Research Article

Analysis of container terminal accidents using fuzzy c-means

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DOİ: 10.51513/jitsa.957371

Abstract: Maritime transportation is the key element of global trade in recent years. Moreover, container shipping companies aim to complete door-to-door cargo operation with lower costs and increased speed. Determination of delays and possible accidents play vital role on cargo transportation process in a container terminal. In this scope, 65 container terminal accident reports are evaluated with Fuzzy C-means method to cluster within scope of root cause analysis. Three, four, and five number of clusters are created to determine possible causes of accidents. Accident cases are grouped in the view of relation of operations as cargo and port. Port related accidents are found mainly as related with maintenance processes in weekdays. On the other hand, cargo related accidents occurred in weekends and during night shifts. In this scope, the results revealed that Fuzzy C-Means method could be used to analyse container terminal accidents.

Anahtar Kelimeler: Maritime Transportation, Accident Analysis, Fuzzy logic, Container terminal, Clustering

Bulanık c-ortalama kümeleme algoritması ile konteyner terminali kaza analizi

Özet: Deniz taşımacılığı, son yıllarda küresel ticaretin kilit unsuru olarak görülmektedir. Ayrıca konteyner taşımacılığı yapan denizcilik şirketleri, kapıdan kapıya kargo operasyonunu daha düşük maliyetler ve artan hızlar ile tamamlamayı hedeflemektedir. Konteyner terminalinde kargo taşımacılığı sürecinde gecikmelerin ve olası kazaların tespiti hayati önem taşımaktadır. Bu kapsamda 65 konteyner terminali kaza raporu, Bulanık C-ortalama kümeleme algoritması ile kök neden analizi kapsamında kümelenerek değerlendirilmiştir. Olası kaza nedenlerini belirlemek için üç, dört ve beş adet küme oluşturulmuştur. Kaza vakaları, operasyonların ilişkisine göre kargo ve liman olarak gruplandırılmıştır. Limanla ilgili kazalar daha çok bakım süreçleriyle ilgili olarak bulunmuştur ve hafta içi meydana geldiği görülmüştür. Öte yandan, hafta sonu ve gece saatlerinde kargo ile ilgili kazalar meydana geldiği çalışma sonucunda elde edilmiştir. Bu kapsamda, sonuçlar Bulanık C-ortalama kümeleme algoritmasının konteyner terminal kazalarını analiz etmek için kullanılabileceğini ortaya koymuştur.

Key words: Deniz taşımacılığı, Kaza analizi, Bulanık mantık, Konteyner terminali, Kümeleme

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Received 29.03.2022; accepted 10.04.2022
Peer review under responsibility of Bandirma Onyedi Eylul University.

1. Introduction

Maritime cargo operations consist of multiple equipment planning as well as port worker assignments. Optimisation of these elements could provide precious advantages of better cargo handling times and increased cargo throughput. In contrast, missing of safety culture practices during port congestion could cause to interrupt cargo operations. Accidents, near-misses, or incidents which lead to undesired circumstances could affect the performance of maritime ports. On the other hand, determining human errors in operations is the key element of achieving safety culture.

Human factor analysis could provide better understanding of cargo operations. These analyses explain factors such as distraction, lack of resources, stress, pressure, lack of awareness, lack of teamwork, and complacency. The International Maritime Organization (IMO) defined human elements as error, performance, environment, safety, mental action, and management (Sha, 2020). In this scope, this study focuses to find possible port accident causes which could be related to port worker age, experience, time of the accident, and relationship of maintenance or cargo operations using unsupervised clustering method as Fuzzy C-means. The aim of the study is to cluster 65 different accident cases with Fuzzy C-means method and compare groups in the view of accident case variables. Accident reports are analysed with unsupervised algorithm to determine which factor could lead an accident in a cargo operation rather than using root cause analysis methods.

The paper is organized as following: the second section is devoted to the literature. In the third section, the methodology is explained. The case study is explained in the section 4. The results and discussions are presented in section 5. The conclusions are specified in the last section.

2. Literature

Maritime stakeholders and management companies aim to complete cargo operation with the lowest carbon footprint and voyage times. To achieve the best port turnaround time, the authority of the terminal calculates berth and quay allocations with optimized quantity of workers and equipment. In this manner, every port worker needs to perform assigned duties within the range of specified time. Due to limited time of operation and extended watch, the worker could fail to comply with safety rules which prevents incident, accident, or near-misses. Human factor analysis could help to improve and maintain optimized cargo operation. In this scope, the literature section is focused on maritime accidents, clustering, and other related studies using fuzzy logic.

Zhang et al. (2021) introduced Geospatial techniques of Kernel Density Estimation (KDE) and K-means clustering method to obtain the profile of global maritime accidents using data from 2003 to 2018. The authors indicated that diverse accident places and specifications were found. Paolo et al. (2021) investigated 1079 maritime accidents using Semi-supervised Recursively Partitioned Mixture Models to categorize and identify causal themes. The results showed that poor education and training of seafarers with lack of monitoring were common causes in accidents. Yang et al. (2018) aimed to analyse the causes of maritime accidents using Apriori algorithm with real maritime accident data. The authors stated that the characteristics and causes of maritime accidents in Zhejiang were summarized. In similar, Changhai & Shenping (2019) used Apriori algorithm to carry out association rule learning of maritime accidents data. The potential relation between causal factors was found.

Budiyanto & Fernanda (2020) studied work accidents in container terminals using Fault Tree Analysis method. The authors carried out a risk assessment with a risk matrix method. The result showed that traffic accidents were the highest risk value in container terminal operations. Moreover, the negligence in operating vehicles/equipment caused accidents with a higher rate. Ding & Tseng (2013) used fuzzy risk assessment tool to investigate safety operations in a container terminal. The results provided that the factor of communication misunderstanding influenced risk frequency while human negligence and error factor influenced risk severity. John et al. (2014) proposed a novel fuzzy risk assessment technique to facilitate uncertainties and to optimise performance effectiveness in seaport operations. The study revealed a robust mathematical framework of the system and a step-by-step analysis. Khan et al. (2022) analysed 352 cargo accidents from 1960 to 2018 in ports. The authors developed the Human

Factors Analysis and Classification System for Port Environment Hazardous Cargo Accidents approach. The findings indicated that the most prominent factors such as violations, limited intellect, inappropriate supervision, and an inadequate safety culture were found in hazardous cargo accidents. Khorram (2020) proposed port risk assessment model which utilized a fuzzy analytical hierarchy process–VIKOR combined approach in a port container terminal. The proposed AHP-entropy-based framework helped to implement decision makers' subjective judgments by Z-numbers and to regulate subjective weights. Mokhtari et al. (2012) used fuzzy set theory to evaluate and describe risk factors in the port and terminal operations. The proposed approach proved that the decision support framework could be used to model risk evaluation of ports and terminals. Mollaoğlu et al. (2019) aimed to identify risk factors using Fuzzy AHP method by calculating expert judgements. The human factor and communication level were found the most important factors that have a vital role on Occupational Health and Safety (OHS). Özdemir (2016) investigated to identify factors caused occupational accidents in ports using Fuzzy DEMATEL and Fuzzy TOPSIS methods. The most important factors were found as human error, administrative reasons, insufficient equipment, improper use of equipment, and working environment and conditions. Qiao et al. (2020) introduced human factor analysis framework named multidimensional analysis model of accident causes (MAMAC). The authors integrated intuitionistic fuzzy set theory and Bayesian Network to MAMAC. The aim of the study is to form a dynamic human factors analysis using a sand carrier accident database for maritime accident scenarios. The results of the study revealed that unsafe acts were not a focus for maritime scholars and investigators. Sur & Kim (2020) analysed 9 types of fishing vessel accidents from 1988 to 2016 using the fuzzy comprehensive evaluation method. Furthermore, the authors calculated and classified risks of each type of accidents to establish risk reduction measures for decision makers. Wang et al. (2021) studied an ordered logistic regression model to explore the relationship between influencing factors and the severity of marine accidents. The worldwide accident reports were used to assist maritime authorities for preventing the occurrence of serious marine accidents. The results showed that the severity of accidents was positively related to sinking accidents, inadequate ship manning, poor theoretical knowledge, and less sea experience.

3. Methodology

The Fuzzy C-means method which is a soft clustering algorithm was introduced by Dunn (1973) and advanced by Bezdek et al. (1984). The minimization objective function of the method is:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} \left\| x_i - v_j \right\|^2 ; \quad 1 < m < \infty \tag{1}$$

m : fuzzy partition matrix exponent

u_{ij} : the degree of membership of x_i in the cluster j

x_i : the ith pattern in D-dimension data

v_j : jth cluster centre in the D-dimension

The FCM clustering procedure is defined as (Saxena et al., 2017):

First, a value of c (number of cluster) is set up. Second, initial cluster prototype $V_1, V_2, \ldots, V_c$ from X_i, i=1, 2, …, N is selected. Then, the distance $||X_i\text{-}V_j||$ between prototypes and objects are computed. Later, the elements of the fuzzy partition matrix (i = 1, 2, …, N; j = 1, 2, …, c) $u_{ij} = \left[\sum_{l=1}^{c}\left(\frac{||x_i - v_j||}{||x_i - v_l||}\right)\right]^{-1}$ and the cluster prototypes (j = 1, 2, …, c) $V_j = \frac{\sum_{i=1}^{N} u_{ij}^2 . x_i}{\sum_{i=1}^{N} u_{ij}^2}$ are calculated. Finally, if the number of iterations exceeds a given limit or the convergence is attained, calculations are finalized. If the criteria are not met, third step should be repeated.

4. Case study

The dataset of the study is gathered from accident report occurred in two different container terminals located in Turkey for a six-year period beginning from 2012 to 2018. 65 different accident cases are analysed to determine human errors or possible effects on operation differences. Both container terminals have similar quay for various size of vessels. The vessel dimensions in terminals diverse from 100 meters to 399 meters. On the other hand, turnaround times of the vessels are found similar in the scope of port congestion situations. Accident cases are divided into two groups as cargo operation and others. To give an example, maintenance accident of port equipment is classified as the other group. In similar, two variables are created to determine effects of day and night shifts as well as weekdays and weekends. The main idea of analysing the time of the operation is to determine whether human factors are related with circadian rhythms or not. Moreover, port workers could feel more relaxed in the weekends due to general rest days of other industry workers although vessel cargo operations are not correlated with weekends or weekdays.

The causes of the 65 different accident cases are analysed, and more than one day off accident cases are found in main groups as following: Struck by moving object, slips, falls from height, vehicle collisions, cuts, falling objects, equipment malfunction, and improper stowage of containers. The dataset of the study which is accident reports is analysed with Fuzzy C-means (FCM) clustering method to determine accident cases using unsupervised algorithm. The advantage of FCM is to provide flexibilities to identify data point which could belong to more than one cluster. In this manner, the cases which might be affected by multiple variables and could belong to more than one cluster are calculated.

5. Results and discussion

The dataset was analysed with Fuzzy C-means clustering method using MS Win 10 operating system and R programming language. Moreover, different libraries were used with R as “ppclust, psych, fclust, cluster, etc.”. the clustering process is completed for three, four, and five different groups to calculate similar accident cases. The metrics of the clustering calculation is in Table 1.

Table 1. *Cluster performance metrics*

Number	Fuzzy Silhouette Index	Partition Entropy	Partition Coefficient
3	0.7421	0.4811	0.7360
4	0.6498	0.6744	0.6404
5	0.6325	0.7713	0.6059

As seen on the results, different performance metrics are found with three, four, and five number of clusters. Although metrics could be used to determine the best cluster, Figure 1 is created to compare accidents for three, four, and five number of clusters as the best and worst.

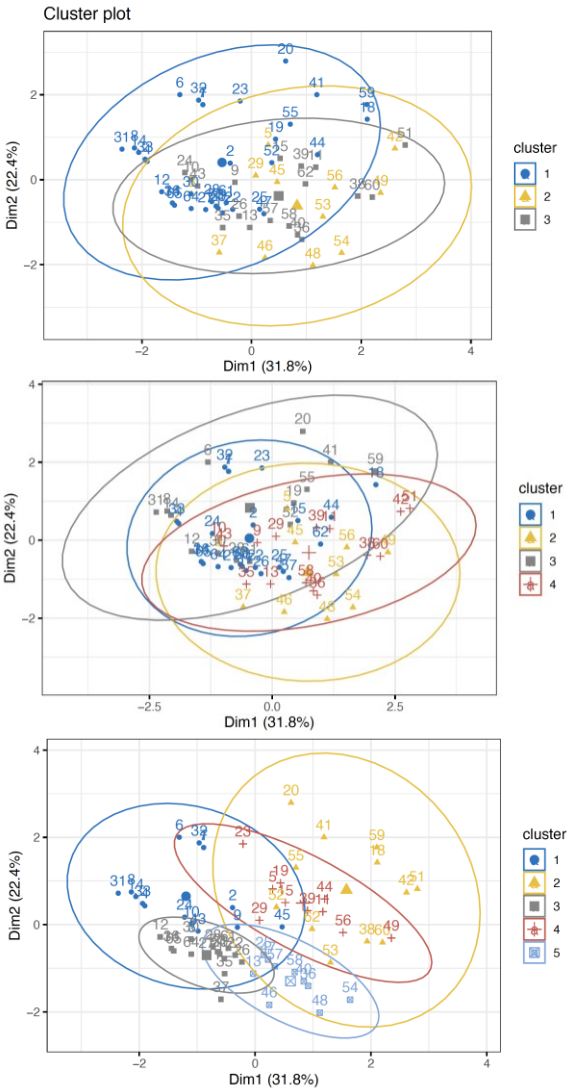

Figure 1. *The plot of clusters.*

The plots of the number of clusters are proved if accident cases could be illustrated better with a five number of clusters. In this scope, mentioned cluster number is selected to analyse accidents further. Accidents belong to single cluster are selected and explained in Table 2.

Table 2. *Accident cases*

	Cluster #1	Cluster #2	Cluster #3	Cluster #4
Case	4, 6, 8, 10, 14, 24, 31, 33	18, 20, 41, 42, 51, 59	37	46

Table 3. *Result of the model*

Cluster	Case	Day of the week	Time of day	Relation	Day off	Age	Experience
1	4	Weekday	Day	Port	3	34	2
	6	Weekday	Night	Port	3	31	2
	8	Weekday	Night	Port	1	28	2
	10	Weekday	Night	Port	10	41	4
	14	Weekday	Day	Port	3	30	2
	24	Weekday	Day	Port	7	38	4
	31	Weekday	Day	Port	5	29	1
	33	Weekday	Night	Port	5	33	2
2	18	Weekend	Night	Cargo	45	34	7
	20	Weekday	Night	Cargo	5	30	5
	41	Weekend	Night	Cargo	2	24	5
	42	Weekend	Night	Cargo	5	47	7
	51	Weekend	Night	Cargo	5	45	8
	59	Weekend	Night	Cargo	1	27	8
3, 4	37	Weekday	Day	Cargo	3	54	1
	46	Weekday	Day	Cargo	1	55	4

In the first cluster, eight different accidents occurred in weekdays during port operations which aim to maintenance purpose. Time of the accident is diverse from day to night. In contrast, experiences of port workers are 2.38 years which could be called as an inexperienced worker.

In the second cluster, six different accidents are analysed for weekends and night shifts. These accidents are found related with cargo operations. On the other hand, experience of workers which are responsible for cargo operations are found 6.67 years.

In the last cluster, two accidents are clustered in cargo operations. These results are not directly related with same specific cluster. The scope of the illustration is to determine whether direct relationship or not. In this view, first two clusters are used for calculation process of accident cases.

The results showed that FCM method could be used to cluster container terminal accidents. Moreover, risk assessment process or root cause analysis could be carried out to understand and prevent possible accidents.

In the first cluster, the accident causes are found as struck by moving object, slips, and falling objects. In similar, falls from height, struck by moving object, and falling objects factors are found for the second cluster. In this manner, two main accident causes are determined as struck by moving object and falling objects.

The accident cases are investigated to determine contributing factors which lead to accidents. Recklessness, physical environment (slippery ground), inexperienced worker, intersecting traffic, poor preplanning, complacency, poor communication, and overtired personnel are found as contributing factors for container terminal accidents.

The limitation of the study could be summarized as three topics. Firstly, possible causes of accidents are found within the group of cases. This process would provide precious assumptions. On the other hand, root cause analysis methods could help to increase safety culture of terminals. Root causes and contributing factors would identify which lead to the incident, accident, or hazards. Secondly, 16 accident cases are found using FCM method. Missing 49 different accident cases would prevail various results with different methods. Lastly, other container terminal accidents reports could be used for international cases.

6. Conclusion

Container terminal accidents could cause delays or interruption of precious cargo operations. Analysing any undesired situation of vessel operation is vital for optimized cargo flow. From near misses to major accidents, these situations should be predicted or prevented.

In this study, 65 container terminal accident cases are analysed with Fuzzy C-means method to cluster reports in the scope of possible similar causes. The results revealed that FCM method could be used to cluster accident cases. The number of clusters are proved identical accident specifications are found such as day of the week, time of the day, and relation of operations. The results could be used to identify potential hazards in a container terminal.

For future studies, risk assessment, root cause analysis, or accident prediction studies could be performed to further analyse causes of accident cases. Moreover, proposal of risk reduction measures would be available for container terminals with FCM method.

Acknowledgement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest Statement

No conflict of interest was declared by the author.

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