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Fuzzy *c*-means clustering-based key performance indicator design for warehouse loading operations

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ABSTRACT

Performance measurements are important motivators in evaluating a company's strategy. The performance improvement process starts with the measurement of the current situation. Therefore, companies use various metric quantities for the efficiency and productivity of warehouse management. Recently, many studies have been conducted on key performance indicators. In this study, an artificial intelligence-aided key performance indicator is intended for the loading performance of a warehouse, and the analysis is performed based on various scenarios. In the pre-processing phase, five inputs are taken as the unit price, monthly demand quantities, the number of products loaded from the warehouse, the demand that cannot be loaded on time, and the average delay times of the products that cannot be loaded on time. The outputs of the pre-processing phase are clustered using a fuzzy *c*-means clustering algorithm. Then a key performance indicator for the warehouse loading operations is proposed using the fuzzy *c*-means clustering result. Researchers and engineers can easily use the proposed scheme to achieve efficiency in warehouse loading management.

1. Introduction

Logistics management refers to the process of organizing the cost-effective flow of raw materials to the marketplace through the company and operations beyond the suppliers, with customer satisfaction during the coordination of material and information flow (Lambert et al., 1998). Companies need to reduce their costs and improve their customer service quality which covers the process from the raw material to the finished goods. One of the critical components of the logistics management system is the warehouse. In the past, warehouses were considered cost centers that did not create value and only act as a buffer between the producer and the consumer. The limited visibility of stocks and the lack of data visualization in the supply chain, and the slow flow of stocks have forced companies to hold more stocks than necessary. A series of changes have occurred in warehouse operations with the change of the production centers around the world, the increase in electronic commerce, and the demand from customers (Richards, 2011). The warehouse management that was previously considered only as keeping products and protecting them against external influences, has evolved to a new paradigm with the integration of storage, material handling, monitoring of stock movements, production, and marketing functions. Thus, it has become a necessary supply chain function for the companies to provide value-added services to customers at the point of preparing products and delivering them to customers (Sahin, 2014).

In line with the needs, these important changes in warehouse management from the past to the present have led to the emergence of modern warehouse management systems with the development of information technologies and finally the addition of warehouse management software. Warehouse activities, which are of great importance in terms of reducing transportation and production costs, balancing supply and demand, and contributing to the production and marketing process, play a vital role in achieving the desired level of customer service at the lowest possible cost. In this study, an artificial intelligence-aided key

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performance indicator (KPI) designed to be used in the analysis of loading performance in warehouses is introduced.

Management does not have the opportunity to use large amounts of quality data at a low cost without using new technologies, processes, and strategies. At this point, the best strategy that can be adopted is performance management. The basis of performance management is the measurement of the performance of the organization in certain areas with various indicators and the effective use of resources by evaluating the results (Bergeron, 2018). Monitoring and evaluating the performance of the supply chain reveals the difference between scarcity and implementation and enables companies to identify potential challenges and areas of change. However, it is known that it is very difficult to establish KPIs or benchmarks, and several realistic guidelines on them are not readily available for companies and professionals in supply chain management (SCM) (Chae, 2009). KPIs, which allow changes in the behavior in the business environment, improve operational performance and thus improve outputs, have applications in sectors such as manufacturing (Vanany, 2003; Zhu et al., 2017; Amrina and Vilsi, 2015; Závadský et al., 2019; Meier et al., 2013), banking (Wu, 2012), education (Montoneri et al., 2012; Authoni and Suryani, 2014), health (Sungkar et al., 2011; Jiang et al., 2020; Berler et al., 2005), SCM (Chae, 2009; Akkawuttiwanich and Yenradee, 2018; Andika et al., 2013), energy (Xiang et al., 2016), construction firms (Skibniewski and Ghosh, 2009), and logistics companies (Chen et al., 2017).

As in many fields, studies based on taxonomic research and literature research have been carried out for studies on KPIs. Domínguez et al. (2019) conducted a taxonomic study that reveals the general characteristics of KPIs to improve the understanding of KPI management or to help users decide on the most appropriate solution for their needs. Karl et al. (2018) investigated the impact of non-financial KPIs in building supply chain resilience. For this, they conducted a literature review with 57 peer-reviewed academic articles published from 2000 to 2017.

Studies in which multi-criteria decision methods are used in the categorization and prioritization of KPIs can be found in the literature. Kusrini et al. (2019) identified the importance weight of 30 KPIs using the AHP method for a sustainable warehouse for the leather manufacturing industry. Kucukaltan et al., (2016) proposed a comprehensive decision support model that utilizes a combination of the Analytic Network Process (ANP) and the stakeholder-informed Balanced Scorecard (BSC) for the identification and prioritization of KPIs in the logistics industry. They categorize into four points of view as monetary, inner handle, partners, learning, and development, and prioritize the performance indicators. Gözaçan and Lafci (2020) outlined the KPI for implementing total quality management (TQM) across the logistics sector. The research is focused on the quality values of logistics companies in the logistics industry, which is analyzed with main performance measures using the Analytical Hierarchy Process (AHP) Integrated Approach and SMART Goal Setting. Dev et al. (2019) proposed a combination of discrete event simulation, fuzzy-ANP, and TOPSIS methods led by the big data analytics environment to help companies find the KPIs in a systematic real-time manner across the entire supply chain. Laosirihongthong et al. (2018) developed an integrated method consisting of Q-sort, fuzzy-AHP, and integer programming methods to prioritize general performance metrics associated with warehouse operations in manufacturing, third-party logistics service provider, and retail industry supply chains. The measurements divided into categories by the Q-sort method are weighted with FAHP and priority categories are validated with integer programming. Torbacki and Kijewska (2019) formulated the KPIs from the point of view of three areas: Industry 4.0, Logistics 4.0, and sustainable development in the area of products distribution to and from production plants. Ultimately, they calculated the relationships between the parameters by determining their meaning within the three areas using the DEMATEL technique.

There are also studies using questionnaires and structured interviews to define and categorize KPIs. Vlachos (2013) conducted a semi-structured interview practice in the fruit cooperative to determine to what extent the adoption of RFID can improve supply chain performance in agri-food supply chains. Khalifa and Khalid (2015) used qualitative survey methods through conducting semi-structured interviews to describe in detail the complete process of developing a group of strategic KPIs to monitor and improve the performance of a tertiary care hospital, including different services. Mahmodabadi et al. (2019) used a semi-structured questionnaire to determine the KPIs of the hospital pharmacy department. The indicators consisted of three areas, including administrative indicators (satisfaction, education, staffing, and department management), clinical indicators (patient safety), and financial indicators (income, costs, and financial utilization). Karim et al. (2020) used a literature review and semi-structured questionnaire to transform the basic warehouse performance metrics used for benchmarking efficiency performance into a series of internationally adopted productivity measurement indicators. They conducted an extensive study using directed content analysis and descriptive analysis to analyze existing warehouse efficiency indicators. Gardas et al. (2019) identified the performance indicators of green supply chain management through a literature survey and the opinions of field experts. And then, they analyzed 14 PIs of GSCM in the agro-sector using the interpretive structural modeling (ISM) approach. Torabizadeh et al. (2020) used the structural equation model approach to identify KPIs for a sustainable warehouse management system.

When the studies in the literature are examined, it is seen that many studies have been conducted to determine the performance indicators and to weight the indicators. It was determined that questionnaire and multi-criteria decision methods were generally used in these studies. In this study, a fuzzy *c*-means clustering (FCM) based KPI is designed to evaluate the loading performance of a warehouse according to different scenarios. This paper tries to answer the following research questions:

- How is the new key performance indicator for loading performance on warehouse management?
- What are the uncertainties over the on-time loading process?
- Can the fuzzy *c*-means approach use for eliminating these uncertainties to establish a new KPI methodology?
- Using the created scenarios, can be the proposed KPI effectively met the expected condition to the actual condition?

The organization of this paper is as follows: In the materials and methods section, the fuzzy logic concept, the structure of the fuzzy *c*-means clustering algorithm, and the proposed fuzzy *c*-means clustering-based KPI that consider the delays in the loading process of a warehouse are given. In Section 3, the data set, the output of the pre-processing phase, and the fuzzy-clustering phase are presented using a case study under various scenarios. Finally, the discussions on the proposed method and conclusions of the research are given.

2. Materials and methods

2.1. Fuzzy logic

Lutfi Asker Zadeh introduced fuzzy logic in his article published in 1965, as one of the many forms based on soft computation, which he succeeded in getting accepted in the scientific literature after more than five years of hard work (Zadeh, 1965). Fuzzy logic forms the basis of fuzzy set theory: Unlike the assumption in Aristotle set theory which accepts that an element is either an element of a set or not, the degree of membership defined by the membership of existing elements in a set is defined with a different and infinite number of membership degrees between 0 and 1. Using the If-Then rule structure for reasoning with fuzzy logic, a nonlinear mapping between input and output can be obtained (Ross, 2016). On the other hand, the importance and effect of fuzzy thinking in solving many industrial problems, semi and final products, and also scientific studies cannot be ignored for real-life applications at present.

2.2. Fuzzy c-means clustering algorithm

Data analysis is the process of evaluating data by analyzing, clearing, transforming, and modeling. It provides a useful software tool for processing large data volumes and the application of such analysis is ever-increasing (Ott and Longnecker, 2020). Data clustering is an essential data analysis technique that is typically used for classifying data or finding similarities and differences between the elements of a data set. It is used in many different fields such as machine learning, data mining, pattern recognition, image analysis, and bioinformatics (Rao and Vidyavathi, 2010).

Putting each point of the data set in a single cluster based on Aristotle's cluster theory is the basis of the traditional clustering methods, in which the clustering algorithm divides the unlabeled data set into different groups according to similarity. Compared to data classification, data clustering is considered as an unsupervised learning process that does not require any tagged data set known as training data, and the performance of the data clustering algorithm is generally worse than the classification problem. Although data classification provides better performance, it requires a data set labeled as training data. Therefore, there are many suggested algorithms to improve the clustering performance. Clustering is considered to be a classification of similar objects, or in other words, the precise division of data sets into clusters so that the data in each set share some common characteristics. Hierarchical, partitioning and mixed model methods are the three main types of clustering operations applied to organize data. The choice of implementation of a particular method usually depends on the desired output type, known performance of the method with certain data types, available hardware and software facilities, and the size of the data set (Rao and Vidyavathi, 2010).

k-means or hard *c*-means clustering is a segmentation method applied to analyze data. It treats observations of data as objects based on locations and distance between various input data points. The division of objects into *k* sets of mutually exclusive clusters is done in such a way that the objects in each cluster stay as close as possible to each other, but as far as possible from objects in other clusters. In the hard *c*-means algorithm, each cluster is characterized by its center point, i.e. the center of gravity. Often used in clustering, this distance information does not represent spatial distances. In general, the problem of finding the global optimum at which objects are closest to each other but furthest from objects in other clusters is a starting point selection problem. For this purpose, the use of several iterations, usually with a random starting point, leads to a solution, namely a global optimum (Ramamoorty, 2019). In a data set, in the desired number of *k* clusters with predefined initial values, the *k*-means clustering algorithm finds the preferred number of different clusters and their centers. A center of gravity is the point whose coordinates are obtained by calculating the mean of each of the coordinates of the points of the samples assigned to the clusters.

The steps of the *k*-means clustering algorithm can be given as follows.

Algorithm 1. *The steps of the k-means clustering algorithm* (Kanungo and Mount, 2002)

Step 1) Select the scalar parameter *k* (must be specified to select the preferred number of clusters).
Step 2) Initial selection: Select *k* starting points used as initial predictions of cluster centers. These selections are taken as starting cluster centers.
Step 3) Classification: Take each point in the data set and assign it to the cluster whose center point is closest to it.
Step 4) Center of gravity calculation: After assigning each point in the data set to a cluster, calculate the new cluster centroids.
Step 5) Termination criteria: The new cluster centers of gravity are then considered as new initial values and steps (3) and (4) of the algorithm are repeated. This process continues until the data point no longer changes or the centers of gravity move.

At the end of these 5 steps, clustering is obtained with the *k*-means clustering algorithm. Real data samples are collected before implementing the clustering algorithm. Priority should be given to the features that define each data sample in the database (Kanungo and Mount, 2002). The values of these properties form a feature vector $(x_{i1}, x_{i2}, x_{i3}, \cdots, x_{im})$; where x_{im} is the value of m dimensional space. As with other clustering algorithms, the *k*-means clustering algorithm requires a distance measure between points to be defined. This distance measure is used in step (3) of Algorithm 1. A common measure of distance is Euclidean or Manhattan distance. If the different features used in the feature vector have different relative values and ranges, the distance calculation may be distorted, and therefore scaling may be required in the feature vector.

The fuzzy *c*-means clustering (FCM) method has been introduced to the literature for the first time by Bezdek (1981) by discussing the hard *c*-means clustering method and the fuzzy set concept together. FCM is an unsupervised clustering algorithm applied to a wide variety of problems associated with feature analysis, clustering, and classifier design. FCM is widely used in pattern recognition, image analysis, medical diagnosis, shape analysis, and target recognition (Yong et al., 2004). In the FCM method, every point in the data set can be a member of more than one set with certain degrees, thanks to membership rating in the fuzzy logic set concept. This property naturally allows obtaining the relation of a point with different cluster centers, which cannot be obtained in hard *k*-means clustering (Ross, 2016).

The FCM clustering algorithm is derived from a natural interpretation of fuzzy membership degrees. In other words, the concept of membership degree in fuzzy logic has a clustering feature by its nature, and in this respect, it is very useful to benefit from fuzzy logic theory for clustering. Therefore, in this study, it was decided to focus on clustering with fuzzy logic. The steps of the FCM algorithm are similar in structure to the *k*-means clustering algorithm and can be given as:

Algorithm 2. *The steps of the FCM algorithm* (Ross, 2016)

Step 0.a) First, the number of clusters (c) is determined ($2 \le c < n$ and $c \neq 1$).
Step 0.b) Then the initial value of the $\mathbf{U}(0)$ quotient matrix is assigned. Each step in this algorithm will be labeled r ($r = 0, 1, 2$).
Step 1) The c center vectors $\{v_{ij}\}$ are calculated for each step:
$$v_{ij} = \frac{\sum_{k=1}^{n} (\mu_{ik})^m . x_{kj}}{\sum_{k=1}^{n} (\mu_{ik})^m}$$

(continued on next page)

Step 2) The distance matrix **D** of size *cxn* is calculated.
$D_{ij} = \left(\sum_{j=1}^{m}\left(x_{kj} - v_{ij}\right)^{2}\right)^{1/2}$
Step 3) The partitioning matrix $\mathbf{U}(r)$ is calculated at each r step:
$\mu_{ij}^{r} = \left(\frac{1}{\sum_{j=1}^{c}\left(d_{ik}^{r}/d_{jk}^{r}\right)^{\frac{2}{m-1}}}\right)$
If the value of $(\mathbf{U}(k+1) - \mathbf{U}(k))$ for any newly obtained $U(k+1)$ is less than a specified value, the algorithm is terminated. Otherwise, cluster centers are updated and all transactions continue from step 1.

The scientific computing environment code for the FCM algorithm within the scope of the study is shown in Algorithm 3.

Algorithm 3. *FCM code*

```
[nInputs, nInputSamples ] = size(inputs);
  % Number of Clusters
   nC = nClusters;
  % fuzzification parameter
  m = fuzzification;
  % Generate the random association of inputs to the clusters,
  values [ 0, 1 ]
  n = rand(nInputs, nC);
   nTotal = sum(n, 2);
   RandomAssociationValues = (n./nTotal);
  % Initial Membership Matrix
  U = RandomAssociationValues;
  % Cluster's centroids
  C = zeros(nC, nInputSamples);
  % Aux Parameters
  t = 0;
   currentError = 1;
  while currentError > error
  U0 = U;
  % Calculate the cluster's centroids
  for i = 1 : 1 : nC
  for j = 1 : 1 : nInputSamples
  C(i, j) = (sum (inputs(:, j) .* (U(:, i).^m)))/(sum (U(:, i).^m));
  end
  end
  % calculate dissimilarly between the inputs and centroids using
  % euclidean distance
  distanceFromCluster = zeros(nInputs, nC);
  for k = 1 : 1 : nC
  distance = sum(((inputs - C(k, :)).^2), 2);
  distanceFromCluster(: , k) = sqrt(distance);
  end
  % update membership matrix values
  den = sum(((1./distanceFromCluster).^(1/(m-1))), 2);
  for z = 1 : 1 : nC
  num = ((1./distanceFromCluster(:, z)).^(1/(m-1))) ./ den;
  U(:, z) = num';
  end
  currentError = (sqrt((U - U0).^2));
  t = t + 1;
   endofwhile
```

2.3. Proposed FCM based key performance indicator

The sample data set and calculation steps for the KPI developed for the measurement of shipments in pre-defined periods in a warehouse are explained in this section. The process flow chart for KPI calculations is given in Fig. 1.

In Fig. 1, the unit price (UP), monthly demand quantities (MD), the number of products loaded from the warehouse (PQL), the demand that cannot be loaded on time (ADD), and the average delay times (ADT) of the products that cannot be loaded on time are entered into the data preparation block as input data. At the output of the preprocessing phase, the ratio of late quantities (PLA) for each product using Eq. (1), the cost of the late products (CDP), normalized CDP values for each product according to total cost (NCDP) using Eq. (2) and Eq. (3), and normalized values of the average delay times according to the maximum delay time (NVADT) using Eq. (4) are obtained as follows:

$$PLA_i = \frac{ADD_i}{MD_i} \tag{1}$$

$$NCDP_i = ADD_i \times (UnitPrice)_i \tag{2}$$

$$NCDP_i = \frac{CDP_i}{(TotalCDP)} \tag{3}$$

$$NVADT_i = \frac{ADT_{A^{\circ}}}{Max(ADT_i)} \tag{4}$$

As seen in Fig. 1, the vectorial values of PLA, NCDP, and NVADT obtained at the end of the first calculation process are given as input to the fuzzy *c*-means clustering algorithm. The second layer (function) in Fig. 1 is the fuzzy clustering step. The output of the fuzzy clustering layer will be the C matrix showing the values of the centers and the U matrix expressing the fuzzy set. The KPI calculation process is given in the third block in Fig. 1. In this block, firstly, the distances of the three center point to the origin using Eqs. (5)–(7) and the center points distance vector (dcV) using Eq. (8) are calculated and given as follows:

$$dc_1 = \sqrt{\sum_{j=1}^{3} C_{1j}^2} \tag{5}$$

$$dc_2 = \sqrt{\sum_{j=1}^{3} C_{2j}^2} \tag{6}$$

$$dc_3 = \sqrt{\sum_{j=1}^{3} C_{3j}^2} \tag{7}$$

$$\mathrm{dcV} = [dc_1 dc_2 dc_3] \tag{8}$$

Then, for N products, the number of products in each fuzzy cluster using Eqs. (9)–(11) is calculated as a fuzzy value ($nc_i \in \mathbb{R}^+$) and then ncV using Eq. (12) are obtained as:

$$nc_1 = \sum_{i=1}^{N} U_{i1} \tag{9}$$

$$nc_2 = \sum_{i=1}^{N} U_{i2} \tag{10}$$

$$nc_3 = \sum_{i=1}^{N} U_{i3} \tag{11}$$

$$\mathrm{ncV} = [nc_1 nc_2 nc_3] \tag{12}$$

The ncV vector elements are divided by the number of products (N) as ncN in Eq. (13):

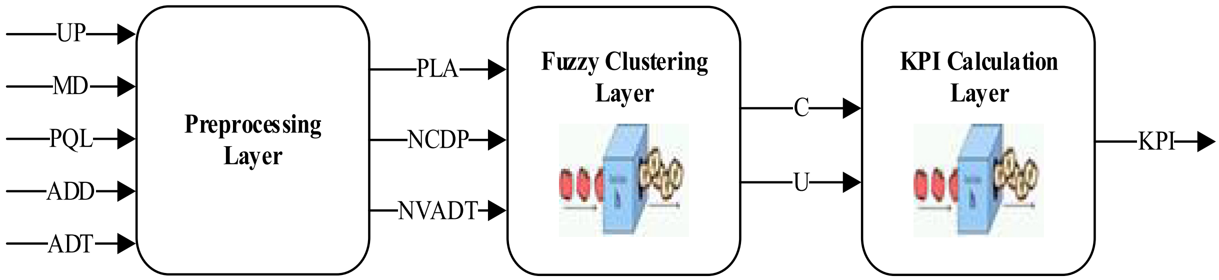

Fig. 1. The KPI calculation process flow chart.

$$\mathrm{ncN} = \left[\frac{nc_1}{N}\ \frac{nc_2}{N}\ \frac{nc_3}{N}\right] \tag{13}$$

Warehouse loss performance scale value (Ax) using Eq. (14) is obtained by making the inner product of the ncN and dcV vectors:

$$Ax = \mathrm{dcV} \otimes \mathrm{ncN} \tag{14}$$

At this stage, maximum ($maxS$) and minimum ($minS$) performance values of the examined warehouse must be defined to express the performance of the warehouse system. For the $minS$ value, it is assumed that the warehouse is running at full performance without any delay. In this case, $minS$ will always take the value 0 ($minS = 0$). However, the $maxS$ value is a parameter specific to the repository under consideration and must be obtained specifically for the relevant repository. For this purpose, to calculate the $maxS$ within the scope of the study, the working condition of the warehouse with the worst possible performance has been tried to be obtained. The $maxS$ value can be adjusted instantaneously according to the dynamics of the warehouse in real warehouse systems. In this study, for calculating the $maxS$, it is assumed that the product requests from the consumers could be loaded with a delay of an average of 30 days for that month.

After scaling the value of Ax with the obtained [$minS$, $maxS$] value between 0 and 100, the scaled warehouse loss performance scale AxN value using Eq. (15) is obtained as follows:

$$AxN = \mathrm{round}\left(\frac{(Ax - minS) \times (maxA - minA)}{(maxS - minS)} + minA\right) \tag{15}$$

As a result, by subtracting the obtained AxN value from the number 100, the KPI in Eq. (16) that provides holistic data in pre-defined periods for the entire warehouse is obtained as follows:

$$KPI = 100 - AxN \tag{16}$$

In this section, the steps of the FCM algorithm-based model, which enables the calculation of the KPI value depending on the delays in the loads for the warehouse, are explained. When the industrial application phase is passed, the maxS values for the warehouses used in the sector of the application will be produced and the KPI obtained with the Eq. (16) for the system will be made compatible with the real warehouse method system. The scenarios regarding this proposed KPI model and the outputs related to these scenarios are discussed in the following section.

3. Results

3.1. Defining the data set

The product names, product prices, and demand volumes were obtained from the study conducted by Zenkova and Kabanova (2018), and some arrangements were made to be used in the analysis given in Table 1. Then, Table 2 also develops for KPI design. The demand data for January and the price data of the products are taken from Table 1, and the PQL, ADD, and ADT data are randomly determined and Table 2 is obtained as case data in this paper.

3.2. Processing the data set for calculations

Table 3 shows the calculations for the default data set. This data set will be used as Scenario 1 (original data set) in the following sections.

The **C** and **U** matrices, which are the outputs of the FCM for Scenario-1 (S1), are shown in Table 4. For the **U** matrix, the bold

Table 1
Basic data set (Zhu et al., 2017).

Name of the product	Unit price	Demand in January
SKU-1	98	1202
SKU-2	250	119
SKU-3	194	322
SKU-4	350	100
SKU-5	200	103
SKU-6	100	98
SKU-7	30	280
SKU-8	286	20
SKU-9	100	50
SKU-10	230	18

Table 2
Default data set to be used for analysis.

Name of the product	Unit price	Demand in January	PQL	ADD	ADT
SKU-1	98	1202	1000	202	12
SKU-2	250	119	119	0	0
SKU-3	194	322	275	47	5
SKU-4	350	100	90	10	7
SKU-5	200	103	103	0	0
SKU-6	100	98	67	31	3
SKU-7	30	280	200	80	1
SKU-8	286	20	20	0	0
SKU-9	100	50	49	1	10
SKU-10	230	18	16	2	9

Table 3
Calculated values for PLA, NCDP, NVADT, and NADT.

Demand in January	ADD	PLA	ADT	NCDP	NVADT	Normalized ADT (NADT)
1202	202	0.1681	12	1176	0.1534	1.0000
119	0	0.0000	0	0	0.0000	0.0000
322	47	0.1460	5	970	0.1265	0.4167
100	10	0.1000	7	2450	0.3196	0.5833
103	0	0.0000	0	0	0.0000	0.0000
98	31	0.0000	0	0	0.0000	0.0000
280	80	0.0000	0	0	0.0000	0.0000
20	0	0.0000	0	0	0.0000	0.0000
50	1	0.0200	10	1000	0.1304	0.8333
18	2	0.1111	9	2070	0.2700	0.7500

Table 4
C and **U** matrices for Scenario 1.

$$\mathbf{C}\ \text{Matrix} = \begin{bmatrix} 0.0103 & 0.0012 & 0.0058 \\ 0.1000 & 0.2061 & 0.7941 \\ 0.2486 & 0.0590 & 0.2611 \end{bmatrix} \qquad \mathbf{U}\ \text{Matrix} = \begin{bmatrix} 0.0023 & \mathbf{0.9898} & 0.0079 \\ \mathbf{1.0000} & 0.0000 & 0.0000 \\ 0.0333 & 0.0588 & \mathbf{0.9079} \\ 0.0142 & \mathbf{0.9089} & 0.0769 \\ \mathbf{1.0000} & 0.0000 & 0.0000 \\ 0.0010 & 0.0001 & \mathbf{0.9989} \\ 0.1619 & 0.0032 & \mathbf{0.8349} \\ \mathbf{1.0000} & 0.0000 & 0.0000 \\ 0.0005 & \mathbf{0.9981} & 0.0014 \\ 0.0001 & \mathbf{0.9997} & 0.0002 \end{bmatrix}$$

Table 5
Definitions of the Scenarios.

Scenario	Definition
*K*0	The warehouse has been turned off. Thus, no orders that had to be loaded that month could be fulfilled. Zero unit loading and 30 days delay.
*I*0	The warehouse worked at full efficiency. There were no orders from the warehouse that could not be met on time. Unloaded quantities and delays are zero for all orders
*K*1	Different from the original data (S1), SKU1/SKU2/SKU3's late quantity and times are increased. The time for the SKU3 product has not changed. The statuses of all other orders are fixed.
*I*1	Different from the original data set (S1) SKU1/SKU3/SKU4's late quantity and times are reduced. Everything about the remaining products is fixed.
*K*2	The amount of delay (12 units) and times (12 days) are taken equally for all orders in the warehouse.
*S*1	Original data set. It is the data set to be used as a reference data set.
*S*2	Different from S1, the number of on-time loaded deliveries has been increased by 1 (SKU-1). The SKU-1 for that month is loaded on time.
*S*3	Different from S1, the number of on-time loaded deliveries has been increased by 2 (SKU-1 and SKU-2). SKU-1 and SKU-2 for that month are loaded on time.
*S*4	Different from S1, the order quantities of all products that cannot be loaded are 30 days late.

numbers indicate the cluster with the maximum value. As a soft clustering technique is used with FCM, an item has membership with a degree to all clusters. These matrices are the inputs of the block belonging to the KPI calculation process, as seen in Fig. 1.

Table 5 includes the definitions for nine different scenarios. Then, the outputs of the **C** and **U** matrices for each scenario using the FCM algorithm are summarized in Table 6-8 respectively.

Performance indicators, Ax, and KPI values for all the scenarios explained above are summarized in Table 9.

4. Discussion

In this study, in order to simulate the KPI under different situations, nine scenarios are conducted. These scenarios express the worst case of the warehouse performance with Scenario- K0 and the best case with Scenario-I0. Other scenarios express performance levels corresponding to different situations between these two endpoints. Simulation studies analyze whether the proposed method accurately measures the end-points and intermediate states. KPI values were obtained, where the proposed approach produced the expected results in the planned scenarios. This situation is shown in detail in Table 9. When the scenarios are examined, it is understood from the KPI and Ax values given in Table 9 that the KPI based on the FCM approach produces systematically acceptable logical results. In order to provide the on-time loaded warehouse, the system's max and min Ax values were found and a scalable KPI in the range of 0–100 was obtained using these values for the FCM based KPI. The lower and upper limits set for Ax can be used as generalized parameters and the KPI proposed with this structure applies to many different sectors. As a result, it can be easily argued that the proposed KPI based on the FCM approach works well with scenarios and is theoretically generalizable.

5. Conclusions

In this study, an artificial intelligence-aided KPI is designed for the loading performance of a warehouse, and the analysis is made based on different scenarios. The basic philosophy of engineering studies can be expressed as the application of scientific knowledge to technology. Different metric measures are being proposed to measure the effectiveness and efficiency of warehouse processes. These developed measures are used to indirectly measure the level of customer satisfaction. Considered in this context, the proposed KPI integrated with the fuzzy *c*-means approach that can directly affect customer service quality for warehouse management, which is very critical with its economic dimensions, is very important in terms of application. Since the proposed KPI can be used to directly measure the effect on customer satisfaction, it can be argued that it brings an industrial and scientific perspective. Therefore, the proposed system can be straightforwardly used by researchers and engineers to obtain performance gain in warehouse loading man-

Table 6
Function outputs for scenarios K0, I0, K1 based on the FCM approach.

Scenario – *K0*			**Scenario – *I0***			**Scenario – *K1***		
C matrix			**C** matrix			**C** matrix		
1.00	0.17	1.00	0	0	0	0.15	0.14	0.61
1.00	0.04	1.00	0	0	0	0.83	0.31	0.99
1.00	0.12	1.00	0	0	0	0.18	0.02	0.10
U matrix			**U** matrix			**U** matrix		
0.0000	**0.9997**	0.0003	0	0	0	**0.9399**	0.0431	0.0170
0.0439	0.0012	**0.9549**	0	0	0	0.0000	**1.0000**	0.0000
0.0016	0.0023	**0.9961**	0	0	0	0.3581	0.0128	**0.6291**
0.9961	0.0003	0.0036	0	0	0	**0.9749**	0.0021	0.0230
0.0006	0.0005	**0.9890**	0	0	0	0.0121	0.0005	**0.9874**
0.0001	**0.9994**	0.0005	0	0	0	0.0181	0.0008	**0.9811**
0.0011	**0.9931**	0.0058	0	0	0	0.0150	0.0001	**0.9849**
0.9508	0.0005	0.0487	0	0	0	0.0104	0.0006	**0.9880**
0.0001	**0.9994**	0.0005	0	0	0	**0.9945**	0.0009	0.0046
0.0003	0.00004	**0.9993**	0	0	0	**0.9999**	0.0000	0.0001

Table 7
Function outputs for scenarios I1, K2, 1 based on the FCM approach.

Scenario – I1			Scenario – K2			Scenario – 1/original data set		
C matrix			C matrix			C matrix		
0.28	0.05	0.20	0.08	0.09	1.00	0.0103	0.0012	0.0057
0.01	0.03	0.06	0.21	0.07	1.00	0.0100	0.2060	0.7940
0.07	0.35	0.95	0.63	0.14	1.00	0.2490	0.0590	0.2610
U matrix			**U** matrix			**U** matrix		
0.0003	**0.9996**	0.0001	**0.9782**	0.0214	0.0003	0.0023	**0.9898**	0.0079
0.0016	**0.9983**	0.0001	**0.9788**	0.0211	0.0001	**0.9998**	0.0001	0.0001
0.0010	**0.9989**	0.0001	**0.9971**	0.0028	0.0002	0.0333	0.0587	**0.9080**
0.2430	**0.7541**	0.0029	**0.8038**	0.1948	0.0014	0.0142	**0.9089**	0.0769
0.0017	**0.9982**	0.0001	**0.9681**	0.0318	0.0001	**0.9998**	0.0001	0.0001
0.9939	0.0057	0.0004	**0.8199**	0.1800	0.0001	0.0011	0.0002	**0.9987**
0.9761	0.0237	0.0002	**0.9500**	0.0499	0.0001	0.1619	0.0032	**0.8349**
0.0016	**0.9982**	0.0002	0.0001	0.0001	**0.9998**	**0.9998**	0.0001	0.0001
0.0007	0.0004	**0.9989**	0.0012	**0.9987**	0.0001	0.0005	**0.9980**	0.0015
0.0007	0.0004	**0.9989**	0.0001	0.0001	**0.9998**	0.0001	**0.9996**	0.0003

Table 8
Function outputs for scenarios 2, 3, 4 based on the FCM approach.

Scenario – 2			Scenario – 3			Scenario – 4		
C matrix			C matrix			C matrix		
0.08	0.27	0.86	0.08	0.31	0.87	0.70	0.04	1.00
0.01	0.00	0.01	0.00	0.00	0.00	0.87	0.12	1.00
0.25	0.07	0.32	0.30	0.03	0.20	0.99	0.12	1.00
U matrix			**U** matrix			**U** matrix		
0.0000	**1.0000**	0.0000	0.0000	**1.0000**	0.0000	0.0865	**0.8849**	0.0286
0.0000	**1.0000**	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0006	**0.9994**
0.0946	0.0273	**0.8781**	0.0000	**1.0000**	0.0000	0.0001	**0.9996**	0.0003
0.9779	0.0035	0.0186	**0.9885**	0.0031	0.0074	0.0087	**0.8162**	0.1751
0.0000	**1.0000**	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000	1.0000
0.0002	0.0002	**0.9996**	0.0004	0.0027	**0.9969**	**0.9997**	0.0003	0.0000
0.0041	0.2920	**0.7039**	0.0002	0.0148	**0.9850**	**0.9998**	0.0002	0.0000
0.0000	**1.0000**	0.0000	0.0000	**1.0000**	0.0000	0.0002	0.0070	**0.9928**
0.9938	0.0013	0.0049	**0.9951**	0.0016	0.0033	0.0025	0.0586	**0.9389**
1.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000	**0.9998**	0.0002	0.0000

Table 9
KPI scenario analysis based on FCM approach.

Scenarios	KPI	Ax	Explanation	Expected Condition	Actual Condition
Scenario – K0	0	14.1860	Warehouse closed	0	0
Scenario – I0	100	0	Full performance	100	100
Scenario – K1	64	5.1405	Pessimistic scenario	Decrease	Correct/Acceptable
Scenario – I1	77	3.2021	Good condition	Decrease	Correct/Acceptable
Scenario – K2	26	10.4674	Bad condition	Decrease	Correct/Acceptable
Scenario – 1	69	4.3427	Original data set	Reference value	Reference value
Scenario – 2	72	3.9177	Good condition	Increase	Correct/Acceptable
Scenario – 3	75	3.4898	Good condition	Increase	Correct/Acceptable
Scenario – 4	5	13.4201	Bad scenario	Decrease	Correct/Acceptable

agement. The fuzzy logic approach is easy to understand, easy to implement, and can be easily coded and developed for the solution of an industrial problem. For that reason, new versions of this study can be easily produced with different input parameters or pre-processing operations and thus can guide the development of different perspectives.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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