J Intell Manuf (2013) 24:1111–1122
DOI 10.1007/s10845-012-0639-4

# A fuzzy QFD approach to determine supply chain management strategies in the dairy industry

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Received: 4 October 2011 / Accepted: 28 March 2012 / Published online: 10 April 2012


**Abstract** The aim of this study is to identify the crucial logistics requirements and supply chain management (SCM) strategies for the dairy industry. For product or service development, quality function deployment (QFD) is a useful approach to maximize customer satisfaction. The determination of design requirements and supply chain management strategies are important issues during QFD processes for product or service design. For this reason, a fuzzy QFD methodology is proposed in this study to determine these aspects and to improve customer satisfaction. Qualitative information is converted firstly into quantitative parameters, and then this data is combined with other quantitative data to parameterize two multi-objective mathematical programming models. In the first model, the most important logistic requirements for the company are determined based on total technical importance, total cost, total feasibility and total value increment objectives, and in the second model, based on these objectives, appropriate supply chain management strategies are determined. Finally, a case study from the Turkish dairy industry is given to illustrate the proposed approach.

**Keywords** Dairy customer needs · Dairy logistics requirements · Supply chain management strategies · Fuzzy QFD · Multi-objective mathematical programming

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## Introduction

Customer service management has become a strategic issue in logistics and supply chain management. Companies may increase customer satisfaction and gain market shares by improving logistics and supply chain performance. As the production lines of dairy products increase daily, the logistics of milk, cheese and yoghurt products continues to gain in importance. The dairy industry is characterized by hypercompetition with average margins of 1–2 % of sales, and it also deals with highly perishable products that also tend to be fragile and have a low value to size ratio. Additionally, the industry must contend with widely varying consumer tastes and a consumer fixation on price. This complex business environment demands an analysis of logistics needs in the dairy industry to facilitate the formulation of the industry's logistical requirements and thus enable the development of more efficient supply chain management strategies. The aim of this paper is to propose a new approach to determining the most suitable logistics requirements and supply chain management (SCM) strategies so that customer satisfaction can be improved. The approach is based on quality function deployment (QFD), a methodology which has been successfully adopted for new products, processes and system development.

QFD is a comprehensive quality system targeting customer satisfaction. The purpose of applying QFD is to incorporate the voice of the customer into the various stages of the product, process or system development cycle and also to achieve the quality demanded by consumers. However, due to the uncertain nature of this field, it is more difficult to assess the performance of this process with accurate quantitative values. For this reason, this study utilizes a fuzzy QFD approach to improve the quality of the responsiveness to customer requirements. The use of fuzzy logics is preferred for modeling uncertainty, vagueness, and impreciseness from data to assess customers' spoken and unspoken needs. In the proposed fuzzy QFD methodology, qualitative information is converted firstly into quantitative parameters and then this data is combined with other quantitative data to parameterize two multi-objective mathematical models. The first model determines the most important logistic requirements and the second one determines the most appropriate SCM strategies for the company.

This paper is organized as follows. the proposed fuzzy QFD methodology is described briefly in the next section. Subsequent sections include our mathematical models and a description of the proposed approach through a case study. Lastly, concluding remarks are given in the last section.

## Literature review

Some researchers have applied fuzzy theory to quantitatively formulate problems for optimizing the improvements of design requirements (DRs). Fung et al. (1998) proposed a fuzzy inference system of customer requirements which allowed product attributes to be mapped out. Moskowitz and Kim (1997) presented a decision support system for optimizing product designs. The development of these systems generally requires professional knowledge and experience to establish the rules and facts to ensure that the system works properly. Kim et al. (2000) used a fuzzy theoretical modeling approach to QFD by developing fuzzy multi-objective models under the assumption that the function relationships among DRs and between customer requirements (CRs) and DRs could be recognized based on the benchmarking data set of customer competitive analysis. Justifying this assumption in a general situation is difficult, particularly when developing an entirely new product. Some researchers, such as Shen et al. (2001), Vanegas and Labib (2001), Wang (1999), and Zhou (1997), developed some fuzzy approaches, including fuzzy sets, fuzzy arithmetic, and/or defuzzification techniques, to address complex and often imprecise problems regarding customer requirement management. However, in these models the interrelationships among engineering DRs were not taken into proper consideration. In addition, some authors emphasized the necessity of conducting cost consideration and/or taking into account technical difficulties in the models in accordance with the QFD planning effort (Fung et al. 2002; King 1987; Park and Kim 1998; Trappey et al. 1996; Wasserman 1993; Wang 1999; Zhou 1997). Ayag and Ozdemir (2011) also used the fuzzy method integrated analytic network process for machine tool selection problem.

To the best of our knowledge, few studies have dealt with the development and commercial introduction of new products or processes using QFD in the food industry. The existing research includes the work carried out by Holmen and Kristensen (1996), who described the structure of the product development process using the HOQ method in the case of a Danish butter cookie company. They also proposed some upstream and downstream extensions for HOQ which could bring more realism to the application of QFD in the product development activities of the food industry. These extensions incorporate the retailers' specific requirements and link end-product characteristics to the integrated development of ingredients and packaging. In order to improve integration between sensory analysis and market analysis in food product development, Bech et al. (1994) suggested a new structure for HOQ in which the relationships between sensory attributes, technical attributes and consumer requirements are highly detailed. This new structure was later applied in the market-based quality improvement of smoked eel fillet through the building of a modified HOQ in which relevant customer requirements were related to breeding and manufacturing characteristics, as well as to attributes generated by a sensory panel (Bech et al. 1997). Costa (1996) conducted a case study regarding the practical implementation of QFD in a quality improvement project, and the conclusion was that there was a lack of truly quantitative relationships between consumer requirements and food product characteristics, both physically and extrinsically. With regards to the complex nature of consumers' relationships with foods and of food matrix interactions, Costa recommended multivariate statistical methods and the statistical design of experiments for their quantification. Korsten (2000) developed a model in which food technological innovations can be quantitatively evaluated and compared in terms of how well they meet predesigned consumer segment requirements. This model can be used for new food concept selection. Viaene and Januszewska (1999) proposed a method using QFD in the chocolate industry in which a modified HOQ was used to improve the sensory quality of couverture chocolate.

As this overview of the existing studies on the issue indicates, none of the current models have focused on the relationship between customer requirements, engineering DRs, and SCM strategies.

## Proposed fuzzy QFD methodology

The proposed fuzzy QFD methodology includes the following three elements: customer/logistics requirements and supply chain strategies in the dairy industry, related fuzzy set concepts, and multi-objective models.

### Customer/logistics requirements and supply chain strategies in the dairy industry

QFD is a comprehensive quality tool specifically aimed at satisfying customers' requirements. It is defined as a method and technique used for developing a design quality aimed at

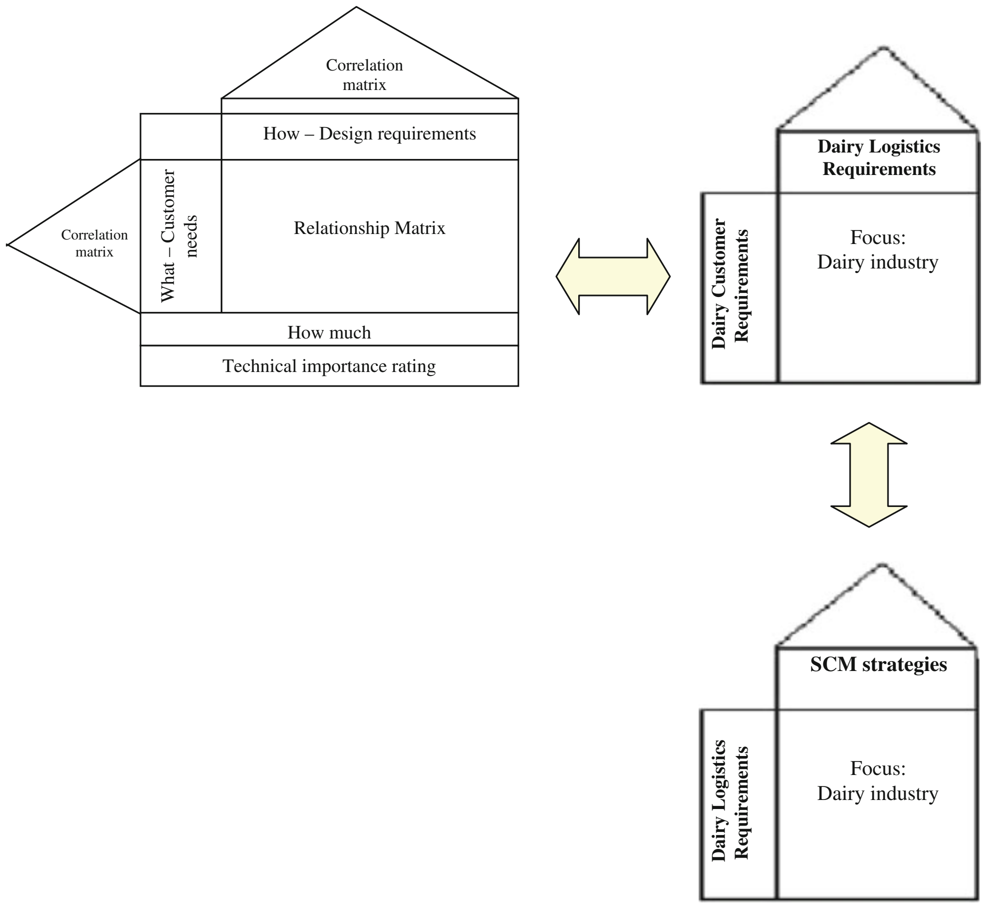


**Fig. 1** General view of the proposed methodology

satisfying the consumer and then translating the consumer's demands into design targets and major quality assurance points to be used throughout the production stage (Akao 1990).

In this study, dairy customer needs are treated as the voice of the customer (WHAT), as these are the requirements of an improved logistics process. All logistics practices that affect each customer need must be identified as the HOWs in a QFD matrix. Following this procedure, a house of quality focus on the dairy industry can be constructed, containing WHATs and HOWs, and their correlations. This generic QFD matrix in Fig. 1 would allow dairy organizations to assess how effective their current logistics practices are, how they can improve them, and to what levels they can be improved.

Through a review of literature and face-to-face meetings with the dairy industry's industrial customers, we identified 23 customer requirements, 17 logistics requirements and 21 supply chain management strategies, and this was backed by our background knowledge and the validation of case company logistics managers (Table 1).

As regards the interaction between customer requirements and logistics, providing a logistics service which meets customer expectations is a continuous process, and this can be summarized in the following steps: understanding the customer's voice, which includes requirements and expectations in terms of relevant logistics performance; assessing customer's perceptions of services; if a gap between perception and requirements occurs, identifying viable steps that can be implemented to improve customer satisfaction; identifying costs and benefits related to each step; and, implementing the most efficient actions to achieve customer satisfaction by means of a cost/benefit analysis.

## Related fuzzy set concepts

The key idea of fuzzy set theory is that an element has a degree of membership in a fuzzy set (Negoita 1985 and Zimmermann 1996), and a fuzzy set is defined by a membership function (all the information about a fuzzy set is described by its membership function). A fuzzy set, therefore, contains elements that have different degrees of membership. In this study, triangular fuzzy numbers, $\tilde{1}$ to $\tilde{9}$, are used to represent subjective pairwise comparisons of the selection process (equal to extremely preferred) in order to capture the vagueness (Table 2). A fuzzy number is a special fuzzy set $F = \{(x, \mu_F(x)), x \in R\}$, where $x$ takes it

**Table 1** Customer, logistics requirements and supply chain management strategies for the dairy industry

| Code | Definition |
|---|---|
| *Enablers "logistics requirements"* | |
| L1 | Qualified employment and training |
| L2 | Usage of information technologies and decision support systems |
| L3 | CRM, getting orders with customer representatives and hiring a representative |
| L4 | Inventory stock and management |
| L5 | Automation of manufacturing processes and warehouse processes |
| L6 | Usage of outsourcing company |
| L7 | Having different kind of temperature degree stock parts in the cold stock warehouse |
| L8 | Real time following the temperature, speed, location etc. of trucks with satellite |
| L9 | Usage demand forecasting system for correct demand forecast |
| L10 | Having quality certification and suppliers pool with quality certifications |
| L11 | Effective reverse logistics |
| L15 | Rapid picking of orders and loading of trucks in the warehouse |
| L13 | Usage distribution network effectively |
| L14 | Analyzing of work processes and continuous improvement |
| L15 | High financial power |
| L16 | Planning |
| L17 | Structure of consumers |
| *Performance aspects "customer requirements"* | |
| C1 | Product quality |
| C2 | Price |
| C3 | Protection of product freshness |
| C4 | Expiration date |
| C5 | Package quality |
| C6 | Becoming a leader brand |
| C7 | Selling circulation |
| C8 | Product satisfaction of last customer |
| C9 | Variety of product |
| C10 | Lead time |
| C11 | Timely delivery |
| C15 | Meeting orders regularly |
| C13 | Supplier reliability |
| C14 | Meeting intermediate orders |
| C15 | Meeting orders correctly |
| C16 | Picking return products |
| C17 | Ergonomics of packaging |
| C18 | Consolidation of orders |
| C19 | Following the stock values of customers |
| C20 | Efficiency of barcode system |
| C21 | Efficient performance management |
| C22 | Suitable management between consumers and suppliers |
| C23 | Different payment options |
| *Performance aspects "supply chain management strategies"* | |
| S1 | Market segmentation |
| S2 | E-marketing |
| S3 | 3PL/4PL logistics service providers |
| S4 | Cross-docking |
| S5 | Direct store delivery |
| S6 | Efficient consumer response (ECR) |
| S7 | Collaborative planning forecasting and replenishment (CPRF) |
| S8 | Postponement |
| S9 | Total cost management |
| S10 | Electronic data interchange (EDI) |
| S11 | Radio frequency identification system (RFID) |
| S12 | Pay by touch |
| S13 | Just-in-time (JIT) delivery |
| S14 | Freight consolidation |
| S15 | Integration of inbound and distribution logistics |
| S16 | Fixed/master routes and variable/dynamic routes |
| S17 | Distribution center consolidation vs. decentralization |
| S18 | Private fleet vs. for-hire fleet |
| S19 | E-commerce |
| S20 | Single/multiple and global sourcing |
| S21 | Environmentally conscious supply chain management |

values on the real line, $R : -\infty < x < +\infty$ and $\mu_F(x)$ is a continuous mapping from $R$ to the closed interval [0, 1]. A triangular fuzzy number denoted as $\tilde{M} = (l, m, u)$, where $l \leq m \leq u$, has the following triangular type membership function:

$$\mu_F(x) = \begin{cases} 0 & x < l \\ x - l/m - l & l \leq x \leq m \\ u - x/u - m & m \leq x \leq u \\ 0 & x > u \end{cases}$$

The triangular fuzzy numbers, $\tilde{1}$ to $\tilde{9}$, are utilized to improve the conventional nine-point scaling scheme. In order to take the imprecision of human qualitative assessments into consideration, the five triangular fuzzy numbers $(\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9})$ are defined with the corresponding membership function. All attributes and alternatives are linguistically depicted by Fig. 2. The shape and position of linguistically terms are chosen in order to illustrate the fuzzy extension of the method.

The triangular fuzzy numbers $(\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9})$ are used to indicate the relative strength of each pair of elements in the same hierarchy. Then, the fuzzy judgment matrix, $\tilde{A}(\tilde{a}_{ij})$ via a pairwise comparison is constructed as given below:

**Table 2** Definition and membership function of fuzzy number (Ayag 2005)

| Intensity of importance function[a] | Fuzzy number | Definition | Membership function |
|---|---|---|---|
| 1 | $\tilde{1}$ | Equally important/preferred | (1, 1, 2) |
| 3 | $\tilde{3}$ | Moderately more important/preferred | (2, 3, 4) |
| 5 | $\tilde{5}$ | Strongly more important/preferred | (4, 5, 6) |
| 7 | $\tilde{7}$ | Very strongly more important/preferred | (6, 7, 8) |
| 9 | $\tilde{9}$ | Extremely more important/preferred | (8, 9, 10) |

[a] Fundamental scale used in pairwise comparisons (Saaty 1989)

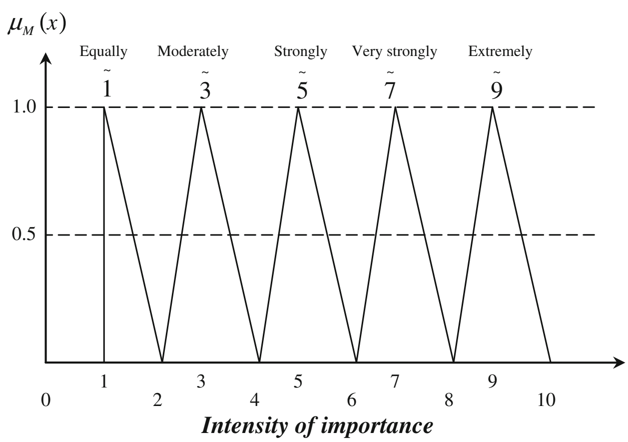


**Fig. 2** Fuzzy membership function for linguistic values for attributes or alternatives

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & .. & .. & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & .. & .. & \tilde{a}_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \tilde{a}_{n1} & \tilde{a}_{n2} & .. & .. & 1 \end{bmatrix}$$

where, $\tilde{a}_{ij} = 1$, if $i$ is equal $j$, and $\tilde{a}_{ij} = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$ or $\tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}$, if $i$ is not equal $j$.

When scoring is done for a pair, a reciprocal value is automatically assigned to the reverse comparison within the matrix. That is, if $\tilde{a}_{ij}$ is a matrix value assigned to the relationship of component $i$ to component $j$, then $\tilde{a}_{ij}$ is equal to $1/\tilde{a}_{ij}$.

Alternatively, by defining the interval of confidence level $\alpha$, the triangular fuzzy number can be characterized using the following equation, Eq. 1:

$$\begin{aligned} \forall\alpha \in [0, 1] \quad \tilde{M}_\alpha &= \left[l^\alpha, u^\alpha\right] \\ &= \left[(m-l)\,\alpha + l, -(u-m)\,\alpha + u\right] \end{aligned} \tag{1}$$

Some main operations for positive fuzzy numbers have been described by the interval of confidence, as done by Kaufmann and Gupta (1985), as given below:

$$\begin{aligned} &\forall m_L, m_R, n_L, n_R \in R^+, \tilde{M}_\alpha = \left[m_L^\alpha, m_R^\alpha\right], \\ &\quad \tilde{N}_\alpha = \left[n_L^\alpha, n_R^\alpha\right], \alpha \in [0, 1] \\ &\tilde{M} \oplus \tilde{N} = \left[m_L^\alpha + n_L^\alpha, m_R^\alpha + n_R^\alpha\right] \\ &\quad \tilde{M} \Theta \tilde{N} = \left[m_L^\alpha - n_L^\alpha, m_R^\alpha - n_R^\alpha\right] \\ &\tilde{M} \otimes \tilde{N} = \left[m_L^\alpha n_L^\alpha, m_R^\alpha n_R^\alpha\right] \quad \tilde{M}/\tilde{N} = \left[m_L^\alpha/n_L^\alpha, m_R^\alpha/n_R^\alpha\right] \end{aligned}$$

While $\alpha$ is fixed, the following judgment matrix can be obtained after setting the index of optimism $\mu$ in order to estimate the degree of satisfaction. The eigenvector is calculated by fixing the $\mu$ value and identifying the maximal eigenvalue.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{21}^\alpha & .. & .. & \tilde{a}_{1n}^\alpha \\ \tilde{a}_{21}^\alpha & 1 & .. & .. & \tilde{a}_{2n}^\alpha \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \tilde{a}_{n1}^\alpha & \tilde{a}_{n2}^\alpha & .. & .. & 1 \end{bmatrix}$$

$\alpha - cut$ is known to incorporate the confidence of experts or decision maker(s) over his/her preference or judgments. The degree of satisfaction for the judgment matrix is estimated by the index of optimism $\mu$ determined by the decision maker. A larger value of index $\mu$ indicates a higher degree of optimism. The index of optimism is a linear convex combination (Lee 1999) as defined in the following equation, Eq. 2:

$$a_{ij}^\alpha = \mu a_{iju}^\alpha + (1-\mu)\, a_{ijl}^\alpha, \quad \forall\mu \in [0, 1] \tag{2}$$

Once the pairwise comparisons are completed, the local priority vector $w$ (also referred as e-Vector) is computed using Eq. 3 as the unique solution:

$$Aw = \lambda_{\max} w \tag{3}$$

where, $\lambda_{\max}$ is the largest eigenvalue of $A$.

After constructing all required pairwise judgment matrices between component/attributes levels, the consistency ratio ($CR$) should be calculated for each.

The deviation from consistency, which is the measure of inconsistency, is called the consistency index ($CI$) and is calculated using the following equation (Eq. 4):

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{4}$$

where, $n$ is matrix size.

The *CR* is used to estimate directly the consistency of pairwise comparisons, and is computed by dividing the *CI* by a value obtained from a table of Random Consistency Index (*RI*), the average index for randomly generated weights (Saaty 1981), as shown in Eq. 5.

$$CR = \frac{CI}{RI} \tag{5}$$

If the *CR* is less than 10 %, the comparisons are acceptable; otherwise, they are not.

The proposed approach presented in this paper only deals with the following steps of AHP process integrated fuzzy logic: determining goals, constructing a pairwise comparison matrix, performing judgment of the pairwise comparison, synthesizing the pairwise comparison and performing the consistency analysis (in all of these steps, we make fuzzy calculations using triangular fuzzy numbers). These steps are used to calculate the weights of the goals in order to use them in the study of multiple objective analyses.

## Multi-objective models

In the proposed methodology, two mathematical models are created to select the logistic requirements for further consideration and then to select the appropriate SCM strategies. These two mathematical models are structurally the same with the exception that in the first model, the logistic requirements are selected and in the second model SCM strategies are selected. Therefore, only the first model is presented below in Eqs. 6– 11, and the notation differences of the second model is presented in parentheses. In both of these models, *total technical importance*, *total cost*, *total feasibility* and *total value increment* objectives are taken into consideration based on the information given by the Bahçıvan Gıda company, which, in the case study, includes 17 logistic requirements and 21 SCM strategies. The notations and mathematical models are presented below.

$N$: Total number of logistic requirements (or SCM strategies)

$NRTIR_j$: Normalized relative technical importance rating for each logistic requirement (or SCM strategy) $j$

$COST_j$ : Cost of providing logistic requirement (or SCM strategy) $j$

$FEASIBILITY_j$ : Feasibility of logistic requirement (or SCM strategy) $j$

$VALUE_j$: Value increment of logistic requirement (or SCM strategy) $j$

*BUDGET*: Total budget for logistic requirements (or SCM strategies)

$X_j$: Binary decision variable that equals 1 if logistic requirement (or SCM strategy) $j$ is selected, and 0 otherwise

$$\max \; f_1(x) = \sum_{j=1}^{N} NRTIR_j X_j \tag{6}$$

$$\min \; f_2(x) = \sum_{j=1}^{N} COST_j X_j \tag{7}$$

$$\max \; f_3(x) = \sum_{j=1}^{N} FEASIBILITY_j X_j \tag{8}$$

$$\max \; f_4(x) = \sum_{j=1}^{N} VALUE_j X_j \tag{9}$$

$$s.t. \; \sum_{j=1}^{N} COST_j X_j \le BUDGET \tag{10}$$

$$X_j \;\; binary \quad \forall j \tag{11}$$

In the model, the first objective (Eq. 6) represents the maximization of the total importance of the logistic requirements (or SCM strategies) that are selected. The second objective (Eq. 7) is for the minimization of total cost of selected logistic requirements (or SCM strategies). The third objective (Eq. 8) is for the maximization of total feasibility and the fourth (Eq. 9) is for the maximization of the total value increment of selected logistic requirements (or SCM strategies). Equation 10 ensures that total budget is not exceeded and Eq. 11 represents the binary decision variables. Note that once the minimization of the total cost objective (Eq. 7) is converted into a maximization problem (by multiplication with −1), the mathematical model becomes a 4-objective maximization model.

Since we have four competing objectives in both of these mathematical models, a multi-criteria decision making method is needed to find efficient solutions. Here, for simplicity, we have used the weighted sums approach (weighting method) as the multi-criteria decision making technique. Below are the related definitions and the implementation.

Let's say a multi-objective program (MOP)

$$\begin{aligned} \max \quad & f(x) = \{f_1(x), f_2(x), \ldots, f_k(x)\} \\ s.t. \quad & x \in X \end{aligned} \tag{12}$$

is assumed to have $k (k \ge 2)$ competing objective functions ($f_i : \Re^n \to \Re$) that are to be maximized simultaneously. Then,

**Definition** A decision vector $x^* \in X$ is *efficient* (*Pareto optimal*) for MOP (Eq. 12) (all criteria are in the form of maximization criteria) if there does not exist a $x \in X,\ x \ne x^*$ such that $f_i(x) \ge f_i(x^*)$ for $i = 1, \ldots, k$ with strict inequality holding for at least one index $i$. ($x^* \in X$ is efficient, $f(x^*)$ is non-dominated) (Miettinen 1999).

**Definition:** A decision vector $x^* \in X$ is *weakly efficient* (*weakly Pareto optimal*) for MOP (Eq. 12) if there does not exist a $x \in X,\ x \neq x^*$ such that $f_i(x) > f_i(x^*)$ for $i = 1, \ldots, k$. ($x^* \in X$ is weakly efficient, $f(x^*)$ is weakly non-dominated) (Miettinen 1999).

The purpose of the weighting method is to associate each objective with a weighting coefficient $w_i$ which expresses the relative importance given to each objective function, and to transform multiple objective functions into a single objective by maximizing the weighted sum of these objectives as shown in the problem below (Eq. 13).

$$\begin{aligned} &\max \ \sum_{i=1}^{k} w_i f_i(x) \\ &s.t.\ \ x \in X, \\ &\text{where}\ \ w_i \geq 0\ \ \text{for all}\ \ i = 1, \ldots k\ \ \text{and}\ \ \sum_{i=1}^{k} w_i = 1 \end{aligned} \tag{13}$$

The solution of the weighting problem (Eq. 13) is weakly Pareto optimal. The solution of the weighting problem (Eq. 13) is Pareto optimal if the weighting coefficients are positive, that is $w_i > 0$ for all *i=1,…,k* (Miettinen 1999).

In this paper, the weighting method is applied to both of these mathematical models as shown in the below problem (Eq. 14) in order to find efficient solutions.

$$\begin{aligned} &Max\ \ z = w_1 \sum_{j=1}^{N} NRTIR_j X_j - w_2 \sum_{j=1}^{N} COST_j X_j \\ &+ w_3 \sum_{j=1}^{N} FEASIBILITY_j X_j + w_4 \sum_{j=1}^{N} VALUE_j X_j \\ &s.t. \\ &\sum_{j=1}^{N} COST_j X_j \leq BUDGET \\ &X_j\ \ binary\ \ \forall j \\ &w_j \geq 0\ \ \ j = 1, \ldots 4\ \ \text{and}\ \ \sum_{j=1}^{4} w_j = 1 \end{aligned} \tag{14}$$

## Case study

We applied our proposed approach to Bahçıvan Gıda Co. (http://www.bahcivan.com.tr), which was founded in 1956 and launched seasonal cheese production in Eastern Anatolia and South Eastern Anatolia with modest growth. In the following years, in order to sell the produced cheese, cold storages units were rented in Istanbul and the cheese was transferred to Istanbul and went on the market there. Because of increasing demand and the sector's requirements, Bahçıvan Gıda, which was regularly growing, began to increase its capacity as of 1998 and completed its technological infrastructure modifications in the middle of 2001. With this new investment, production capacity was redoubled and in addition a new whey and milk powder facility went into operation. Today, Bahçıvan Gıda makes a major contribution to the Turkish economy with a daily production capacity of 250 tons.

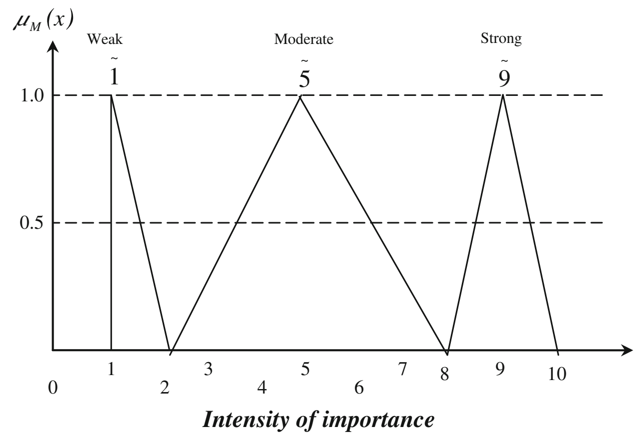


**Fig. 3** Fuzzy membership function for linguistic values for customer and logistics requirements

### Application of the proposed approach

In conventional QFD, the pairwise comparison is made by using a ratio scale. We defined a three-point scale ($\tilde{1}, \tilde{5}, \tilde{9}$) integrated fuzzy logic (Fig. 3), which is based on the nine-point scale of Saaty and the comments of the decision-makers in the company of Bahçıvan Gıda. It shows the participants' judgments or preferences from among the options of *strong*, *moderate* and *weak*. In this study, triangular fuzzy numbers are used to represent subjective pairwise comparisons of evaluation in order to capture vagueness. A fuzzy number is a special fuzzy set where $x$ takes its values on a real line and is a continuous mapping from $R$ to the closed interval [0, 1].

Based on the scale ($\tilde{1}, \tilde{5}, \tilde{9}$), we constructed the fuzzy QFD matrix first. Then, we used $\alpha - cut$ analysis to construct the second QFD matrix showing the interval values for each element of the matrix. Finally, the judgment matrix $\tilde{A}$ is estimated by the index of optimism $\mu$, and confidence value $\alpha(\mu = 0.5, \alpha = 0.5)$. Tables 3 and 4 along with Figs. 4 and 5 show the QFD matrices after $\alpha - cut$ analysis.

We also used Saaty's nine point scale (Table 1; Fig. 2) integrated with fuzzy logic to determine the weights of the goals. Tables 5, 6 and 7 show the fuzzy calculations of determining the weights of the goals.

**Table 3** QFD matrix after $\alpha - cut$ analysis ($\mu = 0.5, \alpha = 0.5$)

| Weight/ importance | Performance aspects "customer demands | Enablers' "logistics requirements" | | | | | | | | | | | | | | | | | Total ATIR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | L10 | L11 | L12 | L13 | L14 | L15 | L16 | L17 | |
| 10 | C1 | 5 | | | | | | 9 | 9 | | 9 | | | | | | 9 | 9 | |
| 10 | C2 | | | | 9 | 9 | 9 | | | | | | 9 | | 9 | | 9 | 9 | |
| 10 | C3 | | | | | | | 9 | 9 | | | | | | | | 9 | 9 | |
| 10 | C4 | 5 | 9 | 9 | 9 | 9 | 5 | | 9 | 5 | 9 | 9 | 5 | 9 | 9 | 1.5 | 9 | 9 | |
| 10 | C5 | 9 | | | | 9 | 9 | 5 | 9 | | | | 5 | 9 | 9 | | | 9 | |
| 10 | C6 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| 10 | C7 | | 9 | 9 | 9 | 9 | 5 | | | 9 | | | | 9 | | | | 5 | |
| 10 | C8 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| 7 | C9 | | 9 | | 5 | | | | | | | | | 9 | | | | 9 | |
| 10 | C10 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| 10 | C11 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| 10 | C12 | 5 | 5 | 9 | 5 | 5 | 9 | 5 | 5 | 5 | 5 | 5 | 5 | 9 | 5 | 5 | 9 | 9 | |
| 10 | C13 | 5 | 5 | 9 | 5 | 5 | 9 | 5 | 5 | 9 | 5 | 9 | 5 | 5 | 9 | 5 | 5 | 5 | |
| 8 | C14 | 5 | 5 | 9 | 9 | 5 | 9 | 5 | 5 | 5 | 5 | 5 | 5 | 9 | 5 | 5 | 9 | 9 | |
| 10 | C15 | 9 | 5 | 5 | 9 | 9 | 9 | 5 | 5 | 5 | 5 | 5 | 9 | 9 | 5 | 5 | 5 | 9 | |
| 10 | C16 | | | 9 | | | | | | | | 9 | | | 9 | | 9 | 9 | |
| 10 | C17 | | | | | | 9 | 9 | | | | | | 9 | 9 | | | 5 | |
| 10 | C18 | | 9 | 9 | | | | | | | | | | 9 | | | 9 | 5 | |
| 10 | C19 | | 9 | | 9 | | | | | | | | | | | | 9 | 9 | |
| 8 | C20 | 1.5 | 1.5 | 1.5 | 9 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 9 | 1.5 | 1.5 | 9 | 9 | |
| 8 | C21 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 9 | 9 | 5 | 9 | 9 | |
| 10 | C22 | 1.5 | 1.5 | 9 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 9 | 9 | 1.5 | 9 | 9 | |
| 10 | C23 | | | | | | | | | | | | | | | 9 | | 9 | |
| | Max. | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| | ATIR | 847.0 | 1040.0 | 1164.0 | 1144.0 | 1017.0 | 1139.0 | 937.0 | 977.0 | 797.0 | 797.0 | 837.0 | 847.0 | 1409.0 | 1182.0 | 632.0 | 1484.0 | 1737.0 | 17987.0 |
| | NRTIR= RTIR × 100 | 4. 7 | 5. 8 | 6. 5 | 6. 4 | 5. 7 | 6. 3 | 5. 2 | 5. 4 | 4. 4 | 4. 4 | 4. 7 | 4. 7 | 7. 8 | 6. 6 | 3. 5 | 8. 3 | 9. 7 | |

**Table 4** QFD matrix after $\alpha - cut$ analysis ($\mu = 0.5, \alpha = 0.5$)

| Weight/importance | Performance aspects "logistics requirement" | Enablers' "supply chain management strategies" | | | | | | | | | | | | | | | | | | | | | Total ATIR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 | S12 | S13 | S14 | S15 | S16 | S17 | S18 | S19 | S20 | S21 | |
| 5.6 | L2 | 5 | 9 | 5 | 9 | 9 | 9 | 9 | 5 | 9 | 9 | 9 | 5 | 9 | 9 | 9 | 9 | 9 | 5 | 9 | 9 | 9 | |
| 6.7 | L3 | 9 | | 5 | 5 | 9 | 5 | 9 | 9 | 9 | | | | 5 | 9 | 9 | 9 | 9 | | 9 | 5 | 9 | |
| 6.4 | L4 | 9 | 5 | 5 | 9 | 9 | 1 | 9 | 9 | 9 | 9 | | | 9 | 9 | 9 | 9 | 9 | | 9 | 5 | 9 | |
| 5.6 | L5 | 1 | 5 | | 9 | 5 | 1 | 9 | 5 | 9 | 5 | 9 | 5 | 9 | 1 | 1 | | 9 | | 9 | 1 | 9 | |
| 4.9 | L7 | | | | | | | 1 | | 9 | | 5 | | 1 | | | | 9 | | | | 9 | |
| 8.3 | L13 | 9 | | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 1 | 5 | | 9 | 9 | 9 | 9 | 9 | 1 | 9 | 9 | 9 | |
| 6.9 | L14 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| 8.6 | L16 | 9 | | 5 | 9 | 9 | 9 | 9 | 9 | 9 | 1 | 1 | | 9 | 9 | 9 | 9 | 9 | | 9 | 5 | 9 | |
| 10.4 | L17 | 9 | 9 | 1 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | | 9 | 9 | 9 | 1 | 9 | 5 | | 9 | 1 | 9 | |
| | Max. | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| | ATIR | 459 | 266 | 284 | 500 | 504 | 404 | 531 | 482 | 571 | 309 | 238 | 212 | 505 | 482 | 399 | 476 | 529 | 98 | 527 | 312 | 571 | 8, 655 |
| | NRTIR = RTIR × 100 | 5.3 | 3.1 | 3.3 | 5.8 | 5.8 | 4.7 | 6.1 | 5.6 | 6.6 | 3.6 | 2.7 | 2.4 | 5.8 | 5.6 | 4.6 | 5.5 | 6.1 | 1.1 | 6.1 | 3.6 | 6.6 | |

In our case study, Eq. 14 is implemented to find efficient solutions. The weighting coefficients of $NRTIR_j$, $COST_j$, $FEASIBILITY_j$, and $VALUE_j$ are obtained from Table 7 as (e-Vector) = $(w_1, w_2, w_3, w_4)$ = (0.589, 0.237, 0.102, 0.073). First, Eq. 14 is solved to select the most important logistic requirements utilizing the data in Tables 3 and 8. As seen in Table 8, there are $N = 17$ logistic requirements to take into consideration, and data related to $NRTIR_j$, $COST_j$, $FEASIBILITY_j$, and $VALUE_j$ is scaled so that all the values are between 0 and 10. In the implementation, the total budget is taken as 40.

Lingo 7.0 solver is used to solve Eq. 14 with the presented data, and an efficient solution is found as:

$$z = 36.782,\ f_1(x) = 62,\ f_2(x) = 40,\ f_3(x) = 44,\ f_4(x) = 72,\ X_j = (0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1).$$

Based on this solution, logistic requirements 2, 3, 4, 5, 7, 13, 14, 16, and 17 are selected to be considered further, as seen in Table 4. In Table 4, there are 21 SCM strategies listed; so Eq. 14 is solved one more time to obtain an efficient SCM strategy solution, utilizing the data presented in Tables 4 and 9. Note that the data in Table 9 is scaled so that all the values are between 0 and 10.

Lingo 7.0 solver is used to solve Eq. 14 with the presented data, and an efficient solution is found as:

$$z = 35.1375,\ f_1(x) = 65.5,\ f_2(x) = 40,\ f_3(x) = 32,\ f_4(x) = 38,\ X_j = (0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1).$$

Based on this solution, SCM strategies 4,5,7,8,9,10,14,15,16, 19,20, and 21 are selected to be considered for implementation at the case company. Note that, while selecting the logistics requirements and SCM strategies, infeasibilities and conflicts do not occur due to lack of negative correlations. The correlations on top of the House of Quality matrices are all-positive (weak or strong) or blank (no correlation) as shown in Figs. 4 and 5. Therefore, in both of these mathematical models, constraints related to infeasibility issues due to negative correlations are not included.

## Conclusion

In this study, we analyzed the dairy industry and identified important dairy logistics requirements and SCM strategies using QFD, a useful approach for maximizing customer satisfaction. Determining the design requirements is an important issue during QFD processes for product or service design. For this reason, we integrated fuzzy logic with a QFD method to create a fuzzy QFD methodology. First, qualitative

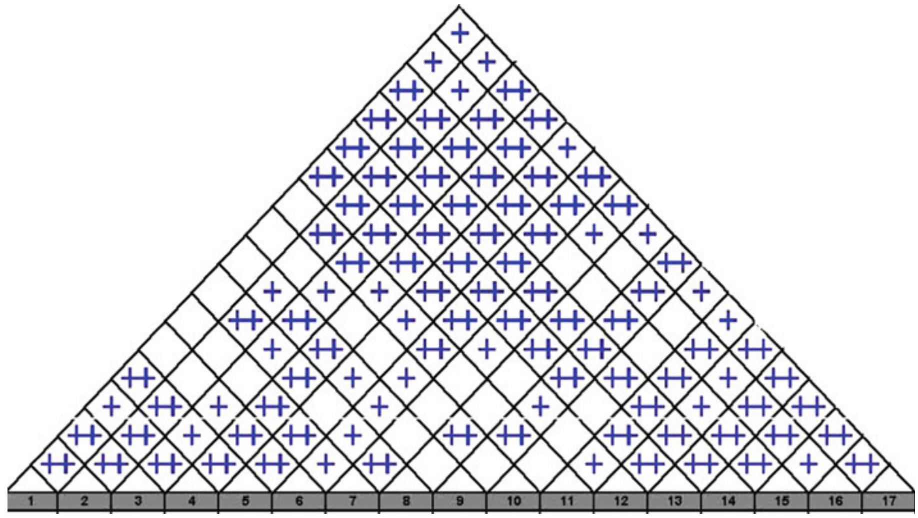


**Fig. 4** The correlations between 17 logistic requirements (weak positive correlation (*plus*), strong positive correlation (*double plus*), no correlation (*blank*))

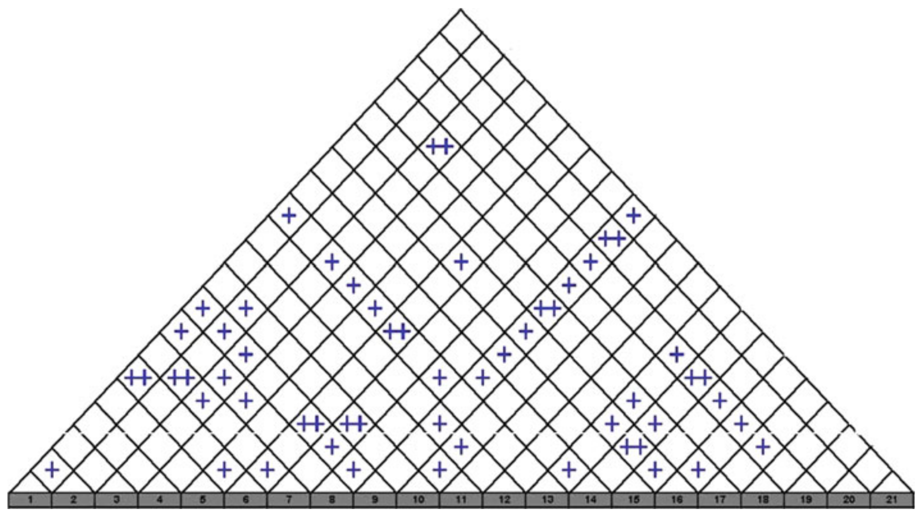


**Fig. 5** The correlations between 21 supply chain management strategies (weak positive correlation (*plus*), strong positive correlation (*double plus*), no correlation (*blank*))

**Table 5** Fuzzy comparison matrix of criteria

| | Importance | Cost | Feasibility | Value increment |
|---|---|---|---|---|
| Importance | 1 | $\tilde{3}$ | $\tilde{5}$ | $\tilde{9}$ |
| Cost | $\tilde{3}^{-1}$ | 1 | $\tilde{3}$ | $\tilde{3}$ |
| Feasibility | $\tilde{5}^{-1}$ | $\tilde{3}^{-1}$ | 1 | $\tilde{1}$ |
| Value increment | $\tilde{9}^{-1}$ | $\tilde{3}^{-1}$ | $\tilde{1}^{-1}$ | 1 |

**Table 6** $\alpha - cuts$ fuzzy comparison matrix of criteria ($\alpha = 0.5$)

| | Importance | Cost | Feasibility | Value increment |
|---|---|---|---|---|
| Importance | 1 | [2, 4] | [4, 6] | [8, 10] |
| Cost | [1/4, 1/2] | 1 | [2, 4] | [2, 4] |
| Feasibility | [1/6, 1/4] | [1/4, 1/2] | 1 | [1, 2] |
| Value increment | [1/10, 1/8] | [1/4, 1/2] | [1/2, 1] | 1 |

information was converted into quantitative parameters and then the resulting data was combined with other quantitative data to parameterize two multi-objective mathematical programming models. The model was applied to a firm in the Turkish food sector, Bahçıvan Gıda Co., and the results of the study were sent to the company's logistics managers who examined and confirmed them. If the company is able to effectively respond to these logistics requirements and SCM strategies, it will be able to improve profits and increase its market share.

**Table 7** Pairwise comparison matrix for the relative importance of criteria

| | Importance | Cost | Feasibility | Value increment | e-Vector |
|---|---|---|---|---|---|
| Importance | 1.000 | 3.000 | 5.000 | 9.000 | 0.589 |
| Cost | 0.375 | 1.000 | 3.000 | 3.000 | 0.237 |
| Feasibility | 0.208 | 0.375 | 1.000 | 1.500 | 0.102 |
| Value increment | 0.113 | 0.375 | 0.750 | 1.000 | 0.073 |
| | | | | $\lambda_{max}$ | 4.165 |
| | | | | CI | 0.055 |
| | | | | RI | 0.90 |
| | | | | CR | 0.061 < 0.10 |

**Table 8** Logistic requirements data for the case company

| Logistic requirement $j$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $NRTIR_j$ | 4.7 | 5.8 | 6.5 | 6.4 | 5.7 | 6.3 | 5.2 | 5.4 | 4.4 | 4.4 | 4.7 | 4.7 | 7.8 | 6.6 | 3.5 | 8.3 | 9.7 |
| $COST_j$ | 8 | 4 | 5 | 2 | 6 | 10 | 4 | 9 | 10 | 10 | 9 | 9 | 5 | 5 | 10 | 4 | 5 |
| $FEASIBILITY_j$ | 0 | 4 | 8 | 4 | 4 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 6 | 6 | 0 | 2 | 2 |
| $VALUE_j$ | 0 | 6 | 6 | 6 | 10 | 0 | 10 | 0 | 0 | 0 | 0 | 0 | 8 | 6 | 0 | 10 | 10 |

**Table 9** SCM strategies data for the case company

| SCM strategy $j$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $NRTIR_j$ | 5.3 | 3.1 | 3.3 | 5.8 | 5.8 | 4.7 | 6.1 | 5.6 | 6.6 | 3.6 | 2.7 | 2.4 | 5.8 | 5.6 | 4.6 | 5.5 | 6.1 | 1.1 | 6.1 | 3.6 | 6.6 |
| $COST_j$ | 6 | 4 | 5 | 2 | 6 | 5 | 4 | 1 | 3 | 3 | 7 | 5 | 9 | 1 | 4 | 1 | 10 | 6 | 5 | 4 | 6 |
| $FEASIBILITY_j$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 8 | 0 | 0 | 0 | 0 | 8 | 0 | 10 | 4 | 0 | 0 | 0 | 0 |
| $VALUE_j$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 10 | 0 | 0 | 0 | 0 | 10 | 0 | 8 | 10 | 0 | 0 | 0 | 0 |

**Acknowledgments** The authors would like to acknowledge all of the industrial experts and Bahçıvan Gıda managers, especially Hacer Asma (the logistics director of Bahçıvan Gıda) and Seher Kırımlıoğlu (the logistics planning expert of Bahçıvan Gıda) for their contributions, without which this study could not have been accomplished.

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