

## IMPROVING IDSs ALERTS TO IMPROVE HIGH QUALITY NETWORK SECURITY BY USING DATA MINING TECHNIQUE

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### Abstract

Intrusion-Detection-Systems (IDSs) are the best and most effective techniques when it comes to addressing the threats (such as malware and cyber-attacks etc.) being faced by computer networks; indeed, these systems have been used for more than 20 years. However, these systems generate a huge number of alerts, a large percentage of which are false or incorrect. This problem adversely affects the performance and effectiveness of network security. In this paper, we propose a new system to eliminate duplicated and redundant IDS alerts; the overall aim is to improve network security by minimizing the rate of false positive alarms. This system consists of two major phases, as well as various sub-phases. The first phase involves removing duplicated alerts by applying a new filtering algorithm which has been prepared for this purpose. The aim of the second phase is to reduce false alerts by eliminating the redundant alerts; this is achieved by applying association rules and mining frequent itemset algorithms. This system is evaluated and tested by using five weeks of data from the DARPA 99 dataset. The results show that this system significantly reduces the number of FP alarms by 97.98%. These results also demonstrate the system's substantial ability to reduce the very large number of false alarms related to IDSs.

**Keywords:** Network Security; IDSs; False Positive (FP) Alert; Alert Evaluation; Threat Degree of Alerts.

## VERİ MADENCİLİĞİ TEKNİĞİNİ İLE ID'LER KULLANARAK AĞ GÜVENLİĞİNİN YÜKSEK KALİTELİ HALE GETİRİLMESİ

### Özet

Saldırı Tespit Sistemleri (IDS), bilgisayar ağları tarafından karşılaşılan tehditleri (kötü amaçlı yazılımlar ve siber saldırılar gibi) ele almaya gelince en iyi ve etkili tekniklerdir; Gerçekten de, bu sistemler 20 yıldan fazla kullanılmaktadır. Bununla birlikte, bu sistemler çok sayıda uyarı üretir; bunların büyük bir yüzdesi yanlış veya yanlıştır. Bu sorun, ağ güvenliğinin performansını ve etkililiğini olumsuz olarak etkiler. Bu yazıda, çoğaltılmış ve gereksiz IDS uyarılarını ortadan kaldırmak için yeni bir sistem öneriyoruz; genel amaç, yanlış pozitif alarm oranını en aza indirerek ağ güvenliğini artırmaktır. Bu sistemin yanı sıra çeşitli alt safhalar olmak üzere iki ana safhadan oluşur. Birinci aşamada, bu amaçla hazırlanmış yeni bir filtreleme algoritması uygulayarak çoğaltılan uyarıların kaldırılması gerekir. İkinci aşamada hedef, gereksiz uyarıları ortadan kaldırarak yanlış uyarıları azaltmaktır; bu ilişki kurallarını uygulayarak ve sık öge seti algoritmalarını kullanarak gerçekleştirilir. Bu sistem, DARPA 99 veri kümesindeki beş haftalık verileri kullanarak değerlendirilir ve test edilir. Sonuçlar, bu sistemin FP alarm sayısını% 97.98 oranında önemli ölçüde düşürdüğünü göstermektedir. Bu sonuçlar, aynı zamanda, sistemin IDS'lerle ilgili çok sayıda yanlış alarmı azaltma kabiliyetini de göstermektedir.

**Anahtar Kelimeler:** Ağ Güvenliği; IDS; Yanlış Olumlu (FP) Uyarı ; Uyarı Değerlendirmesi; Tehditler Derece Uyarıları.

## 1. INTRODUCTION

Over the last two decades, there has been a huge increase in the usage of both network computers as well as internet access in all sectors of life; this has led to a subsequent rise in both external and internal threats to computer networks security. Of particular note is the fact that such attacks have increased rapidly over the last few years. For example, 3 years ago, 200 new threats to networks security per minute were identified [1]. At this point, it is worth mentioning a number of defense security devices and network systems, such as Firewalls, Intrusion-prevention systems, Intrusion-Detection-systems (IDSs), anti-virus systems, and many other systems and devices. Over recent years, these systems have been embedded in diverse layers and infrastructures of the computer networks. Most of these devices are designed to detect and deny the influx of malicious network traffic from inside and outside of the network; this is achieved by detecting intrusion activity and triggering alerts which enable the network security systems to block malicious traffic from accessing their destinations.

One of these systems is the Intrusion-Detection-System (IDS), which has become more popular in the field of network security since the beginning of the last decade. The work of these systems is reflected in the monitoring of incoming packets from outside or inside of the network, which are classified based on their behaviors. These alerts are generated when malicious behaviors are detected by IDSs, which provide the security analyst with the chance to react instantly to the possible malicious activities [3]. Moreover, of particular note is the emergence of a significant problem which has increased the frailty of the IDSs when they are used extensively. This problem relates to vast numbers of alerts generated by IDSs, which often reach thousands per day. In actual fact, most of these alarms are False-Positive (FP) alerts [2, 4]. FP alerts are alarm messages generated by the IDSs which mark a non-malicious traffic activity. The number of these alerts has increased due to rises in both malicious activity and complex network structures; as such, it is practically impossible and complex to verify the legality of each alert [4].

Previous researchers have adopted different techniques and approaches to address the problems of IDS log file alerts, which are considered extremely significant when it comes to tackling the threats which have threatened computer networks security for more than 10 years. In fact, these threats are caused by hackers or intruders, who break down the network security by using different types of threats, including denial of service (DoS) attacks, U2R, Probe, and R2L [5]. IDSs represent an efficient technique when it comes to defending against attacks which target computers and networks. In actual fact, these systems are considered the second defensive line in the security environment of computer networks. Nevertheless, the IDS systems face a significant problem in terms of the number of alerts generated, around 99% of which are FP alerts [2, 8, 9]. This problem has affected the objective of IDS systems, which is to precisely differentiate between malicious behavior and natural behavior; therefore, the FP alerts have affected the accuracy and the performance of IDS systems [7, 10].

This paper is arranged as follows: Section 2 presents an overview of previous approaches and research aimed at reducing the FP alarms of IDSs. Section 3 describes and explains the methodology employed in this paper, while Section 4 presents the results, along with details of the experiment and the proposed system. Finally, Section 5 summarizes the conclusions and paths for future work.

## 2. RELATED WORK

There are two different approaches which have been used to reduce the number of false positive IDS alerts: a false positive reduction in log-file alerts, and a false positive reduction, at the sensor-level, of IDSs. This paper focuses solely on the studies concerning the reduction of false positive alerts after the detection level (log-file).

Pietraszek (2006) [6] proposed an incremental classifier called ALAC, which is based on two main factors; the first factor is background knowledge, while the second factor is human analyst feedback. This study improved the limitations of the RIPPER algorithm by using batch learner and weighting to build the incremental classifier. However, this system has a disadvantage, as an infinite growth size is needed to test a system throughout its lifetime; as such, Pietraszek's system is incompetent.

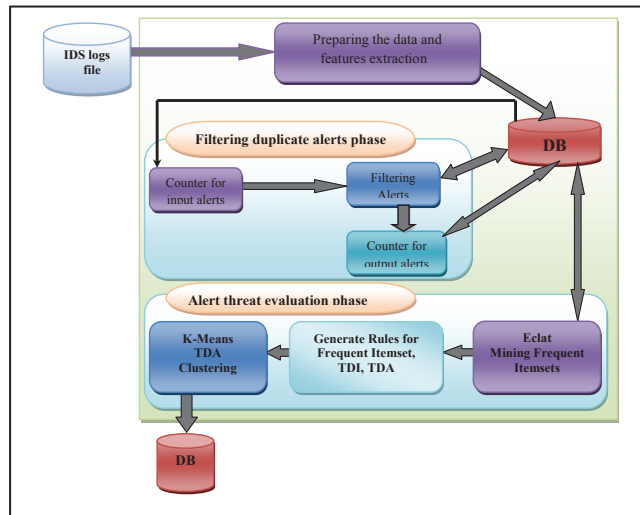
Along similar lines, Alshammari et al. (2007) [11] constructed a hybrid neuro-fuzzy system to minimize the false positive alerts (FP), and considered the effect of adding background knowledge to the alerts data. Their system is based on multiple factors, including Membership Function (MF), Fuzzy Sets Variables, Rule Weights, Learning Rate, Cross-validation, and Number of Epochs. The MFs provided by NEFCLASS include Trapezoidal, Triangular, List function, and Bell-shaped. In actual fact, they used all four of these MFs with Confidence Factor (CF=0.99) within background knowledge classes. Moreover, they employed different Fuzzy variables (including 3, 4, and 5 variables). This approach was tested by using the first three weeks of the DARPA 99 dataset, while the other weeks were used to evaluate the system. Their system reduced the false alarms efficiently by 90.92%; this was achieved through the use of (IP class with 10 features) 4 Fuzzy Sets Variables with trapezoid MF.

Another approach, this time based on data mining, was proposed by Zhang and Al-Mamory (2010) [14]; the main objective of this technique is to reduce (FP) false positive alerts. Their approach aimed to create a generalized alert from each cluster when the alerts are gathered into sets of clusters. To reduce the number of future alerts, this technique converted the root causes into a filter. The authors took into account the concept of nearest neighboring and generalization in their proposed technique. As part of this technique, a new measurement was used to calculate the distances between alert feature values. This involved performing a calculation process based on the background knowledge of the observed network. This approach was evaluated by using the fifth week of the DARPA 99 dataset, with the results showing a reduction average of around 82% of the total alerts used.

Mohiuddin and Ahmed (2014) [15] proposed a new method based on improving the K-Means algorithm. Their approach was called CAD (Collective\_Anomaly\_Detection), while their improved algorithm was termed X-Means. They employed this improved algorithm to cluster the alerts and thus distinguish the anomaly alerts from normal alerts by measuring the similarity between the alerts' datasets. Following this, they clustered the anomaly alerts to detect the DoS attacks. Their approach is examined by using the DARPA dataset, and this examination is based on only four attributes from the dataset, including Des\_IP, Src\_IP, Protocol\_type, and Payload\_length to detect DoS attacks. In actual fact, their approach focused on detecting only the DoS attacks, despite the fact that these datasets contained various types of attacks, such as U2R, R2L, and Probe.

### 3. METHODOLOGY

Over the past few years, malicious attacks on computers have become an increasingly critical and complicated problem. Intrusion-detection-systems are used to look for the intrusive activity, which differs from normal activity. Thus, the IDSs are used to achieve the main security goals: integrity, confidentiality, and availability of computer networks and system [13]. The purpose of using the IDSs is to complement the existing infrastructure of networks security measures. As such, the aim of IDSs is to monitor the network traffic, to detect the malicious traffic activity, and generate alarm notifications when the potential intrusion activity is detected. Therefore, the IDSs are considered a main and integral part of computer networks security, and the second line of defense for the networks and systems. Nevertheless, these systems generate a number of alarms, 99% of which are false positive alerts [12]. The proposed system is very considerable, and eliminates the duplicated and redundant alerts. This system has been designed using C# language, and consists of two main phases, namely the Filtering Duplicate Alerts (FDA) phase and the Alert Threat Evaluation (ATE) phase. Figure 1 describes the architecture of the proposed system.



**Figure 1.** The Proposed System architecture

The first process of the system involves extracting the standard attributes from the alerts database. This system provides the system analyst and system administrator with the ability to choose the significant attributes; indeed, one attribute is selected from the DARPA dataset to be a Transaction-ID (TID), following which several attributes are selected to generate frequent itemsets with these TIDs.

#### 1.1 Filtering Duplicate Alerts (FDAs) phase

The aim of the FDA phase is to remove duplicated alerts, which constitute the majority of false positive (FP) alerts [18]; this will be achieved by using the proposed new algorithm to filter said alerts. In this section, we explain the method behind the aforementioned algorithm. Figure 2 shows the pseudocode of the Filtering Duplicate Alerts (FDAs) phase.

```
FDA- Algorithm  
Input: Alerts_file  
Output: Filtered Alerts_file  
1: Reads the alert from Alerts_file as Alert [A1, A2, A3..., An]  
2: While Search for similar alerts Do  
3: Delete all similar alerts found with retain only one alert for  
   each similarity  
4: Else Search for similar alerts based on Time Stamp Attributes  
5: Delete all similar alerts found that similar in all Attributes But  
   The difference in Time Stamp Attributes with retaining  
   only one alert for each similarity  
6: End While
```

**Figure 2.** The Pseudocode of FDA Phase

As shown in Figure 2, this phase passes through two sub-processes. The first sub-process is designed to find any similarities between the items of the alert attributes. There are two pointers which are used to read the items of the alerts; the first alert from the database is read by the first pointer, while the second alert is read by the second pointer, so as to make a comparison between the items of the alerts attributes for these two alerts. The second alert will be deleted, and the first alert will only be kept if the similarity exists. If no similarity exists, the second pointer will be moved from the second alert to the third alert, and so on until all the alerts have been compared and those with similarities have been identified. The second sub-process is based on similarities between the alerts attributes and the Timestamp attributes. This process removes the duplicated alerts when similarities are found between attributes' items that have only differences in timestamp and when these values of timestamp are very close to each other; indeed, the latter situation indicates that these alerts are generated from a single event but in successive and very close time periods.

## 1.2 Alert Threat Evaluation (ATE) phase

The ATE phase is considered the main part of the proposed system. This phase consists of three sub-phases, each of which is responsible for performing a function. The function of the first sub-phase is to mine frequent itemsets which are based on the Eclat algorithm, as will be explained in Section 3.2.1. The second sub-phase is accountable for generating rules for frequent itemsets and establishing the threat degree based on the improved Generate Rules algorithm; the second sub-phase and the function of the third sub-phase, which is responsible for clustering the threat degree of alerts based on the K-Mean algorithm, will be explained in Section 3.2.2.

### 1.2.1 Eclat algorithm

This section presents a detailed explanation of the process of the standard Eclat algorithm in mining frequent itemsets. This algorithm is developed and enhanced so as it is possible to implement the items of the single alerts attribute. Moreover, this enhancement helps to turn the itemsets of the alerts feature into

more convenient approaches. This algorithm is characterized by its high flexibility when applied with the different types of items data of alert attributes without specifying whether or not these items are digital. Indeed, this enhanced algorithm performs very well. Figure 3 shows the pseudocode of the ECLAT algorithm [16]. The objective of this sub-phase is to mine frequent 1-itemsets and frequent 2-itemsets with their support values, which will be the input for the second sub-phase.

```

Algorithm 1 Basic Eclat algorithm.
input: alphabet A with ordering  $\leq$ ,
multiset  $T \subseteq P(A)$  of sets of items,
minimum support value  $\text{minsup} \in \mathbb{N}$ ;
output: set F of frequent itemsets and their support counts.
1) For ( $i=1, i \leq \text{data.Length}$ ) do
2)  $F := \{(\emptyset, |T|)\}$ ;
3)  $C_\emptyset := \{(x, T(\{x\})) \mid x \in A\}$ ;
4)  $C'_\emptyset := \text{freq}(C_\emptyset) := \{(x, T_x) \mid (x, T_x) \in C_\emptyset, |T_x| \leq \text{minsup}\}$ ;
5)  $F := \{C'_\emptyset\}$ ;
6) addFrequentSupersets ( $\emptyset, C'_\emptyset$ );
7) end for
function addFrequentSupersets():
Input: frequent itemset  $p \in P(A)$  called prefix,
Incidence matrix C of frequent 1-item-extensions of p.
Output: add all frequent extensions of p to global variable F.
8) for ( $(x, T_x) \in C$ ) do
9)  $q := p \cup \{x\}$ ;
10)  $C_q := \{(y, T_x \cap T_y) \mid (y, T_y) \in C, y > x\}$ ;
11)  $C'_q := \text{freq}(C_q) := \{(y, T_y) \mid (y, T_y) \in C_q, |T_y| \geq \text{minsup}\}$ ;
12) if  $C'_q \neq \emptyset$  then
13) addFrequentSupersets ( $q, C'_q$ );
14) end if
15)  $F := F \cup \{(q, |T_x|)\}$ ;
16) end for

```

**Figure 3.** Pseudocode of the Eclat Algorithm [17]

As shown in Figure 3, step 1 accompanies the items ( $C_\emptyset$ ) with their TIDs and counts the length of their TID\_lists. Step 4 involves mining for frequent items whose TID\_lists length is equal to or greater than the  $\text{min\_sup}$  threshold from the candidate items generated in step 3. Following this, step 6 adds these frequent items into F, which represents the 1-itemset.

This function of the Eclat algorithm, from step 8 to step 16, scans only the frequent items that are generated from the previous process without the need to rescan the origin database. To generate the 2-candidate frequent itemsets ( $C_q$ ) from F, which is called the prefix, it is necessary to join each pair of items and then find the intersection in their TID\_lists; this process is implemented in step 10. Counting the length of intersected TID\_lists for each pair of items ( $C'_q$ ) to be these values as the support value for these items. Step 11 searches for any pairs of items that have a support value which satisfies the  $\text{min\_sup}$  threshold. Steps 12-15 are used to add the generated frequent 2-itemsets to F (large frequent itemsets), so that they can be processed later to generate 3-itemsets. Interestingly, this process is repeated many times until no new frequent itemsets are found. In fact, the proposed system intentionally makes the  $\text{min\_sup}$  threshold of the Eclat algorithm equal to 1. As such, there will be no infrequent candidates.

Thus, the implementation of this algorithm in our approach will suffice with the findings from only the 1-itemsets and 2-itemsets. The Eclat algorithm will generate an abundance of frequent items due to the min\_sup value which has been used in this approach; as such, no infrequent itemsets will be found. Figure 4 explains an example to trace the behavior of the Eclat algorithm with min\_sup=1 based on [17]. Firstly, the algorithm extracts items from alerts attributes and calculates their support value by ensuring that each item is accompanied by its TIDs to generate 1-itemset (support value represents how many times this item appears with this TID and the other TIDs). Secondly, the algorithm joins each of the two items with their TIDs from frequent 1-itemset to generate the 2-itemset by intersecting the TIDs of each two joined items, as shown in the example in Figure 4.

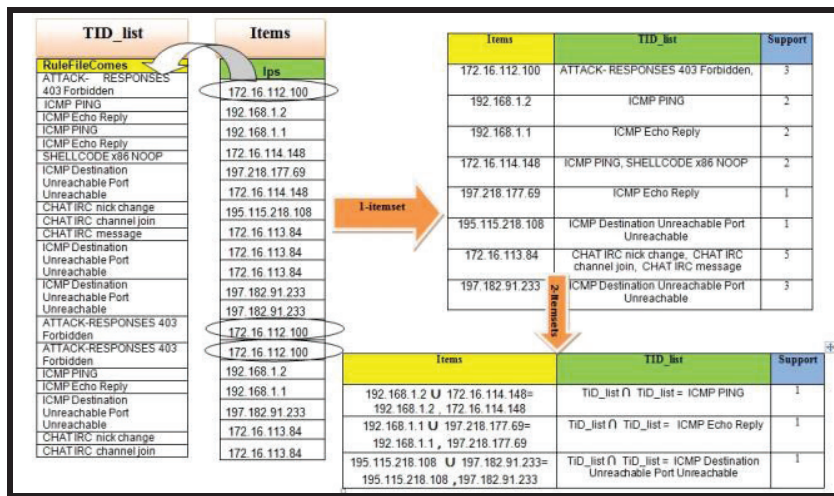


Figure 4. The Implementation of the Eclat Algorithm

### 1.2.2 Rules Generation algorithm

The second sub-phase of the second phase (ATE) is responsible for generating rules for frequent 2-itemsets and then calculating the threat degree for each item (TDI) while also extracting the threat degree for each alert (TDA). This algorithm is the same as the generation-rule algorithm, but is improved to calculate the TDI for each item and TDA for each alert. While the original algorithm generates rules only and calculates the confidence value, this improved algorithm calculates the threat degree of items based on equation (1). Moreover, this improved algorithm extracts the threat degree of alerts depending on equation (2). As such, these functions of the Rules Generation algorithm are passed through three processes. The improved algorithm is explained in detail in Figure 5.

```

Rules_Generation (L);
Input: 1-itemset, 2-itemsets;
Output: Rule itemset, Alert threat degree;
1. for all large k-itemsets  $L_k, k \geq 2$  do
2. begin
3.  $H_1 = \{\text{Sets of rules from } L_k, \text{ with one item in the Set}\}$ 
4. ap-genrules ( $L_k, H_1$ )
5. end
6.  $TDA = (\sum_{j=1, k=0}^{\text{No\_Attributes}} (TDI) / \text{No\_Selected\_Attributes}$ 
7. ap-genrules ( $L_k, H_m$ );
8. if  $k > m+1$  then
9. begin
10.  $H_{m+1} = \text{Eclat-gen}(H_m)$ ;
11. for all  $h_{m+1} \in H_{m+1}$  do
12. begin
13.  $\text{conf} = \text{support}(L_k) / \text{support}(L_k - h_{m+1})$ 
14. if  $\text{conf} \geq \text{min\_conf}$  then
15.         add ( $L_k - h_{m+1} \Rightarrow h_{m+1}$ ) to the rule set
16. else
17.         delete  $h_{m+1}$ , from  $H_{m+1}$ 
18. end
19. ap-genrules ( $L_k, H_{m+1}$ )
20.  $TDI = \frac{\sum_{i=1}^n \text{conf}_i}{n}$ 
21. end

```

**Figure 5.** The Pseudocode of the Rules Generation Algorithm

The first process of the ATE phase involves generating rules for frequent itemsets; these steps (1-3) read the 1-itemsets and 2-itemsets, following which rules are generated only for the 2-itemsets. This is identical to the condition of association rules in steps 4-17. The *gen-rules* function is responsible for generating rules and calculating the confidence degree for each rule; the confidence degree is extracted after the rules are generated based on equation (1). This equation will apply if the 2-itemset is A, B [20]:

$$\text{Confidence}(A \Rightarrow B) = \frac{\text{Support}(A \cup B)}{\text{Support}(A)} \quad (1)$$

The second process is applied based on the equation in step 18 after extracting all rule sets with confidence degrees for frequent 2-itemsets. In addition, this equation is proposed to calculate the (TDI) for each item. In essence, this equation is completely based on the rules with confidence degrees that are extracted during the first process through the *gen-rules* function. This equation was designed based on the fact that erroneous faults are the most frequent alerts, and all elements of a single alarm have a direct relationship with the other alert elements of the same attribute. More specifically, the value of confidence has a forthright influence on the relationship between the items and their impact on each other. This value also depends on the support value and the impact of each item on the other, which in fact represents the number of repeated items. Accordingly, TDI is calculated based on equation (2), as follows:

$$TDI = \frac{\sum_{i=1}^s \text{conf}_i}{s} \quad (2)$$

The aim of the third process is to extract the threat degree of each alert (TDA) after the threat degree of each item (TDI) has been extracted via the second process of the improved rule generation algorithm. The input for this process is the TDI, and thus all alerts contain several items, each of which has a TDI



value. The output of this process is the TDA for each alert; these values represent the input for the last sub-phase of the second phase of the proposed system (K-Means clustering). Each item has a TDI value, but to obtain the TDA for each alert, equation (3) should be applied, as follows:

$$TDA = \left( \sum_{j=1, k=0}^{No\_Attributes} (TDI) / No\_Selected\_Attributes \right) \quad (3)$$

The last sub-phase of this system is the K-Means algorithm. The inputs of this sub-phase are the attributes of the TDA values. An effectively-performing K-Means algorithm should provide two attributes values for each object if said algorithm is able to find the distance between these attributes' values by applying the Euclidian distance equation. However, the output of the ATE phase of this system is only one attribute value. As such, this sub-phase has one attribute element (TDA) for each alert; in this case, the attribute elements depend on the method put forth by [19], which states that the K-Means algorithm will be transformed from one method to another. The first method involves finding the similarity among the items by calculating the distances between these items either using Euclidean or Manhattan measures; in contrast, the new method calculates the mean value of k-distributions. Each attribute item is represented as a point in this distribution. This sub-phase generates two distribution groups to classify the alerts based on threat degrees for said alerts. This algorithm clusters the alerts into two classes based on  $C_1$  (centroid 1) and  $C_2$  (centroid 2) values, which represent the threshold values of clustering; indeed, these values play the main role in determining the reduction ratio for false alerts. The output of this algorithm consists of two groups of alerts ( $G_1$  and  $G_2$ ), which represent the false positive alerts and true positive alerts (real attacks) respectively.

#### 4. RESULT

The proposed system was tested and evaluated by using the DARPA 99 dataset to compare its results with the results of other researchers who have used the same dataset within the same area of research. The experiment was conducted using different clustering threshold values. The total number of alerts from this dataset is 59,720 in a five-week period. This data is generated by MIT Lincoln lab between 16<sup>th</sup> September 1999 and 1<sup>st</sup> October 1999 [16]. This dataset has been used partially and entirely so as to compare it with other studies which have also used the dataset partially or entirely. The proposed system provided the system analysts with the ability to increase the number of attributes which can be used.

The clustering threshold plays a significant role in the classification of alerts based on the process of calculating the similarities of TDA for alerts among k-distributions; several results were obtained using several different thresholds (0.10-0.40), (0.20-0.50) and (0.25-0.75). For these thresholds of clustering, the obtained averages alert reduction ratios are used, namely 88.48%, 93.6%, and 97.98% respectively.

**Experiment 1:** This experiment has been conducted by using five weeks of the DARPA 99 dataset in order to compare its result with those generated by other authors. The parameters that are used in this experiment are as follows: First is the dataset; five weeks of a DARPA 99 dataset are used, consisting of 59,720 alerts. Second is the No. of Attributes that are selected; indeed, six attributes are selected (the system analyst can change the No. of Attributes). Third is the Min\_sup threshold, where the minimum support used is equal to 1, as explained in detail in Section 3 (the system analyst can also change this threshold).

Finally, there are the clustering thresholds; in this experiment, there are several thresholds used, including: (0.10-0.40), (0.20-0.50) and (0.25-0.75). Moreover, the system analyst can change these thresholds values.

Based on the results of this experiment, it is clear that the (0.25-0.75) threshold has the highest and best reduction ratio when compared with the other thresholds used in said experiment.

In particular, the first week and the third week have generated an extremely high reduction ratio rate, as shown in Table 1. Despite a high number of alerts in the second, fourth, and fifth weeks which are used by our system, this number does not exceed the number of alerts used in other systems. However, the system does generate a higher reduction percentage than the previous systems.

Figure 2 explains the reduction ratio for these five weeks with threshold (0.25-0.75), as follows:

**Table 1.** Results of the DARPA 99 Datasets from our System

Week	No. of Input Alerts	No. of Output Alerts	Reduction ratio
<b>First week</b>	7,293	35	99.49%
<b>Second week</b>	24,005	617	96.88 %
<b>Third week</b>	6,304	36	99.40 %
<b>Fourth week</b>	8,053	185	97.23 %
<b>Fifth week</b>	14,065	336	97.44 %
<b>Total</b>	<b>59,720</b>	<b>1209</b>	<b>97.98%</b>

Here, it is important to compare the results of the proposed approach with those of other previous approaches; the results which have been obtained by [6] and [14] are compared in Table 2. These studies used all five weeks of the DARPA 1999 dataset.

**Table 2.** Comparison of the results for five weeks from DARPA dataset with Other Approaches

Approaches	No. input alerts	No. output alerts	Weeks	Reduction Ratio %
<b>(Pietraszek, 2006)</b>	<b>59,512</b>	<b>23,925</b>	<b>5 weeks</b>	<b>60%</b>
<b>(Al-Mamory et al., 2010)</b>	<b>233,615</b>	<b>4,2051</b>	<b>5 weeks</b>	<b>82%</b>
<b>Proposed system 2017</b>	<b>59,720</b>	<b>1,209</b>	<b>5 weeks</b>	<b>97.98%</b>

Table 2 shows the results of the study by Pietraszek et al. (2006), who unveiled a lower reduction rate, despite the number of alerts used in relation to the number of alerts used by our system. In contrast,

Al-Mamory et al. (2010) obtained a good ratio of reduction, despite a very high number of input alerts being used. Finally, the proposed system has obtained efficient results when compared with these approaches.

**Experiment 2:** In order to compare the result obtained in this experiment with the approach of [11], two weeks of the DARPA 99 dataset are used. This experiment is evaluated by using the fourth and fifth weeks from the DARPA 99 dataset. The experiment was conducted using the same parameters as those used in experiment 1. Table 2 shows the results for the fourth and fifth weeks of the proposed system, where the total number of alerts used in the experiment is equal to 22,118, with an average reduction rate of 97.35%  $[(97.32+97.44)/2]$ . Table 3 shows the comparison of the result obtained in this experiment using the same two weeks and the approaches put forth by [11].

**Table 3.** Comparison of the results for fourth and fifth weeks from the DARPA dataset with [11] approach.

Approaches	No. input alerts	No. output alerts	Weeks	Reduction Ratio %
(Al-Shammari et al., 2007)	27,877	7,118	2 weeks	90.2%
Proposed system 2017	22,118	521	2 weeks	97.35%

Despite the good results achieved by employing the Al-Shammari method, better results were generated by the proposed system. This demonstrates the effectiveness and high viability of the proposed system in identifying and detecting false alerts of IDSs.

## 5. CONCLUSION

The system proposed here has been designed to reduce the number of FP alerts through two processes: filtering duplicate alerts and evaluating redundant alerts. The aim of both processes is to improve and generate a high-quality network security by solving all the problems that hinder the work of the systems analyst and affect the performance of IDSs. In actual fact, this system has achieved all of its objectives in the present paper by reducing the large number of false positive alerts during the FDA phase and the ATE phase. The main objective of the second phase is to calculate the TDA through three sub-phase processes, namely mining frequent itemsets, generating rules for frequent itemsets (which involves calculating the degree of threat for each item as well as calculating the degree of threat for each alert implicitly within this algorithm), and k-means clustering sub-phases. The efficiency of the generation-rule algorithm has been improved, as clearly shown by the results of the proposed system. For example, by using the first and third weeks of the DARPA 99 dataset, it has been possible to test the efficiency of the system. This system has produced a reduction ratio of 99.48%, which is the best result in comparison with the fact that these two weeks consist entirely of false alerts (free attack label).

Consequently, the proposed system generated a high reduction ratio of 97.98% when the entirety of the DARPA dataset was used. When all of the alerts which were entered into this sub-phase were evaluated,

most of said alerts were evaluated and classified as FP alerts, with the lowest degree of threat ranging from 0.060-0.370. Moreover, the alerts which were classified as true alerts were also evaluated, with threat degrees (TDA) ranging from 0.65-0.95. The values show that these alerts are the most threatening when compared to the rest of the other alerts; said values also indicate that these alerts are alerts resulting from a real attack. This conclusion is based on the obtained results, which show that the strong performance of the ATE phase results in improved efficiency for the system as a whole. Thus, the second phase can be considered an integral part of the system in reducing false alarms; indeed, this subsequently results in a high-resolution reduction of the redundant alerts.

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