Research Article
Turkish Journal of Maritime and Marine Sciences

DOI: 10.52998/trjmms.1069268
Volume: 8 Issue: 2 (2022) 104-114

Comprehensive Analysis of Port State Control on Turkish Flagged Ships Through the Association Rule Mining

Türk Bayraklı Gemiler Üzerine Uygulanan Liman Devleti Denetimlerinin Birliktelik Kuralı Madenciliği ile Kapsamlı Analizi

Türk Denizcilik ve Deniz Bilimleri Dergisi

Cilt: 8 Sayı: 2 (2022) 104-114

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ABSTRACT

Port state control (PSC) inspections are one of the best ways of improving safety at sea. Therefore, it is vital to determine the parameters that cause deficiencies in the prevention of ship accidents. The main purpose of this study is to analyze the PSC inspection results of Turkish flagged ships using the data mining model. Considering a total of 209 PSC inspection reports resulting in the detention of Turkish flagged ships between 2014 and 2019, the Apriori Algorithm was applied using SPSS Modeler 18.0 software to determine the association rules of deficiencies detected. The study found that the safety of navigation, living/working conditions, and emergency systems are the main factors creating association rules in deficiencies. However, when the deficiencies causing detention were analyzed, the most frequently associated variables were safety of navigation, certificate/documentation, and emergency systems. The results of the study are supposed to be useful for the flag state control mechanism to improve the port state control performance of Turkish flagged ships. We recommend that further research collect more data on the PSC inspection of ships flying other flags to update the proposed models and improve their analysis performance.

Keywords: Port State Control, Ship Inspections, Turkish Flagged Ships, Data Mining, Association Rule

Article Info
Received: 7 February 2022
Revised: 14 April 2022
Accepted: 11 May 2022

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To cite this article: Sevgili C., Töz A.C., (2022). Comprehensive Analysis of Port State Control on Turkish Flagged Ships Through the Association Rule Mining, *Turkish Journal of Maritime and Marine Sciences* 8(2): 104-114. doi: 10.52998/trjmms.1069268.

ÖZET

Gemi denetimleri, denizde emniyeti artırmanın en iyi yollarından biridir. Bu nedenle gemi kazalarının önlenmesinde eksikliklere neden olan parametrelerin belirlenmesi hayati önem taşımaktadır. Bu çalışmanın temel amacı, Türk bayraklı gemilerin denetim sonuçlarının veri madenciliği modeli kullanılarak analiz edilmesidir. 2014-2019 yılları arasında Türk bayraklı gemilerin tutulması ile sonuçlanan toplam 209 denetim raporu dikkate alınarak, tespit edilen eksikliklerin birliktelik kurallarını belirlemek için Apriori Algoritması uygulaması SPSS Modeler 18.0 yazılımı kullanılarak yapılmıştır. Çalışmada, seyir emniyeti, yaşam/çalışma koşulları ve acil durum sistemleri eksikliklerinin birliktelik kurallarını oluşturan ana faktörler olduğu bulunmuştur. Bunun yanı sıra, tutulmaya neden olan eksiklikler incelendiğinde, ilişki sıklığı en fazla olan değişkenler seyir güvenliği, sertifika/dokümantasyon ve acil durum sistemleri olmuştur. Çalışmanın sonuçlarının, Türk bayraklı gemilerin liman devleti denetimi performansının iyileştirilmesi için bayrak devleti kontrol mekanizmasına faydalı olacağı düşünülmektedir. Gelecek çalışmalar için önerilen modelleri güncellemek ve analiz performanslarını iyileştirmek adına daha geniş çaplı bir veri setinin kullanılması tavsiye edilmektedir.

Anahtar sözcükler: Liman Devleti Denetimi, Gemi Denetimleri, Türk Bayraklı Gemiler, Veri Madenciliği, Birliktelik Kuralı

1. INTRODUCTION

Port State Control (PSC) is an inspection mechanism applied to foreign-flagged ships, aims to protect navigational safety and the marine environment by detecting substandard ships. Although the control of the safety standards of the ships is in the flag state, the inadequacy of both the flag state and the recognized organizations in the detection of substandard ships has led to the emergence of PSC. Today, PSCs, which are applied in most of the world and considered as the last stage for the safety of ships, have been expanded with regional memorandums (MoU) and agreements. The control of the standards in the PSC inspections is carried out according to the requirements of the international conventions put into effect by the International Maritime Organization (IMO) and the International Labor Organization (ILO). If the ships cannot meet the standards in these conventions, some deficiencies can be revealed by port state control officers, moreover, ships are subject to a certain degree of detention according to the importance of the deficiencies detected (Tsou, 2019; Osman *et al.*, 2020).

PSCs are usually stored in databases of memorandums of which the port state is a member. Although the format and content of the PSC inspection reports vary from memorandum to memorandum, generally, there is information such as ship profile information (ship name, IMO number, flag, age, tonnage, classification society, etc.), inspection information (date of inspection, port state performing inspection, type of inspection, etc.), inspection result (main and sub-deficiencies and deficiencies grounding detention). Over the years, the PSC inspection reports that have accumulated and continue to accumulate in the database of memorandums have created big data related to PSC. This big data can also enable us to reveal hidden information in PSC inspection reports by using data mining methods. In this context, this study analyzed the Turkish flagged ships detained by port state controls using the association rule mining method. This study aims to determine the information that is related to the variables in the PSC inspection reports of ships detained. It is thought that this information will be especially useful for the flag state authority, recognized organizations, and Turkish flagged ship owners to ensure safety standards. Additionally, the fact that there are very few studies on the analysis of PSC with association rule mining in the literature may make this study important in terms of filling the gap in the literature.

The other parts of the study are designed as follows; Literature review related subject and method is given in section 2. Material and method are explained in Section 3. The findings are shown in Section 4. A comparison of study findings with other studies is given in section 5, which is the results and discussion section. Finally, the study concludes with the conclusion section (Section 6).

2. LITERATURE REVIEW

Due to the importance of PSC in maritime safety, researchers have conducted extensive studies on this area. Data from PSC inspections have been used by researchers from different perspectives and methods in the studies. In the beginning, it is seen that the studies were generally on econometric analysis such as logistic regression and correlation analysis, but today, there is a tendency towards data mining and machine learning algorithms. There are a limited number of studies on association rule mining, which is one of the descriptive areas of data mining, and these studies have been conducted recently. Tsou (2019) investigated deficiencies of detention of Tokyo MOU using association rule mining method one of the data mining techniques. Big data analysis showed that the regularity relationship between the deficiencies and the factors related to these deficiencies is accurate and objective. In another study on the Tokyo MoU, the inspection results were examined with association rule mining using the Apriori Algorithm (Fu *et al*., 2020). Ship type, ship age, deadweight (DWT), and gross tonnage (GRT) of ship and deficiencies were included for analysis in their study. Osman *et al*. (2020) analyzed ships inspected in Malaysian ports using the same association rule algorithm. It has been stated that the knowledge discovery in the study can be used in the development of the ship target system and in determining the strategies in PSC inspections. Similarly, Chung *et al*. (2020) also analyzed Taiwan's major ports using the same algorithm. In this study, it was determined that deficiencies related to 'water/watertight conditions' and 'fire safety' were significantly related. Also, the authors determined that ship type has more effect on rule formation than other variables. In addition to the association rule, PSC inspections were also analyzed using various predictive data mining methods of such as Bayesian Networks, Support Vector Machines, Random Forest, Decision Tree (Wang *et al*., 2019; Xiao *et al*., 2020; Fu *et al*., 2020b; Yan *et al*., 2020; Yan *et al*., 2021). The common purpose of these studies was to develop a prediction model that could detect the PSC inspection results and to identify the variables that affect the inspection result.

When the studies on Turkish flagged ships are examined, it is seen that the studies are based on descriptive and relational (chi-square) analysis. Yılmaz and Ece (2017) investigated ship inspection results of Paris MOU (2011-2016). The detention rate of Turkish flagged ships has been found higher than the mean detention rate of Paris MOU. Also, it was determined that if a ship has had 5 or more deficiencies or has been older than 13 years, the risk of detention has been high. Akyar and Çelik (2018) analyzed 578 PSC inspection results of Turkish flagged ships inspected in Black Sea MOU. According to chi-square analyses, results showed that there is a significant relationship between the number of deficiency and inspection results and age. The main most frequently detected deficiencies have been life-saving appliances and safety of navigations. In another study, Tokyo MOU inspection results of the Turkish flagged (2016-2018) were evaluated using descriptive analysis. Life-saving appliances, safety of navigation, and fire safety deficiencies have been the most frequent main deficiencies in a total of 115 inspection results and 226 deficiencies (Bolat, 2019).

3. MATERIAL AND METHOD

In this study, the association rule method, which is one of the descriptive method of data mining, was applied. Data mining, which is also called knowledge discovery in a database, extracts implicit, previously unknown, and probable useful information from big databases (Chen *et al*., 1996).

Data mining is generally divided into two categories as descriptive and predictive. The association rule is included in descriptive data mining, which is used to summarize and generalize. This method, firstly developed by

Agrawal *et al*. (1993), is one of the most important and the most used techniques in data mining. The association rule aims to extract important correlations, frequent patterns, and associations among variables in databases (Zhao and Bhowmick, 2003; Maragatham and Lakshmi 2012). Association rule mining can describe as follows; *"Let I=I_1, I_2,· · ·, I_m be a set of m distinct attributes, T be transaction that contains a set of items such that T ⊆ I, D be a database with different transaction records T_s. An association rule is an implication in the form of X⇒Y, where X, Y⊂I are sets of items called itemsets, and X ∩ Y = ø. X is called antecedent while Y is called consequent, the rule means X implies Y".* Although there are various measurement units in the association rule, the most important ones are support (s) and confidence (c) values. Support (s) is the percentage of records containing X ∪ Y to the total number of records in the database, and the calculation of support is shown in Equation 1 (Zhao and Bhowmick, 2003).

$$Support(X \rightarrow Y) = \frac{Support\ count\ of\ XY}{Total\ number\ of\ transactions\ in\ D} \quad (1)$$

Confidence (c) is the ratio of the number of transactions containing X∪Y to the total number of records containing X, if the percentage passes the confidence threshold, an interesting association rule X⇒Y can construct (Zhao and Bhowmick, 2003). Confidence is calculated as Equation 2;

$$Confidence(X \rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \quad (2)$$

There are various association rule algorithms such as Apriori, Predictive Apriori, FP-Growth, and high performance is obtained in studies using these algorithms (Çakır *et al*., 2021). In this study, we used Apriori Algorithm that is the most commonly used association rule algorithm in the literature (Abaya, 2012).

3.1. Apriori Algorithm

Apriori Algorithm, which is developed by Agrawal and Srikan (1994), aims to generate association rules with high confidence values. This value shows the correctness of the rules and is used for sorting them. The fact that this algorithm provides high performance in studies where this algorithm is used has led to Apriori Algorithm being the most used algorithm in the association rule and the development of new algorithms based on this algorithm (Çakır *et al*., 2021). Some advantages of Apriori algorithm are easy to implement, use and learn by the researchers since the data structure is straightforward. For these reason, Apriori algorithm is called the most basic algorithm for association rules. However, Apriori algorithm requires repeated scanning of the database to generate candidates. In this case, which is the disadvantage of the algorithm, if the pattern is very large and long, this process requires a lot of time and memory (Kumar and Cheizan, 2012; Yuan, 2017; Wicaksono *et al*., 2020). Since the dataset in this study was relatively small, this disadvantage did not cause excessive time and memory requirements in the study.

The main process of Apriori Algorithm is as follows (Li *et al*., 2012);

Step 1. Set the minimum support and confidence by user instruction.

Step 2. Constitute the candidate 1-itemsets. Then, generate the frequent 1-itemsets by pruning some candidate 1-itemsets if their support values are lower than the minimum support.

Step 3. Join the frequent 1-itemsets with each other to construct the candidate 2-itemsets and prune some infrequent itemsets from the candidate 2-itemsets to create the frequent 2-itemsets.

Step 4. Repeat the steps likewise step 3 until no more candidate itemsets can be created.

Additionally, Pseudo code of Apriori Algorithm created by Agrawal and Srikan (1994) is shown below;

L_1 ={large 1-itemsets};
for** (k =2; L_{k-1} ≠ Ø; k++) **do begin
C_k =apriori-gen(L_{k-1}); //New candidate
forall** transactions t ∈D **do begin
C_t =subset(C_k, t); //Candidates contained in t,
***forall** candidates c ∈C_t **do**,*
c.count++;

end,
$L_k = \{c \in C_k \mid c.count \geq minsup\}$,
end,
Answer = $\cup_k L_k$;

3.2. Dataset Details

The dataset used for PSC inspection results, in which association rules are extracted using the Apriori Algorithm, consists of Turkish flagged ships detained between 2014 and 2019. A total of 209 PSC inspection results from 4 different memorandums, namely, Paris, Tokyo, Mediterranean, and Black Sea MoU, were extracted from the databases of the relevant memorandums. All the reports collected about the ships and the inspection results were combined in the MS-Office Excel file. The variables that are not included in the PSC inspection reports but included in the analysis have been added by writing the necessary codes on this file. Finally, in the dataset, there are 8 variables related to ship and inspection conducted and 19 variables related to main deficiencies. In an PSC inspection that results in detention, most of the deficiencies do not cause detention. In other words, a deficiency or some deficiencies may be effective in making the decision to be detained and these deficiencies are also indicated in the PSC inspection reports. Therefore, in this study, a separate data set was created in order to examine the relationship between the deficiencies that caused the detention. Before the analysis, necessary corrections were made by applying pre-processing steps such as data cleansing and data transformation to the dataset. The variables used in dataset and descriptive statistics of them are given in Table 1 and Table 2.

Table 1. Details of variables related to ship and PSC inspection

Variable	Category	Frequency (n)	Percentage (%)
Season	Spring	50	23.9
	Summer	42	20.1
	Autumn	60	28.7
	Winter	57	27.3
Memorandum Region	Paris	83 (4.3%)*	39.7
	Tokyo	10 (3.3%)*	4.8
	Black Sea	98 (4.4%)*	46.9
	Mediterranean	18 (1.7%)*	8.6
Type of Ship	Bulk Carrier	40	19.1
	General Cargo	127	60.8
	Container	6	2.9
	Ro Ro/Passenger	16	7.7
	Tanker	20	9.6
Age of Ship	Under average (<22.5)	104	49.8
	Above average (>22.5)	105	50.2
Size of Ship (GRT)	≤2500 GRT	67	32.1
	2500< . <5000 GRT	74	35.4
	≥5000 GRT	68	32.5
Classification Society of Ship	IACS member	107	51.2
	Not IACS member	102	48.8
Historical Detention Situation of Ship	No	148	70.8
	Yes	61	29.2
Number of Detention of Ship's Company	0	116	55.5
	1	46	22.0
	>=2	47	22.5

*Detention rate in related MoU (number of detentions/total number of PSC inspections)

According to analysis results, Turkish flagged ships were mostly detained in Paris and Black Sea MoU region. Also, the vast majority of ships arrested are general cargo ships (60.8%). Age of ship is divided into two categories according to the average age of Turkish flagged ships and it is seen that these two categories have almost equal ratios. In the same way, the classification societies of the ships are evaluated in two categories as IACS (The International Association of Classification Societies) members and non-members and they are almost at equal frequency. The size of the ship, which has a numerical value, has been made into 3 categories by using the equal frequency binning method using the SPSS Modeler 18.0 program. Safety of navigation (451), life saving appliances (339), and labor conditions (276) are the main deficiency areas with the highest frequency in the PSC inspections resulting in detention. When the deficiencies grounding to detention are examined, the deficiencies with the highest frequency are fire safety (124), safety of navigation (123), and emergency systems (107), respectively.

Table 2. Details of variables related to deficiencies

	Whole Deficiencies	Deficiencies Grounding Detention
Main Deficiency Area	**Frequency(n)**	**Frequency(n)**
Certificate/Documentation	237	46
Structural Conditions	67	25
Watertight Conditions	105	36
Emergency Systems	184	107
Communication	88	23
Ship Equipment	0	0
Fire Safety	270	124
Alarms	13	5
Safety of Navigation	451	123
Cargo Operations	9	1
Life Saving Appliances	339	93
Dangerous Goods	0	0
Main and Aux. Machines	171	45
Living/Working Conditions	143	15
Labor Conditions	276	36
Pollution Prevention	77	19
ISM	137	77
ISPS	7	0
Others	17	1
Total	**2591**	**776**

4. FINDINGS

Association rule analyses made in this section are given in sub-headings according to the variable types used in the analyses. SPSS Modeler 18.0 program was used in all analyses to extract association rules.

4.1. Association Rules of Variables Related to Ship and PSC Inspection

The purpose of this analysis was to determine how there is a correlation among variables related to ship and PSC inspection. In this direction, variables in Table 1 were included in the analysis. Before analysis, the support value was set to 10% and the confidence value to 80%. There is no determined or proven value for the threshold values in the literature. Since each data set has its own unique structure (number of data, number of variables, etc.), threshold values are mostly determined on the basis of the intuitiveness of the user such as trial-and-error approach (Osman et al., 2020). According to the result of the analysis, a total of 37 association rules that fit these threshold values were determined. It was found that the association rule with the highest percentage in the ranking made according to the support value is between ships that are classified IACS member classifications and ships that are under average age, with 51.196%. Additionally, general cargo ships, ships that are classified IACS member classifications and ships that are under average

age were the variables frequently seen in the rules where high support value occurs. Association rules with a support value of 30% and above are shown in Table 3. Of these 37 association rules, the 16 association rules with the highest confidence value (more than 95%) can be seen in Table 4.

Table 3. Association rules of variables related to ship and PSC inspection by support value

Antecedent	Consequent	Support (%)
AGE= underaverage	CLASS= IACS	51.196
TYPE= General Cargo	GRT= 2501< <5000	35.407
AGE= underaverage	GRT= >5001	32.536
CLASS= IACS	GRT= >5001	32.536
TYPE= General Cargo	GRT= <2500	32.057

Table 4. Association rules of variables related to ship and PSC inspection by confidence value

	Antecedent	Consequent	Support (%)	Confidence (%)
1	TYPE=Bulk carrier	GRT≥5001	19.139	100.000
2	TYPE=Bulk carrier and MOU=BlackSea	GRT≥5001	10.526	100.000
3	TYPE=Bulk carrier and AGE=underaverage	GRT≥5001	16.746	100.000
4	TYPE=Bulk carrier and CLASS=IACS	GRT≥5001	18.660	100.000
5	TYPE=Bulk carrier and MOU=BlackSea and CLASS=IACS	GRT≥5001	10.048	100.000
6	TYPE=Bulk carrier and AGE=underaverage and CLASS=IACS	GRT≥5001	16.268	100.000
7	TYPE=Bulk carrier	CLASS=IACS	19.139	97.500
8	TYPE=Bulk carrier and GRT≥5001	CLASS=IACS	19.139	97.500
9	TYPE = Bulk carrier and AGE=underaverage	CLASS=IACS	16.746	97.143
10	TYPE=Bulk carrier and GRT≥5001 and AGE=underaverage	CLASS=IACS	16.746	97.143
11	GRT≤2500 and MOU=BlackSea	TYPE=General cargo	13.397	96.429
12	GRT≥5001 and MOU=BlackSea and AGE=underaverage	CLASS=IACS	11.483	95.833
13	GRT≥5001 and COMPANY HISTORY=0 and AGE=underaverage	CLASS=IACS	11.483	95.833
14	TYPE=Bulk carrier and MOU=BlackSea	CLASS=IACS	10.526	95.455
15	TYPE=Bulk carrier and GRT≥5001 and MOU=BlackSea	CLASS=IACS	10.526	95.455

In the first 6 association rules with the highest confidence, the variable of ship size (≥5001) appears as consequent. The support values of these rules vary between 10% and 20%. Bulk carrier and Black Sea MoU seem to have a high correlation with ships over 5000 GRT. When the other rules with a high confidence value are examined, it is observed that they occur in the rules related to the classification society. In all of these rules, it is seen that ships are classified by IACS member classification societies. As with the size of ship, there is a correlation between the classification societies and especially the bulk carrier and Black Sea MoU. Likewise, when the rules are examined, there is a correlation between classification society (member of IACS) and the size of ship (≥5001). Such that the rule with the highest support value (32.536%) is between these two variables. In addition, the confidence value of this rule is 83.824%.

4.2. Association Rules of Deficiencies

In this analysis, it was attempted to reveal the association rules by analyzing all the deficiencies detected in the PSC inspection reports. The support value was set as 15% and the confidence value as 80% for analysis. The results of the analysis, which included a total of 2591 deficiencies identified in 19 main deficiency areas, can be seen in Table 2. A total of 72 association rules is determined, and the highest support value occurred between life saving appliances and safety of navigation deficiencies with 64.593%. It was highly probable that fire safety and safety of navigation deficiencies can be observed together. Additionally, ISM and certificate/documentation deficiencies were also probably observed together with the deficiencies of safety of navigation. 12 association rules with a support value of 40% and above can be seen in Table 5.

According to the analysis results, 16 rules with the highest confidence values are shown in Table 6. The association rule with the highest confidence value is between safety of navigation and radio communication and emergency systems. This rule has 15.789% support value and 93.939% confidence value. In the analyses, it is seen that the safety of navigation is predominantly consequent. Safety of navigation has a high correlation, especially with emergency systems. In other words, these two deficiency areas are likely to be detected together. This is supported by a 50.718% support value and 84.90% confidence value between the two main deficiency areas. Radio communication and labor conditions are observed as other prominent deficiency areas in the rules.

Table 5. Association rules of deficiencies by support value

Antecedent	Consequent	Support (%)
Life Saving App.	Safety of Nav.	64.593
Fire Safety	Safety of Nav.	61.722
ISM	Safety of Nav.	55.502
Cert/Doc	Safety of Nav.	52.632
Labor Cond.	Life Saving App.	51.196
Labor Cond.	Safety of Nav.	51.196
Emergency	Fire Safety	50.718
Emergency	Life Saving App.	50.718
Emergency	Safety of Nav.	50.718
Emergency and Safety of Nav.	Life Saving App.	43.062
Fire Safety and Life Saving App.	Safety of Nav.	42.584
Labor Cond. and Safety of Nav.	Life Saving App.	40.191

Table 6. Association rules of deficiencies by confidence value

	Antecedent	Consequent	Support (%)	Confidence (%)
1	Radio Comm. and Emergency	Safety of Nav.	15.789	93.939
2	Living/Working Cond. and Emergency	Safety of Nav.	21.531	93.333
3	Propulsion/Auxiliary Mach. and Emergency	Safety of Nav.	19.617	92.683
4	Radio Comm. and Labor Cond.	Life Saving App.	19.139	92.500
5	Radio Comm. and Labor Cond.	Safety of Nav.	19.139	92.500
6	Radio Comm. and Fire Safety	Safety of Nav.	19.139	92.500
7	Living/Working Cond. and Cert/Doc	Safety of Nav.	18.660	92.308
8	Radio Comm. and Labor Cond. and Life Saving App.	Safety of Nav.	17.703	91.892
9	Radio Comm. and Labor Cond. and Safety of Nav.	Life Saving App.	17.703	91.892
10	Radio Comm. and Fire Safety and Life Saving App.	Safety of Nav.	17.225	91.667
11	Propulsion/Auxiliary Mach. and Fire Safety and Life Saving App.	Safety of Nav.	16.268	91.176
12	Labor Cond. and Emergency and Life Saving App.	Safety of Nav.	20.574	90.698
13	Living/Working Cond. and Emergency and Fire Safety	Safety of Nav.	15.311	90.625
14	Labor Cond. and Emergency	Safety of Nav.	24.402	90.196
15	Radio Comm.	Safety of Nav.	29.187	90.164
16	Radio Comm. and Fire Safety	Life Saving App.	19.139	90.000

4.3. Association Rules of Deficiencies Grounding Detention

The purpose of this analysis is to reveal the relationships between the deficiencies that cause the detention. A total of 776 deficiencies stated in the PSC inspection reports were included in the analysis. Since the number of deficiencies that caused the detention was relatively less than in other analyses. the support value was determined as 5% and the confidence value was determined as 70%. A total of 4 association rules were determined at these threshold values (Table 7). According to the results of the analyses, the support values of the association rules are between 5.263% and 6.220%, and the confidence values are between 72.727% and 81.188%. It is seen that the rule with the highest confidence value occurs among certificate/documentation, emergency systems, and safety of navigation. When the 4 rules are examined, it can be said that these deficiency areas are included in most of the rules and have a correlation. besides, there is a correlation between ISM and fire safety, especially (Rule 2 and 4).

Table 7. Association rules of deficiencies grounding detention

	Antecedent	Consequent	Support (%)	Confidence (%)
1	Cert/Doc and Emergency	Safety of Nav.	5.263	81.818
2	Emergency and Safety of Nav. and Fire Safety	ISM	6.220	76.923
3	Cert/Doc and Life Saving App.	Safety of Nav.	5.263	72.727
4	Cert/Doc and Fire Safety	ISM	5.263	72.727

5. RESULTS AND DISCUSSION

According to the results of the analyzes, quite broad results have been obtained about the Turkish flagged ships detained as a result of the PSC inspection. In terms of age, which is one of the important variables affecting the PSC inspection result, it has been determined that Turkish flagged ships have almost equal frequency below and above the average age. In addition, these detained ships are usually of small tannage and general cargo ships. The memorandum an classification soviety of ships have been important variables in association rule creation. Safety of navigation, emergency systems, fire safety, ISM, and life saving appliances have been found to be the predominant areas of deficiencies in association rules regarding deficiency areas. The results obtained in this study and the findings of the studies in the literature are evaluated in the following paragraph.

In this study, it has been determined that the age categories of the Turkish flagged ships detained have almost equal frequency and that the rules consist especially for ships under the average age (<22.5). This differs from the findings in the study by Tsou (2019) that indicates the detention of ships are generally older (over 25 years). Fu *et al.* (2020) also indicated that the detention risk of the older ships is higher. However, the fact that especially small tonnage ships encounter detention is the common output of both studies. Additionally, a correlation was determined between emergency systems and ISM among the deficiencies that cause detention in the study of Tsou (2019). This finding is also similar to this study as seen in Rule 2 in Table 5.

In the study by Osman *et al*. (2020), it was stated that the detention of ships was correlated with the port where the PSC inspection was made. Similarly, it has been determined that the memorandum is one of the prominent variables in the association rules in this study. The finding of Chung *et al*. (2020), which states that the type of ship is also an important factor causing detention, is also in line with this study. In particular, the frequency of detention of general cargo ships is high in Turkish flagged ships. In a study by Fu *et al*. (2020), it was determined that the frequency of detention of general cargo ships was high. Additionally, it can be said that bulk carriers are the dominant ship type in rule-making in association rules. It is the common finding of these two studies that the ship type has a greater effect on rule-making than the ship's classification society.

6. CONCLUSIONS

Port State Control is one of the most important mechanisms for the safety of ships. However, this ship inspection mechanism is a process that requires both cost and time. In addition to reducing these costs, it is critical to make PSC inspections more effective by providing inferences from past PSC inspection results to ensure ship and sea safety. In this direction, data mining can be considered as one of the most effective methods for solving this problem. In this study, the PSC inspection results of the Turkish flagged ships detained were analyzed using association rule mining, which is one of the descriptive methods of data mining. The main purpose of the study is to reveal meaningful relationships from the PSC inspection results.

It has been seen that bulk carriers and ships over 5000 GRT are the prominent variables in the formation of the association rule, as well as the PSC inspections in the Black Sea MoU region and the ships certified by IACS member classification societies are other important variables. Safety of navigation and emergency systems are highly correlated deficiency areas in detected deficiencies. However, there are correlations between safety of navigation, certificate/documentation, and emergency systems for deficiencies that caused the detention of Turkish flagged ships.

The results of the study are supposed to be useful for the flag state control mechanism in order to improve the port state control performance of Turkish flagged ships. Additionally, the study can help Turkish flagged ship owners and recognized organizations to evaluate their safety measures. The limitation of this study was to analyze only detained Turkish flagged ships. It is recommended to expand the data set and use different data mining methods by adding different flagged ships and memorandums for future studies.

ACKNOWLEDGEMENTS

The abstract of this study was presented at the 4th Global Conference on Innovation in Marine Technology and the Future of Maritime Transportation-Global Maritime Conference (GMC'21).

AUTHORSHIP CONTRIBUTION STATEMENT

Coşkan SEVGİLİ: Conceptualization, Methodology, Validation, Writing - Original Draft, Writing-Review and Editing, Data Curation, Software, Visualization, Supervision.
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CONFLICT OF INTERESTS

The authors declare that for this article they have no actual, potential or perceived conflict of interests.

ETHICS COMMITTEE PERMISSION

No ethics committee permissions is required for this study

FUNDING

No funding was received from institutions or agencies for the execution of this research.

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