde{n}}, \tilde{n}, k). \tag{26}$$

In addition to the above constraints, the relationship of the corresponding arrival time (i.e., $t_{i^{\tilde{n}}}^{\text{arr}}(k)$ and $t_{j^{\tilde{n}}}^{\text{arr}}(k)$) associated with any two successive customers (i.e., $i^{\tilde{n}}$ and $j^{\tilde{n}}$) of a given customer group (\tilde{n}) should follow the following conditions, as presented in

$$t_{j^{\tilde{n}}}^{\text{arr}}(k) = t_{i^{\tilde{n}}}^{\text{arr}}(k) + t_{i^{\tilde{n}}}^{\text{ser}}(k) + t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k), \quad \forall (i^{\tilde{n}}, j^{\tilde{n}}, \tilde{n}, k). \tag{27}$$

As can be seen in Eq. (27), given that a given freight vehicle arrives at a given customer $i^{\tilde{n}}$ at time $t_{i^{\tilde{n}}}^{\text{arr}}(k)$, the predicted time ($t_{j^{\tilde{n}}}^{\text{arr}}(k)$) of the given vehicle arriving at any potential next customer $j^{\tilde{n}}$ is then a time-varying function depending on the corresponding service time associated with the given customer $i^{\tilde{n}}$ ($t_{i^{\tilde{n}}}^{\text{ser}}(k)$) and the predicted path travel time departing from $i^{\tilde{n}}$ to $j^{\tilde{n}}$ ($t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k)$). Accordingly, both $t_{i^{\tilde{n}}}^{\text{ser}}(k)$ and $t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k)$ should be dynamically predicted in advance of determining the customer service order in the given en-route goods delivery mission in a given time interval k . The corresponding procedures for the prediction of both $t_{i^{\tilde{n}}}^{\text{ser}}(k)$ and $t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k)$ are detailed below.

To facilitate the aforementioned prediction in terms of $t_{i^{\tilde{n}}}^{\text{ser}}(k)$, we formulated $t_{i^{\tilde{n}}}^{\text{ser}}(k)$ as a linear stochastic model which has a positive proportional relationship with the amount of customer orders ($\psi_{i^{\tilde{n}}}^1(k)$), where $\psi_{i^{\tilde{n}}}^1(k)$, as defined previously in Table 1, refers to the corresponding first type of order-oriented customer attribute associated with a given customer $i^{\tilde{n}}$. Accordingly, $t_{i^{\tilde{n}}}^{\text{ser}}(k)$ is given by

$$t_{i^{\tilde{n}}}^{\text{ser}}(k) = b_1 + b_2 \times \psi_{i^{\tilde{n}}}^1(k) + \zeta, \tag{28}$$

where b_1 and b_2 represent two pre-determined parameters indicating the averaged start-up delay and the deterministic time for serving one unit of goods associated with a given customer group \tilde{n} , respectively; and ζ represents the corresponding stochastic term which is assumed to follow a Gaussian process.

The estimation of $t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k)$ involves the utilization of published shortest-path searching algorithms (e.g., the Bellman–Ford method and the Dijkstra method) coupled with a stochastic system modeling approach proposed in our previous research [45,46]. It should be noted that up to this stage, the major issue remaining here is how to search for the time-varying shortest path, represented by $t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k)$ between any given pair of customers ($i^{\tilde{n}}$ and $j^{\tilde{n}}$) to be visited in sequence in a given customer group (\tilde{n}). Particularly, we consider the link travel cost defined in classical VRP algorithms as the time-varying shortest path travel cost depending on actual traffic flow conditions. This concept stems from our proposed argument that the customer-based nodes denoted in VRP do not correspond to the geographic nodes of traffic networks. Accordingly, $t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k)$ should be dynamically estimated by the sum of the time-varying costs ($g_{i^{\tilde{n}},j^{\tilde{n}}}^{\tau}(k)$) spent in traveling on the geographic links (τ) of the shortest path ($P_{i^{\tilde{n}},j^{\tilde{n}}}$) between the given pair of customer-based nodes $i^{\tilde{n}}$ and $j^{\tilde{n}}$, and is given by

$$t_{i^{\tilde{n}},j^{\tilde{n}}}^{\text{tra}}(k) = \sum_{\forall \tau \in P_{i^{\tilde{n}},j^{\tilde{n}}}} g_{i^{\tilde{n}},j^{\tilde{n}}}^{\tau}(k). \tag{29}$$

Once $g_{i^n, j^n}^\tau(k)$ is obtained, then $t_{i^n, j^n}^{\text{tra}}(k)$ can be readily determined using either the Bellman–Ford method or the Dijkstra method.

In the following, we introduce a stochastic system modeling approach [45,46] to update the time-varying link cost $g_{i^n, j^n}^\tau(k)$ in each given link (τ) of the specified traffic network. The distinctive feature of the proposed model here is that the time-varying link travel cost $g_{i^n, j^n}^\tau(k)$ is derived using the estimated lane-based traffic variables, rather than link-based traffic flows, as in previous D-VRP literature.

Briefly, the proposed traffic estimation model mainly involves two groups of time-varying equations, including recursive equations ($\mathbf{Y}[y(t_2), k]$) and measurement equations ($\mathbf{Z}(t_2)$), as shown in

$$\mathbf{Y}[y(t_2), k] = \mathbf{Y}[y(t_1), k] + \mathbf{L}[y(t_1), k]\mathbf{V}_Y(t_1, k), \quad (30)$$

$$\mathbf{Z}(t_2) = \mathbf{H}[y(t_2), k] + \mathbf{V}_Z(t_2, k), \quad (31)$$

where

$$t_1 = t_{i^n}^{\text{arr}}(k), \quad \forall(i^n, \tilde{n}, k), \quad (32)$$

$$t_2 = t_{i^n}^{\text{arr}}(k) + t_{i^n}^{\text{ser}}(k), \quad \forall(i^n, \tilde{n}, k). \quad (33)$$

Herein, Eq. (30) represents the generalized form of recursive equations referring to the time-varying relationships of the predicted intra-link lane traffic states (i.e., $y(t_2)$ vs. $y(t_1)$); and Eq. (31), termed measurement equations, characterizing the time-varying relationships of the raw traffic data collected from point detectors and these intra-link lane traffic states. The capital notations shown in Eqs. (30) and (31) represent time-varying vectors used to depict the aforementioned time-varying state relationships in the stochastic system. Herein, vectors $\mathbf{V}_Y(t_1, k)$ and $\mathbf{V}_Z(t_2, k)$ represent the state-independent noise terms associated with recursive and measurement equations, respectively, and both of them are assumed to follow Gaussian processes. In contrast, $\mathbf{L}[y(t_1), k]$ represents a state-dependent noise vector. Details about the fundamentals and equations can be readily found in the literature [45,46]. Employing the aforementioned stochastic model together with an extended Kalman filtering-based algorithm, the time-varying link travel cost $g_{i^n, j^n}^\tau(k)$ associated with each given link can then be predicted for further use in the process of searching for the corresponding shortest path ($t_{i^n, j^n}^{\text{tra}}(k)$) between any given pair of customers (i^n and j^n) in a given time interval k .

3. Numerical results

The main purpose of this numerical study is to demonstrate the potential advantages of the proposed logistics distribution approach relative to existing distribution strategies. The study case examines a private manufacturer, which produces automobile and computer accessories, and is located in southern Taiwan. To facilitate input data acquisition, we contacted this targeted manufacturer, where the data processed from customer orders were used to generate input data and parameters required by the proposed method. Here, samples of customer orders were drawn from a 5-day database of the targeted manufacturer. Then, the relative performance of the proposed method was evaluated by comparing with the existing logistics distribution strategy using the sampled customer demand data.

The original logistics distribution strategy conducted by the targeted manufacturer was mainly based on subjective judgment of the corresponding logistics manager of the targeted manufacturer subject to the 5-vehicle fleet size available in this study case. The original frequency of vehicle dispatch of the targeted manufacturer was once a day, departing from the corresponding warehouse at 9:00 am. Herein, vehicular en-routing paths depended mainly on personal experiences of the corresponding drivers and their responses to instantaneous road traffic conditions. In some cases, the quick-response (QR) strategy may be implemented to satisfy the urgent needs of customers, particularly for special requests by target customers.

In the model evaluation scenario, a total of 41 order entries which were scheduled to be served in the given 5-day testing period were sampled. The corresponding geographical relationships of these customers are depicted in Fig. 2, where each customer is coded with a specific number, indicating the sequence of order entry times associated with these sampled customers.

Using the proposed distribution method, we re-processed the sampled order entries, and classified the customers into specific groups by the customer classification mechanism built into the proposed algorithm. The

results of customer grouping are summarized in Table 3, which also involves the original delivery service schedule for comparison. In addition, the above clustering results are also presented in Fig. 3 to illustrate the potential effect of pre-route customer grouping on the operations of logistics distribution. Conveniently, it is assumed that there is no new order entry received in this study case.

After the aforementioned pre-route customer classification and service priority determination phases, the vehicle routing operations were implemented by conducting the proposed en-route goods delivery algorithm. It is worth mentioning that the computational difficulties existing typically in large-scale NP-hard VRP problems may not remain in this study because the delivered customer orders have been divided into several groups using the proposed method. Thus, once the instantaneous link travel times among customers are determined using the proposed model, the optimal solutions of the resulting group-based good delivery problem can then be readily solved using existing optimization packages, e.g., LINGO. The corresponding vehicle routing results obtained in this scenario are summarized in Table 4.

We compared the operational results obtained from the proposed distribution strategy and the original strategy, utilizing two major criteria defined as follows:

- (1) *TT*, which represents the total transportation costs, including the normal operational costs spent in vehicle routing and induced penalties caused by violation of customers' time-of-day windows;

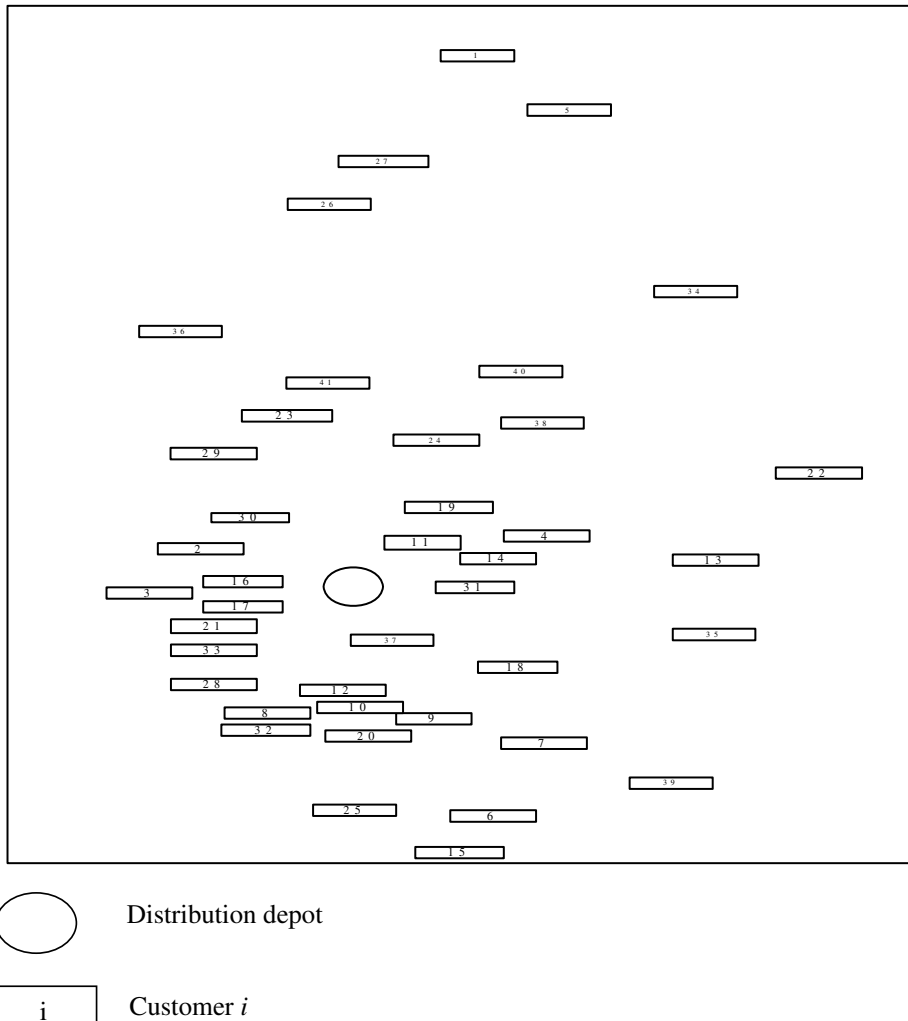


Fig. 2. Geographical relationships of customers.

Table 3
Summary of the estimated customer groups

Original strategy	Customers (scheduled to be served)		
	1, 4, 5, 8, 11		
	Customer group	Group member	Service priority
<i>Day 1</i>			
Proposed method	Group 1	2, 3, 4, 8	1
	Group 2	1, 5, 11	2
	Customers (scheduled to be served)		
	14, 15, 16, 17, 20, 26, 27, 33		
	Customer group	Group member	Service priority
<i>Day 2</i>			
Proposed method	Group 3	14, 16, 17	3
	Group 4	6, 10, 12, 15, 20	4
	Group 5	21, 26, 27, 33	5
	Customers (scheduled to be served)		
	3, 12, 22, 23, 24, 25, 28, 29		
	Customer group	Group member	Service priority
<i>Day 3</i>			
Proposed method	Group 6	19, 23, 24, 38, 40, 41	6
	Group 7	25, 28, 29	7
	Group 8	13, 22, 31, 37	8
	Customers (scheduled to be served)		
	10, 18, 19, 21, 30, 31, 32, 34, 35, 41		
	Customer group	Group member	Service priority
<i>Day 4</i>			
Proposed method	Group 9	30, 34, 36	9
	Group 10	7, 9, 18, 32, 35, 39	10
	Customers (scheduled to be served)		
	2, 6, 7, 9, 13, 36, 37, 38, 39, 40		
<i>Day 5</i>			
Proposed method	None		

(2) \overline{ST} , which represents the average lead time \overline{ST} associated with each given customer, and is measured by averaging the time difference between when an order is received and when the goods delivery service is completed for all the sampled customers.

The comparison results according to the aforementioned criteria are summarized in Table 5.

Overall, the comparison results shown in Table 5 revealed that there was a certain improvement in the performance of logistical distribution using the proposed methodology. Two resulting generalizations are summarized in the following. First, as can be seen in Table 5, the overall relative improvement of the logistics system performance results mainly from the reduction in the aggregate transportation costs. According to our observation from this numerical study, such a group-based vehicle dispatching strategy coupled with the proposed ITS-based D-VRP algorithm appear to make benefits with en-route goods delivery efficiency, thus contributing to significant improvement in transportation costs as high as 28.8%. Second, through appropriate pre-route customer classification and group-based logistics resource allocation strategies, grouped customers can be served more efficiently. As observed in Tables 4 and 5, out of the 41 sampled customers, 14 customers can be served with shorter service time, relative to the original delivery schedule, thus contributing to the relative improvement 12.2% in terms of average lead time (\overline{ST}). To a certain extent, this implies that higher customer service performance can be achieved using the proposed logistics distribution methodology.

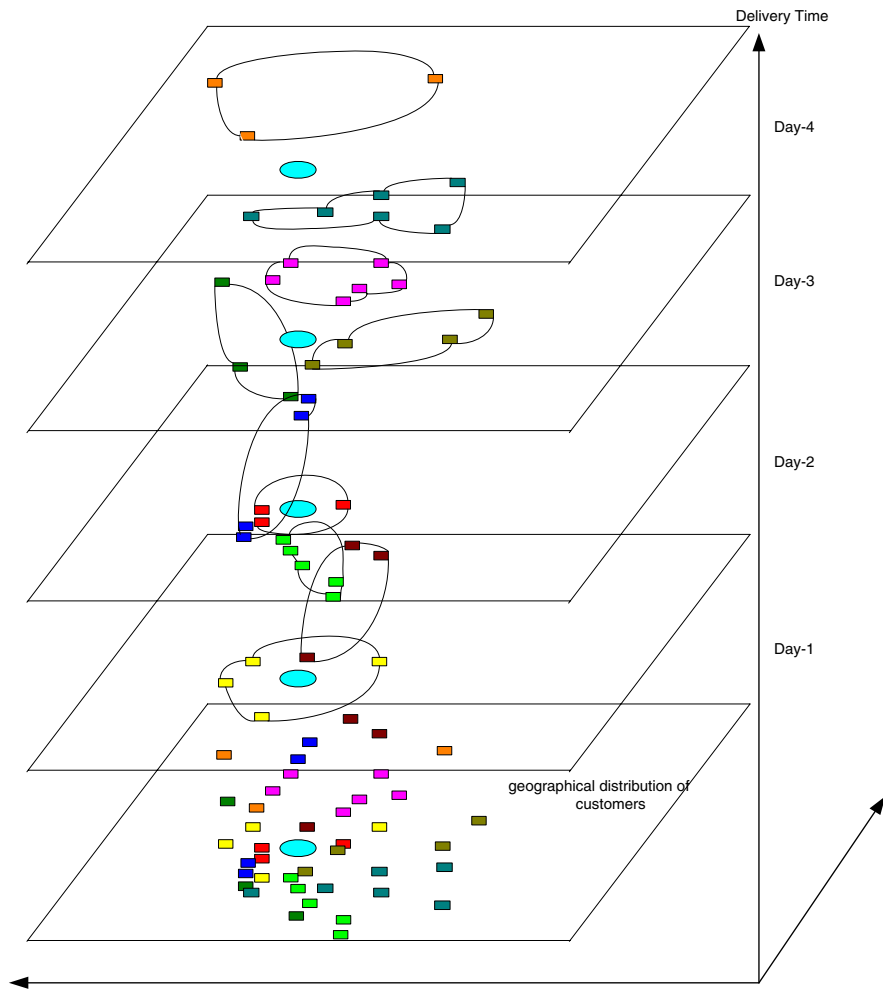


Fig. 3. Illustration of pre-route customer grouping on logistics distribution.

Table 4
Grouping-based vehicle routing results

Date	Customer group	Group member	Service priority
Day 1	Group 1	2-3-8-4	1
	Group 2	11-5-1	2
Day 2	Group 3	14-16-17	3
	Group 4	6-15-20-10-12	4
	Group 5	33-21-26-27	5
Day 3	Group 6	19-38-40-41-23-24	6
	Group 7	29-28-25	7
	Group 8	31-22-13-37	8
Day 4	Group 9	30-36-34	9
	Group 10	32-9-7-39-35-18	10

Correspondingly, it also implies that more customers could be served by the same number of vehicles in the same amount of time.

Table 5
Comparison of system performance

Criteria strategy	TT (US\$)	\overline{ST} (day)
Proposed	1543	4.3
Original	2168	4.9
Relative improvement (%)	28.8	12.2
Overall improvement (%)		20.5

In addition, several implications are summarized below for further discussion:

- (1) Although the proposed logistics distribution method appears to reduce lead time to a certain extent, timeliness remains as an issue worth more investigation. For instance, to implement time-based logistics control strategies, e.g., just-in-time (JIT) inventory control, the major request from customers may no longer be shorter lead time, but the more exact goods delivery time. Sometimes earlier goods delivery service is not a benefit to those customers who implement JIT strategies since they may have to bear more inventory costs.
- (2) Despite the measurements of TT and \overline{ST} , both indicating certain improvements in transportation cost and service time, it appears that the operational performance of logistics distribution can also be improved by integrating either advanced vehicle routing technologies or ITS-related technologies, e.g., global positioning systems (GPS), two-way communication devices, and dynamic fleet management software for real-time applications.
- (3) The computational efficiency could be another potential advantage of the proposed method. According to our observation in corresponding data processing and computational procedures, such a group-based logistics distribution measure enables a great time savings in algorithmic execution. Using the same database, one simple algorithm mimicking classical VRP models was conducted elsewhere [37], in which vehicle routing was performed merely based on the geographical relationships of customers subject to corresponding time windows and logistics resource constraints the same as those pre-set in this study. By contrast, it was found that the proposed customer group-based goods delivery algorithm could save time to a remarkable extent (more than 95%), compared to that simple algorithm. Note that the averaged algorithmic computational time of the proposed method in this numerical study takes around 5 min to process daily customer groups, whereas the corresponding computational time for the aforementioned un-clustered case is about 216 min.

In the following test scenario, simple sensitivity analyses aiming at some critical parameters are conducted. These targeted parameters include the corresponding weights (i.e., ε_1^n and ε_2^n) associated with two disaggregate objective functions ($f_1^n(k)$ and $f_2^n(k)$), and the unit early and delay penalty costs (i.e., CL_{j^n} and CU_{j^n}). The purpose of this scenario is to investigate the corresponding effects of these parameters, particularly on the relative improvement in the measurements of TT , in contrast with the original logistics distribution strategy. Note that in the previous numerical study, these two weights ε_1^n and ε_2^n are set to be consistent (i.e., $\varepsilon_1^n = \varepsilon_2^n = 0.5$). In this scenario, all the pre-set parameters of the proposed method remain the same, excluding these four targeted parameters. The corresponding numerical results are summarized in Tables 6 and 7.

According to the numerical results of Tables 6 and 7, two major generalizations are summarized below:

- (1) Compared to the demand-oriented weight ε_1^n , the supply-oriented weight ε_2^n may have relatively significant effect on the reduction of total transportation costs (TT). As can be seen in Table 6, the relative improvement of TT turns out to be monotonically increased with the increase of ε_2^n ; and however decreased with the increase of ε_1^n . This also implies that using the proposed methodology, the relative improvement of total transportation costs might depend mainly on reduction of the aggregate transportation expenses, rather than on the reduction of penalty costs. Following the above implication, we further deduce that the proposed methodology might have grouped those customers with compatible

Table 6
Results of sensitivity analyses with respect to weights $e_1^{\bar{n}}$ and $e_2^{\bar{n}}$

Target parameter		System performance	
Demand-oriented weight ($e_1^{\bar{n}}$)	Supply-oriented weight ($e_2^{\bar{n}}$)	Total transportation costs (TT)	Relative improvement, % (compared to original strategy)
1.0	0	1864	14.0
0.9	0.1	1794	17.3
0.8	0.2	1701	21.5
0.7	0.3	1637	24.5
0.6	0.4	1592	26.6
0.5	0.5	1543	28.8
0.4	0.6	1460	32.7
0.3	0.7	1398	35.5
0.2	0.8	1271	41.4
0.1	0.9	1229	43.3
0	1.0	1192	45.0

Table 7
Results of sensitivity analyses with respect to unit penalty costs $CL_{j^{\bar{n}}}$ and $CU_{j^{\bar{n}}}$

Target parameter	Increment (%)	Total transportation costs (TT)	Relative improvement, % (compared to original strategy)
Unit early penalty cost ($CL_{j^{\bar{n}}}$)	-100	1513	30.2
	-75	1521	29.8
	-50	1528	29.5
	-25	1537	29.1
	0	1543	28.8
	+25	1547	28.6
	+50	1553	28.4
	+75	1560	28.0
	+100	1566	27.8
	Unit delay penalty cost ($CU_{j^{\bar{n}}}$)	-100	1489
-75		1502	30.7
-50		1518	30.0
-25		1526	29.6
0		1543	28.8
+25		1559	28.1
+50		1568	27.7
+75		1574	27.4
+100		1588	26.8

time-of-day windows prior to the procedure of vehicle routing for goods delivery. Accordingly, the relative improvement induced by the reduction of the corresponding penalty costs may not be significant as the corresponding weight $e_1^{\bar{n}}$ changes.

- (2) Giving the same weights $e_1^{\bar{n}}$ and $e_2^{\bar{n}}$, the decrease in the unit delay penalty costs ($CU_{j^{\bar{n}}}$) may be able to reduce the total transportation costs to a greater extent, relative to the corresponding effect of the early-arrival penalty costs ($CL_{j^{\bar{n}}}$). Such a generalization is consistent with most arguments presented in previous literature. In general parameter setting, it is suggested that $CU_{j^{\bar{n}}}$ should be greater than $CL_{j^{\bar{n}}}$, considering their different impacts on customer service performance. Accordingly, the resulting effect of $CU_{j^{\bar{n}}}$ on reduction of transportation costs is overall greater than that induced by $CL_{j^{\bar{n}}}$, as shown in Table 7.

Nevertheless, using the proposed method as a decision-making support tool, all the corresponding measures of relative improvement shown in the above numerical results are positive, compared to the existing logistics distribution strategy conducted by the targeted manufacturer.

4. Concluding remarks

This paper has presented an advanced group-based logistics distribution approach which integrates both pre-route customer classification and customer group-based vehicle routing procedures to provide efficient goods delivery service and respond to the variety of customer demand attributes. The proposed methodology involves three major mechanisms: (1) pre-route customer classification using fuzzy clustering techniques, (2) determination of customer group-based delivery service priority and (3) en-route goods delivery using multi-objective optimization programming methods. By analyzing customer demand attributes, seven order-oriented customer attributes were specified as key determinants used for customer grouping. A fuzzy clustering-based algorithm was then proposed to classified customers into given groups. Based on the clustered customer groups as well as specified customer demand attributes, the customer group-based service priority and vehicle routing strategies were then determined using the proposed multi-objective optimization model and corresponding algorithms.

A numerical study aiming at the existing logistics operational case of a private manufacturer was conducted to illustrate the potential advantages of the proposed method. By comparing the performance of the proposed method with that of the existing strategy of the targeted manufacturer, numerical results revealed that the overall logistics system performance could be improved by up to 20.5%, resulting mainly from the significant improvement in total transportation costs. In addition, sensitivity analyses with respect to the corresponding weights associated with objective functions and two unit penalty costs were conducted. Findings observed from these numerical results were also discussed.

Nevertheless, there is still great potential for improving the operations performance of logistical distribution by integrating more elaborate vehicle routing algorithms with the proposed pre-trip customer classification method. In addition, in-depth investigation of the potential advantages of the proposed method relative to other logistics distribution strategies is needed. Furthermore, such an integrated customer group-based logistics distribution operation also appears important to provide efficient goods delivery service in a large-scale logistics network under time-varying traffic network conditions. More specifically, the proposed method permits saving a remarkable amount of computational efficiency in solving large-scale dynamic vehicle routing problems. This appears very important, particularly for the practical use of ITS-based real-time vehicle routing strategies.

It is expected that the proposed customer group-based logistics distribution method can make benefits available not only for developing advanced logistics distribution strategies, but also for clarifying the importance of pre-route customer grouping in the operations of time-based logistics control and management. On the basis of the present results, our further research will aim at incorporating advanced ITS-related technologies into the architecture of the proposed method to improve time-based demand-responsive logistics control and management. Moreover, the applicability of the proposed method for logistics operations in the e-business environment is also of interest to us, and warrants further research.

Acknowledgements

This research was supported by National Science Council grants, Taiwan, NSC 94-2416-H-009-009. The author also wishes to thank the referees for their helpful comments.

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