A Fuzzy Anomaly Detection System based on Hybrid PSO-Kmeans Algorithm in Content-Centric Networks

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Abstract

In Content-Centric Networks (CCNs) as a possible future Internet, new kinds of attacks and security challenges -from Denial of Service (DoS) to privacy attacks- will arise. An efficient and effective security mechanism is required to secure content and defense against unknown and new forms of attacks and anomalies. Usually, clustering algorithms would fit the requirements for building a good anomaly detection system. K-means is a popular anomaly detection method to classify data into different categories. However, it suffers from the local convergence and sensitivity to selection of the cluster centroids. In this paper, we present a novel fuzzy anomaly detection system that works in two phases. In the first phase -the training phase- we propose an hybridization of Particle Swarm Optimization (PSO) and K-means algorithm with two simultaneous cost functions as well-separated clusters and local optimization to determine the optimal number of clusters. When the optimal placement of clusters centroids and objects are defined, it starts the second phase. In this phase -the detection phase- we employ a fuzzy approach by the combination of two distance-based methods as classification and outlier to detect anomalies in new monitoring data. Experimental results demonstrate that the proposed algorithm can achieve to the optimal number of clusters, well-separated clusters, as well as increase the high detection rate and decrease the false positive rate at the same time when compared to some other well-known clustering algorithms.

Keywords: Content-Centric Networks, Anomaly Detection, Particle Swarm Optimization, K-means, Clustering Analysis, Fuzzy Set

1. Introduction

Content-Centric Networking (CCN, also referred to as Information-Centric Networking or Data-Centric Networking, Named-Data Networking) has emerged to overcome the inherent limitations of the current Internet regarding content security and privacy, and to provide a better trust model [1, 2]. Unlike the current Internet (host-centric approach) in which security mechanisms are based on the communication channels between hosts, in the content-centric network, security mechanisms must be applied to the Information Objects (IOs) themselves independently of its storage location and physical representation [3, 4]. Consequently, new information-centric security concepts based on the information itself are required [1]. With this new paradigm, new kinds of attacks and anomalies -from Denial of Service (DoS) to privacy attacks- will arise [5]. Attacks and anomalies are deliberate actions against data, contents, software or hardware that can destroy, degrade, disrupt or deny access to a computer network [6]. Hence, the contents should be resilient against both DoS and new forms of (unknown) attacks or at least limit their effectiveness [7]. In or-

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der to disarm new kinds of attacks, anomalous traffics, and any deviation, not only the detection of the malevolent behavior must be achieved, but the network traffic belonging to the attackers should be also blocked [8, 9, 10]. In an attempt to tackle with the new kinds of anomalies and the threat of future unknown attacks, many researchers have been developing Intrusion Detection Systems (IDS) to help filter out known malware, exploits and vulnerabilities [6, 11]. Anomaly detection systems are becoming increasingly vital and valuable tools of any network security infrastructure in order to mitigate disruptions in normal delivery of network services due to malicious activities, Denial of Service (DOS) attacks and network intrusions [12, 13]. An IDS dynamically monitors logs and network traffics, applying detection algorithms to identify potential intrusions and anomalies within a network [14]. In recent years, data mining techniques specially unsupervised anomaly detection have been employed with much success in the area of intrusion detection [15, 16, 17]. Generally, unsupervised learning or cluster analysis algorithms have been utilized to discover natural groupings of objects and find features inherent and their deviations with similar characteristics to solve the detection problems of the abnormal traffics and unknown forms of new attacks [18, 19]. Data clustering algorithms can be either hierarchical or partitioning [20, 21]. In this paper, we focus on the partitioning clustering and in particular, a popular method called K-means clustering algorithm. The K-means algorithm is one of the most efficient clustering algorithms [22, 23, 24]. This algorithm is simple, easy to implement, straightforward, suitable for large data sets, and very efficient with linear time complexity [25]. However, it suffers from two main drawbacks: (1) the random selection of centroid points and determining the number of clusters may lead to different clustering results, (2) The cost function is not convex and the K-means algorithm may contain many local optimum [26]. In the previous work [27], we employed K-means clustering in our anomaly detection system over CCN. But, the results were not appropriate due to the large number of clusters, trapping in the local optimum solution, and changing results by running the algorithm with the constant parameters in several times. However, if good initial clustering centroids can be assigned by any of other global optimal searching techniques, the K-means would work well in refining the cluster centroids to find the optimal centroids [28, 29].

To overcome these drawbacks, we present a fuzzy anomaly detection system in two phases: training and detection. In the training phase, we apply a meta-heuristic algorithm called PSO (Particle Swarm Optimization) which can find the optimal or near optimal solution by the least iterations [30, 31, 32]. We employ the combination of the ability of global search of the PSO with a novel boundary handling approach and the fast convergence of the K-means to avoid being trapped in a local optimal solution.

On the other hand, the most clustering methods usually try to minimize the Mean Square Error (MSE) between data points and their cluster centroids [33, 34]. The MSE is not suitable for determining the optimal number of clusters. Since it decreases, the number of the clusters increase. We develop our method for globally optimal placement of data points as well-separated clusters by low intra-cluster cohesion and high inter-cluster separation. But the optimal placement can increase MSE [35]. Thus, we apply MSE for local optimization, i.e., in the case of each cluster separately to decrease the error caused by corresponding data points and their cluster centroids. This simultaneous approach -application of two cost functions (well-separated clusters and local optimization)- in PSO can lead to the optimal number of clusters and well-separated clusters. When the optimal placement of clusters centroids and objects are defined, they are sent to the second phase. In the detection phase, we apply a novel fuzzy decision approach to give a fuzzy detection of normal or abnormal results in the new monitoring data that do not appear in the training data set. Because fuzzy approach can reduce the false positive rate with higher reliability in determining intrusive activities, due to any data (normal or attack) may be similar (closest distance) to some clusters.

This paper is organized as follows. Section 2 contains related work. Section 3 presents security issues in CCN. Section 4 provides a general overview of the PSO algorithm. The K-means clustering algorithm and clustering problem are surveyed in Sections 5 and 6, respectively. Fuzzy set theory describes in Section 7. Section 8 describes our proposed method. Section 9 contains experimental results and analysis. Finally, we conclude in Section 10.

2. Related Work

Using hybrid algorithms for improving the clustering performance is not a novel idea. The novelty of our proposed method is using a swarm intelligence algorithm, specifically PSO algorithm, with K-means in order to optimize clustering results based on two simultaneous metrics: (1) well-separated clusters by low intra-cluster and high inter-cluster distances and (2) local optimization by MSE (Mean Square Error). We apply a new boundary handling approach for PSO algorithm to not

Table 1: Comparison of hybrid PSO + K-means approaches in clustering problems

Approach	Raw data	Parameters value	Cost function	Contribution
Junyan Chen (2012) [36]	a commercial website log file with 726 clients and 52 pages which clustered separately to 15, 25 and 35 classes	iteration: 50	$\sum_{j=1}^{m}\sum_{\forall x_n} d(x_n, z_{i,j})$, x_n is the data point, and z_{ij} refers to the j_{th} cluster centroid of the i_{th} particle, and d is the position of the particles.	an hybrid PSO for initial seeds in K-means by incorporating the multidimensional asynchronism and stochastic disturbance model to the velocity, called MSPSO-K.
Zhenkui et al. (2008) [37]	city coordinates of Hopfield-10 TSP (10 records) and Iris (150 records)	$c1 = c2 = 1.3$, w linearly reduces from 1.0 to 0.3, iteration: 10, population size: 10 (first data), 130 (second data)	$\frac{(1) max(\sum_{\forall x_i \in y_j} \frac{d(x_i,y_j)}{\lvert y_j \rvert})}{(2) min(d(y_i,y_j)), \forall i,j,i \neq j}$, (1) is the maximum value of the mean of distances within same classes, and (2) is the minimum value of distances between classes.	a combination of the core idea of K-means with PSO, which it leads to the clustering algorithm with low error rate as compared to K-means.
Cui & Potok (2005) [38]	artificial data sets: ds1 (414, 6429, 9), ds2 (313, 5804, 8), ds3 (204, 5832, 6), ds4 (878, 7454, 10) (*1st*: number of documents, *2nd*: number of terms, *3rd*: number of classes)	$c1 = c2 = 1.49$, $w = 0.72$ (in the PSO, w reduces 1% at each iteration but for hybrid it is constant), iteration: 50, population size: 50	$\text{ADVDC} = \frac{\sum_{i=1}^{N_c}[\frac{\sum_{j=1}^{P_i} d(O_i,m_{i,j})}{P_i}]}{N_c}$, $m_{i,j}$ denotes the jth document vector belongs to the cluster i, O_i is the centroid vector of ith cluster, P_i stands for the document number belongs to the cluster C_i, and N_c stand for the cluster number.	an hybrid PSO-Kmeans document clustering algorithm presents to performs fast document clustering. The cluster quality measured with ADVDC (average distance between documents and the cluster centroid) which the smaller ADVDC value results the more compact clusters.
Merwe & Engelbrecht (2003) [39]	two 2-dimensional artificial data set (n=400 with c=2 and n=600 with c=4), Iris (n=150, c=3, d=4), Wine (n=178, c=3, d=13), Breast-cancer (d=9, c=2), Automotive (n=500, d=11), *n*: number of data, *c*: number of class, *d*: number of attribute	$c1 = c2 = 1.49$, $w = 0.72$, iteration: 1000, population size 10	$\frac{\sum_{j=1}^{N_c}[\sum_{\forall Z_p \in C_{ij}} \frac{d(Z_p,m_j)}{\lvert C_{ij} \rvert}]}{N_c}$, $\lvert C_{ij} \rvert$ is the number of data vectors belonging to cluster C_{ij}, m_j refers to the j_{th} cluster centroid, Z_p denotes the centroid vector of cluster j, and N_c is the number of the cluster centroid vectors.	the result of the K-means algorithm utilized as one particle, while the rest of the swarm is initialized randomly. The quality is measured by the low intra-cluster (distance between data within a cluster), and high inter-cluster distance (distance between the centroids of the clusters).
Xiao et al. (2006) [40]	1st data set for training and developing normal clusters (97,278 normal samples) and the 2nd data set for evaluation (60,593 normal and 250,436 attack samples) from KDDCup 1999	w decreases linearly by $(w_1 - w_2) * \frac{Max\_iter - iter}{Max\_iter} + w_2$, limit the velocity to $sign(v_{id})v_{dmax}$ if it exceeds a positive constant value v_{dmax}	$f = \frac{1}{1+J_c}$, $J_c = \sum_{j=1}^{k}\sum_{X_i \in C_j} d(X_i, Z_j)$, $d(X_i, Z_j)$ is Euclidean distance between a data point X_i and the cluster center Z_j.	it is an anomaly intrusion detection system based on combination of PSO (for initializing K cluster centroids) and K-means (for local search ability to stable the centroids). The results show a false positive rate of 2.8% and the detection rate of 86%.
Our approach	1st data set for training (5,240 normal and 530 attack instances), 2nd and 3rd data sets for evaluation (2,110 normal and 866 attack, and 1,545 normal and 486 attack instances) from three CCN scenarios	*c1=c2=2*, w linearly decreases by $w * Wdamp$ (Inertia Weight Damping Ratio), position and velocity limit by Eqs. (3) and (4), iteration: 1000, number of particles: 25	well-separated clusters through DBI (Eq. (11)) and local optimization through MSE (Eq. (7)).	a fuzzy anomaly detection method in two phases, training and detection (section 8). This method leads to well-separated clusters, high detection rate, and low false positive rate at the same time as compared to some other well-known methods.

only select linearly the best set of parameters but fulfill also exploration and exploitation issues. Then, we propose a fuzzy detection method by the combination of two distance-based methods as classification and outlier. We design this hybrid system over CCNs to find the optimal number of clusters with high separation from neighbor clusters and low compactness of local data points, increase detection rate, and decrease false positive rate at the same time. Table 1 summarizes the comparison of applied PSO with K-means in different domains and with various parameters.

3. Content-Centric Networks (CCNs)

The main idea in the CCN is that, an Interest request for a content object is routed towards the location of the content's origin where it has been published. Any router or intermediate node on the way checks its cache for matching copies of the requested content. If a cached copy of any piece of Interest request is found, it is returned to the requester along the path the request came from. On the way back, all the intermediate nodes store a copy of content in their caches to answer to probable same Interest requests from subsequent requesters [41, 42]. CCN routers must include the following components:

1. Content Store (CS): a storage space for content caching and retrieval,
2. Forwarding Interest Base (FIB): a table with name prefixes and corresponding outgoing interfaces for routing incoming Interests packets,
3. Pending Interest Table (PIT): a table with the currently unsatisfied Interests and their corresponding incoming interfaces.

The following is a list of some of the main security issues in CCN:

1. **Architectural Risks**: Since contents can be cached on each CCN router, the caches can jeopardize user privacy, content privacy and perform cache pollution attacks. Because users leave communication and exchanged data traces in the caches and content can be extracted by attackers [41, 43, 44]. And since, any attacker can get that information from the caches by either using Interest packets with special query features or by probing the caches; user's privacy is very vulnerable [45].

2. **DoS attacks**: There are new ways to perform DoS attacks by either making content unreachable for requests or forcing fake responses [7, 45, 46, 47]. *To make content unreachable for requests*: a source can be disrupted by sending large numbers of new and distinct Interests (Interest Flooding Attacks) or an attacker can decline the cache performance by overloading the cache when a cache receives a legal traffic. When attackers get high access control in a router, they can make disruption in routing by do not forwarding requests or enforce misbehaving in Pending Interest Table (PIT) routers in order to prevent content retrieval. *To serve fake responses*: an attacker can make routers believe a valid content is invalid and reply a "not valid" response, deliberately. A content can also be spoofed by injecting fake responses that are not signed or are signed with a wrong key, hoping that the user accepts the response in source. An old content (which may be unsecured) signed with the right key can be also replaced with the original one, or an attacker may get high access to the source's signing key to sign content with the correct key. Another possible threat is the misbehaving of the distributed directory system (a digital certificate storage of authority identities) where a client should query for a digital certificate of a content provider, e.g., not replying to a query [27, 48].

4. Particle Swarm Optimization (PSO)

The PSO was firstly introduced by Kennedy and Eberhart in 1995 [49]. It was inspired by the social behavior of a bird flock or fish school. It is a population based meta-heuristic method that optimizes a problem by initializing a flock of birds randomly over the search space where each bird is referred as a "particle" and the population of particles is called "swarm". The particles move iteratively around in the search space according to a simple mathematical formula over the particle's position and velocity to find the global best position. In the n-dimensional search space, the position and the velocity of i th particle at t th iteration of algorithm is denoted by vector $X_i(t) = (x_{i1}(t), x_{i2}(t), ..., x_{in}(t))$ and vector $V_i(t) = (v_{i1}(t), v_{i2}(t), ..., v_{in}(t))$, respectively. This solution is evaluated by a cost function for each particle at each stage of algorithm to provides a quantitative value of the solution's utility. Afterwards, a record of the best position of each particle based on the cost value is saved. The best previously visited position of the particle i at current stage is denoted by vector $P_i = (p_{i1}, p_{i2}, ..., p_{in})$ as the personal bests. During this process, the position of all the particles that gives the best cost until the current stage is also recorded as the global best position denoted by $G = (g_1, g_2, ..., g_n)$. The structure of the velocity and the position updates is depicted in Fig. 1. Each iteration is composed of three movements: in the first movement, particle moves slightly toward the front in the previous direction with the same speed. In the second movement, it moves slightly toward the previous itself best position. Finally, in the third movement, moves slightly toward the global position. At each iteration, the velocity and the position of each particle are defined according to Eqs. (1) and (2), respectively:

$$V_i(t) = \omega * V_i(t-1) + c_1\varphi_1(P_i - X_i(t-1)) + c_2\varphi_2(G - X_i(t-1)) \tag{1}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{2}$$

Where, ω denotes the nonzero inertia weight factor that introduces a preference for the particle to continue moving in the same direction. Decreasing the inertia over time introduces a shift from the exploratory (global search) to the exploitative (local search) mode [50, 51]. Generally, the inertia weight ω is reduced linearly. There are several selection strategies of inertia

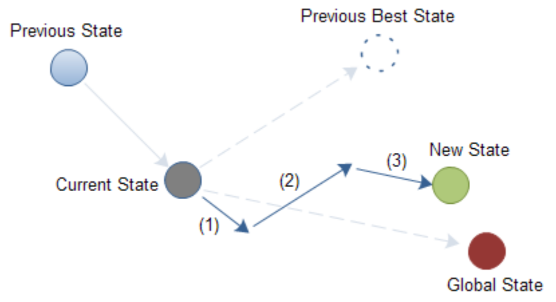


Figure 1: Description of velocity and position updates in PSO for a 2-dimensional parameter space

weight ω which have been described in [52, 53]. c_1 and c_2 are positive constant (social) parameters called acceleration coefficients which control the maximum step size between successive iterations. φ_1 and φ_2 are two independently positive random number drawn form a uniform distribution between 0.0 and 1.0. According to [51], a good starting point is to set ω_{start} to 0.9, ω_{end} to 0.4, and $c_1 = c_2 = 2$.
The velocity and position of a particle might end up positioning the particle beyond the boundary [Var_{min}, Var_{max}] of the search space. Therefore, the need of having a scheme which can bring such particles back into the search space. In our proposal, we apply *Set On Boundary* strategy. According to this strategy the particle is reset on the bound of the variable which it exceeds [54]. Let X_C denote a current velocity or position of a solution, then X_C is set to X_C^{new} as follows:

$$X_C \rightarrow X_C^{new} = \begin{Bmatrix} -0.1 * (Var_{max} - Var_{min}) \\ if X_C < lowerbound \\ \\ 0.1 * (Var_{max} - Var_{min}) \\ if X_C > upperbound \end{Bmatrix} \quad (3)$$

An additional strategy called velocity reflection is also applied. Velocity reflection allows those particles that move toward the outside the boundary to move back into the search space according to Eq. (4).

$$V_i(t+1) \rightarrow -V_i(t+1) \quad (4)$$

5. K-means Clustering Algorithm

The K-means algorithm [23] groups the set of data points into a predefined number of the clusters in terms of a distance function. The most widely used method is Euclidean distance in which a small distance implies a strong similarity whereas a large distance implies a low similarity. The Eq. (5) shows the Euclidean distance calculation between two data points (x and y) with N objects in a n-dimensional space.

$$Distance(x, y) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \quad (5)$$

The standard K-means algorithm is summarized as follows:

1 Randomly initialize the K cluster centroids.

2 Assign each object to the group with the closest centroid. Euclidean distance measures the minimum distance between data objects and each cluster centroid.

3 Recalculate the cluster centroid vector, using

$$m_j = \frac{1}{n_j} \sum_{\forall data_p \in C_j} data_p \quad (6)$$

where, m_j denotes the centroid vector of the cluster j, n_j is the number of the data vectors in cluster j, C_j is the subset of the data vectors from cluster j, and $data_p$ denotes the pth data vector.

4 Repeat step 2 until the centroids do not change any more in the predefined number of iteration or a maximum number of iterations has been reached.

6. Clustering Problem

Mean Square Error (MSE) is the average pairwise distance between data points and the corresponding cluster centroids. Usually distance is Euclidean distance, but other metrics are also used. Given the set of cluster centroids (c), the set of corresponding data points (x), c_x denotes the cluster centroid corresponding to the x, and N is the number of data points, MSE can be calculated as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} d(x_i, c_x)^2 \quad (7)$$

In order to determine the correct and the optimal number of clusters, we must choose the validation criteria. There are several methods (such as K-means) which try to minimize the MSE between data vectors and their cluster centroid to verify the clustering goodness [33, 55]. But, MSE is not enough and suitable metric for determining the number of the clusters, since it decreases as the number of cluster increases. In fact,

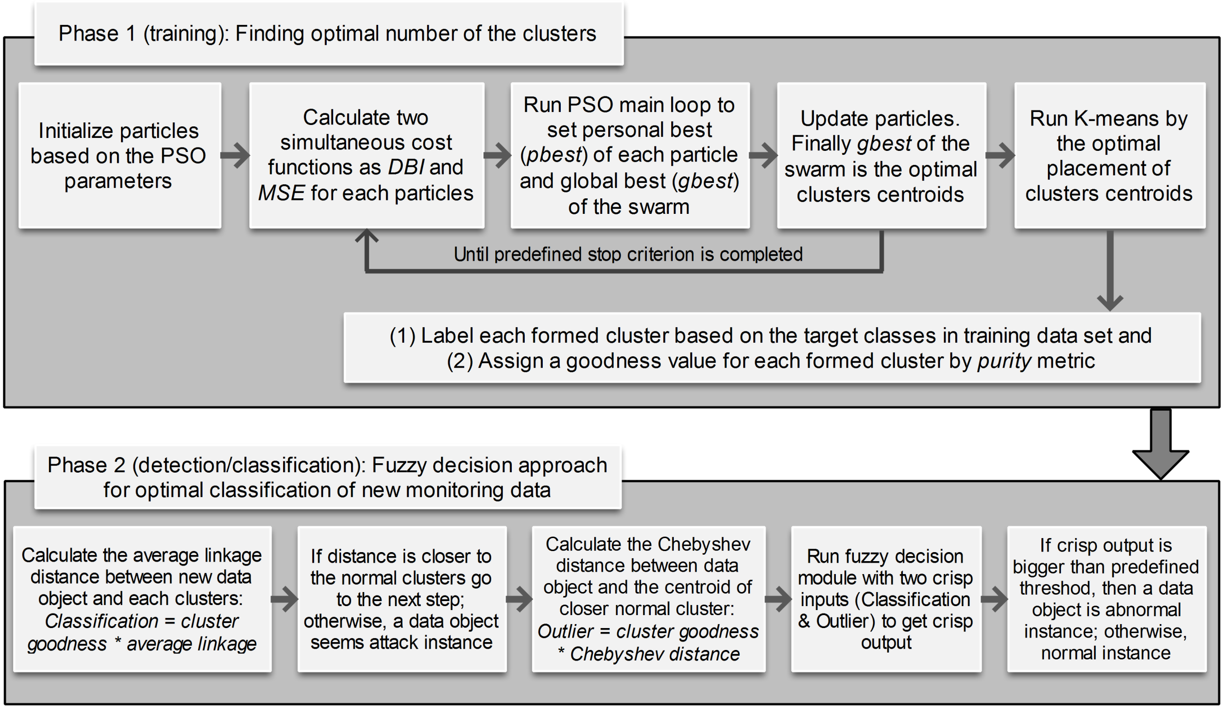


Figure 2: Two steps of the proposed fuzzy anomaly detection system in CCN

the optimal MSE would be number of the cluster equals to data set points, and the MSE=0. Therefore, we apply Davies Bouldin Index (DBI) [56] as the criterion since, in our experiments, we have found it quite reliable among the variety of alternative internal clustering validation metrics; with regard to pointing out the correct number of clusters. DBI takes into account both compactness (intra-cluster diversity) and separation (inter-cluster diversity) criteria that makes similar data points within the same clusters and places other data points in distinct clusters. The intra-cluster diversity of a cluster j is calculated as:

$$MSE_j = \frac{1}{N}\sum_{i=1}^{N} d(x_i, c_x)^2 \tag{8}$$

The inter-cluster distance of the cluster i and j is measured as the distance between their centroids c_i and c_j. According to Eq. (9), the closeness of the two clusters can be calculated by the sum of their MSE divided by the distance of their centroids.

$$Closeness_{i,j} = \frac{MSE_i + MSE_j}{d(c_i, c_j)} \tag{9}$$

Small value of $Closeness_{i,j}$ denotes that the clusters are separated and a large value denotes that the clusters are close to each other. To calculate DBI value, the highest value from Eq. (9) is assigned to cluster as its cluster similarity:

$$Closeness_i = max(Closeness_{i,j}), i \neq j \tag{10}$$

Finally, the overall DBI validity is defined according to Eq. (11), which the lower DBI value means better clustering result.

$$DBI = \frac{1}{M}\sum_{i=1}^{M} Closeness_i \tag{11}$$

7. Fuzzy Set

Fuzzy set theory is a method of representing the vagueness and imprecision which is appropriate for anomaly detection for two major reasons [57, 58]:

1. The anomaly detection problem involves many numeric attributes in collected audit data and various derived statistical measurements. Building models directly on numeric data causes high detection errors, and
2. The security itself involves fuzziness, because the boundary between the normal and abnormal is not well defined.

Fuzzy logic also can work with other popular data mining technique as outlier detection. Since malicious behavior is naturally different from normal behavior, abnormal behavior should be considered as outliers [59, 60]. Fuzzy logic can help to construct more abstract and flexible patterns for intrusion detection and thus greatly increase the robustness and adaption ability of detection systems [58]. Hence, fuzzy approach can reduce the false positive rate with higher reliability in determining intrusive activities, due to any data (normal or attack) may be similar (closest distance) to some clusters.

8. Proposed Fuzzy Anomaly Detection System

This section presents the details of our proposed method. Proposed fuzzy anomaly detection system consists of two phases: training and detection. Fig. 2 shows the proposed fuzzy anomaly detection system steps. Each phase is also described as follows.

8.1. Training Phase

The training phase is based on the hybridization of PSO and K-means clustering algorithm with two simultaneous cost functions: well-separated clusters (low intra-cluster distance and high inter-cluster distance) by DBI and local optimization by MSE to find the optimal number of clusters. Before training process, data samples should be normalized into [0 1], when dealing with parameters of different units and scales [61, 62]. The steps of the training phase is presented as follows:

Step 1: Define problem and PSO parameters

1.$nVar$: number of the cluster centroids, $nPop$: size of the population;

2. Define constriction coefficients parameters, $c1 = c2 = 2$ and initially $w = 1$;

3. Define inertia weight damping ratio ($Wdamp = 0.99$) to linearly decrease w;

4. Define position and velocity limits as $Var_{max} = 1$ and $Var_{min} = 0$;

5. An initial population is generated based on the $nPop$ with following parameters:

$particle.Position$ = a $m \times nVar$ matrix of random numbers generated from the continuous uniform distributions with lower (Var_{min}) and upper (Var_{max}) endpoints. m denotes size of the data set features;

$particle.Cost$ = calculate the DBI for each particle based on the generated $particle.position$;

$particle.Velocity$ = a zero matrix in $m \times nVar$ size;

$particle.Sol$ = [], (Sol is a structure of two objective functions: Cost1 (DBI) and Cost2 (MSE));

$particle.Best.Position$ = [] (keep the personal best of the position);

$particle.Best.Cost$ = [] (keep the personal best of the cost);

$particle.Best.Sol$ = [] (keep the personal best of the Sol);

6. $Globalbest$ = [] (keep the global best of swarm);

7. Repeat the following loop until the target or maximum iteration is completed:

8. Select $Particle(i), i = 1, 2, ..., nPop$ and run the following PSO algorithm for $Particle(i)$:

8.1. Update velocity by Eq. (1);

8.2. Apply velocity limits by Eq. (3);

8.3. Update position by Eq. (2);

8.4. Velocity mirror effect by Eq. (4);

8.5. Apply position limits by Eq. (3);

8.6. Evaluation of two objective functions, DBI by Eq. (11) and MSE by Eq. (7);

8.7. Update personal best:

$if\ (particle(i).Cost == particle(i).Best.Cost)\ AND$
$(particle(i).Sol.MSE < particle(i).Best.Sol.MSE)$
  $particle(i).Best.Position = particle(i).Position;$
  $particle(i).Best.Sol = particle(i).Sol;$
$else\ if\ (particle(i).Cost < particle(i).Best.Cost)$
    $particle(i).Best.Position = particle(i).Position;$
    $particle(i).Best.Cost = particle(i).Cost;$
    $particle(i).Best.Sol = particle(i).Sol;$
  end
$end;$

8.8. Update global best:

$if((particle(i).Best.Cost == GlobalBest.Cost)\ AND$
$(particle(i).Best.Sol.MSE < GlobalBest.Sol.MSE))$
$OR\ (particle(i).Best.Cost < GlobalBest.Cost)$
    $GlobalBest = particle(i).Best;$
$end;$

9. if $i > nPop$ go to the step 10; otherwise, set $i = i+1$ and go to the step 8;

10. Update w by $w = w * Wdamp$;

11. If the maximum iteration or predefined target is not reached, set $i = 1$ and go to the step 7; Otherwise, run K-means clustering algorithm by the obtained positions of cluster centroids from PSO algorithm.

After the main procedure of training phase, each formed cluster is labeled based on the target (original) classes in training data set. It is highly probable that the clusters containing normal data (correct classification) will have a number of abnormal data (incorrect classification) and vice versa. Therefore, we assigned a goodness value in range of [0 1] for each formed cluster by purity metric. The purity metric determines the frequency of the most common category/class into each cluster:

$$Purity = \frac{1}{n}\sum_{q=1}^{k}\max_{1\leq j\leq l} n_q^j \qquad (12)$$

Where, n is the total number of samples; l is the number of categories, n_q^j is the number of samples in cluster q that belongs to the original class $j(1 \leq j \leq l)$. A large purity (close to 1) is desired for a good clustering. If the all samples (data) in a cluster have the same class, the purity value set to 1 as a pure cluster. This purity metric (goodness value) is used in the detection phase.

Table 2: The five applied benchmark data sets

Data set	No. of features	No. of classes	No. of patterns
Iris	4	3	150
Glass	9	6	214
Wine	13	3	178
Ionosphere	34	2	351
Zoo	17	7	101

8.2. Detection Phase

The defined optimal placement of cluster centroids and data objects from training phase are sent to the second phase for outlier and anomaly detection when new monitoring data enter. In the detection phase, a fuzzy decision approach applied to detect attacks and anomalies. We deploy a combination of two distance-based methods, i.e., classification and outlier:

1 **Classification**: The distances between a data object and each clusters are calculated using the *goodness value of the cluster* × *average linkage*. Average linkage approach considers small variances, because it considers all members in the cluster rather than just a single point. However, it tends to be less influenced by extreme values than other distance methods [63]. A data object is classified as normal if it is closer to the one of the normal clusters than to the anomalous ones, and vice versa. This distance-based classification allows detecting known kind of abnormal or normal traffics with similar characteristics as in the training data set.

2 **Outlier**: An outlier (noise) is a data object that differs considerably from most other objects, which can be considered as an anomaly. For outlier detection, only the distance to the normal clusters (obtained from classification phase) is calculated by *goodness value of the closer normal cluster* × *Chebyshev distance*. In the Chebyshev distance (Eq. (13)), distance between two vectors is the greatest of their differences along any coordinate dimension. It allows to detect better new anomalies that do not appear in the training data set. Because it takes into account the maximum value distance approach between any coordinate dimension that would lead to become more strict against data objects measurement.

$$D_{chebyshev}(p, c) = max(|p_i - c_i|) \qquad (13)$$

Where, p is the data object and c is the centroids of the normal cluster with standard coordinates p_i and c_i.
The proposed fuzzy detection method consists of two inputs (classification and outlier), one output, and four main parts: fuzzification, rules, inference engine, and defuzzification. In fuzzification step, a crisp set of input data are converted to a fuzzy set using fuzzy linguistic terms and membership functions. In step 2, we construct rule base. Afterwards, an inference is made and combined based on a set of rules. In the defuzzification step, the results of fuzzy output are mapped to a crisp (non-fuzzy) output using the membership functions. Finally, if the crisp output is bigger than a predefined threshold, an object is considered as an abnormal instance; otherwise, an object is a normal instance. This fuzzy approach can improve our performance criteria (high detection rate and low false positive rate at the same time) as compared to a non-fuzzy approach.

9. Experimental Results and Discussion

9.1. Performance Measurement

We compared and evaluated the training phase of our proposed method with standalone PSO and K-means algorithms as well as preexisting methods from the literature as [36], [37], [38], [39], and [40] which used different parameters and cost functions. We also employed both MSE and DBI criteria on all evaluations. In order to evaluate the performance of each method, we use the Detection Rate (DR), False Positive Rate (FPR) and F-measure criteria. The detection rate is the number of intrusions detected by the system from Eq. (14), the false positive rate is the number of normal traffics that was incorrectly classified as intrusion from Eq. (15) and F-measure is the weighted harmonic mean of precision (positive predictive value) and recall (detection rate) from Eq. (17).

$$DR\ (Recall) = \frac{TruePositive}{TruePositive + FalseNegative} \qquad (14)$$

$$FPR = \frac{FalsePositive}{FalsePositive + TrueNegative} \qquad (15)$$

Table 3: Classification error (%) for our proposed method and applied methods

Method	Type	Criteria	Data set				
			Iris	Glass	Wine	Ionosphere	Zoo
K-means	Training	Ave.	6.86	19.54	18.2	11.64	10.83
		S.D.	2.34	3.61	3.66	3.28	2.73
	Test	Ave.	5.53	17.59	18.26	11.12	9.42
		S.D.	2.32	3.12	3.76	3.1	2.6
PSO (MSE)	Training	Ave.	5.42	17.41	17.8	10.66	10.35
		S.D.	2.14	3.08	3.01	2.86	2.73
	Test	Ave.	4.84	16.41	16.81	9.59	9.64
		S.D.	2.24	3.3	2.98	2.78	2.2
PSO (DBI, MSE)	Training	Ave.	4.9	16.85	17.46	10.75	9.98
		S.D.	1.73	3.01	2.56	3.14	2.48
	Test	Ave.	4.59	16.08	16.41	9.17	8.64
		S.D.	1.62	2.85	2.41	2.72	2.6
PSO-Kmeans (MSE)	Training	Ave.	5.1	16.89	17.54	11.94	11.4
		S.D.	1.23	3.08	3.56	2.91	2.55
	Test	Ave.	4.77	16.81	17.48	9.96	9.35
		S.D.	1.26	3.1	3.26	2.78	2.6
Method [36]	Training	Ave.	4.87	16.32	15.24	11.16	8.58
		S.D.	1.28	3.32	3.4	2.48	2.4
	Test	Ave.	5.4	16.07	15.08	9.92	8.06
		S.D.	1.4	3.63	2.92	2.39	2.02
Method [37]	Training	Ave.	5.92	16.54	16.34	10.42	10.03
		S.D.	1.35	3.47	3.4	3.36	3.3
	Test	Ave.	5.76	16.43	15.6	9.88	10.05
		S.D.	1.5	3.51	3.04	2.68	2.75
Method [38]	Training	Ave.	5.84	18.72	16.98	12.24	11.52
		S.D.	1.34	3.78	3.3	3.79	3.17
	Test	Ave.	5.48	17.18	15.82	11.86	9.56
		S.D.	1.32	3.61	2.98	3.61	3.25
Method [39]	Training	Ave.	6.01	18.59	17.65	10.45	9.31
		S.D.	1.97	4.54	4.76	4.87	5.01
	Test	Ave.	5.98	17.64	16.16	11.06	9.11
		S.D.	1.75	4.85	5.02	4.85	3.97
Method [40]	Training	Ave.	4.91	16.29	15.62	11.18	9.49
		S.D.	1.23	3.33	3.9	2.98	2.35
	Test	Ave.	4.52	16.18	15.14	10.22	8.09
		S.D.	1.38	3.11	3.01	2.84	2.23
Our Method PSO-Kmeans (DBI, MSE)	Training	Ave.	4.01	14.44	14.88	10.04	7.98
		S.D.	1.03	2.29	2.16	2.31	2.11
	Test	Ave.	3.58	13.14	13.04	9.03	7.47
		S.D.	0.98	2.12	2.01	2.26	1.88

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \quad (16)$$

$$F-measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (17)$$

True negative and true positive correspond to a correct operating of the system when traffics are successfully predicted as normal and attacks, respectively. False positive refers to normal traffics when are predicted as attack, and false negative is attack traffic when incorrectly predicted as normal traffic.

9.2. Benchmarking the proposed method

To assess the robustness and accuracy of our proposed method, we applied the five classic benchmark problems from the UCI machine learning repository [64]. Table 2 shows the main characteristics of these data sets. Our proposed method and the other methods mentioned in section 9.1 have been employed to these problems. All experiments were run 20 times, and the average classification error (Ave.) and its standard deviation (S.D.) were computed. In the experiments, 70% of data set is used as training data set in the training phase and the rest is considered as testing data set in the detection phase in order to validate the functionality of the proposed method. We assume that the normal clusters denote the correct classification and abnormal (attack) clusters denote the incorrect classification. For instance, given a data object d in a test data set belongings to class

Table 4: Comparison of our proposed method with some other methods

K	Criteria	Kmeans	PSO (MSE)	PSO (DBI, MSE)	PSO-Kmeans (MSE)	Method [36]	Method [37]	Method [38]	Method [39]	Method [40]	Our Method PSO-Kmeans (DBI, MSE)
50	Correct K	12	10	10	14	15	15	17	18	18	10
	DR (%)	56.18	68.18	77.11	69.12	71.12	73.92	76.55	74.65	73.12	80.22
	FPR (%)	9.19	5.22	7.33	13.157	12.05	12.15	9.43	9.96	8.12	3.489
	F-measure (%)	67.81	78.62	83.58	75.77	77.6	79.4	82.7	83.11	80.65	87.32
75	Correct K	15	12	10	15	15	14	18	18	16	14
	DR (%)	47.24	68.18	77.11	61.05	63.5	72.14	66.55	65.78	74.12	80.22
	FPR (%)	9.338	4.28	3.704	3.122	9.287	13.165	4.32	5.03	9.12	3.489
	F-measure (%)	60.31	79.05	85.28	74.36	76.15	77.81	77.87	76.84	80.85	87.32
100	Correct K	15	15	14	15	16	17	20	19	16	14
	DR (%)	47.24	68.18	77.11	67.145	64.5	72.14	76.55	75.83	76.12	80.22
	FPR (%)	8.558	6.431	7.839	7.819	7.182	12.314	8.12	9.12	12.8	3.489
	F-measure (%)	60.61	78.06	83.35	76.72	75.11	78.17	82.85	80.68	80.52	87.32
125	Correct K	17	10	15	18	18	15	21	21	17	11
	DR (%)	56.18	68.18	77.11	65.123	66.5	72.14	66.55	67.89	77.12	80.22
	FPR (%)	4.738	4.102	3.505	3.935	8.134	9.637	2.98	3.78	10.023	3.489
	F-measure (%)	69.81	79.31	85.37	77.02	76.12	79.33	78.5	78.95	82.38	87.32
150	Correct K	11	14	16	13	14	14	15	16	17	16
	DR (%)	42.93	68.18	77.11	71.147	71.119	72.14	76.55	77.93	77.14	80.22
	FPR (%)	3.738	1.345	1.345	2.101	5.98	12.508	8.88	7.64	12.209	1.314
	F-measure (%)	58.53	80.43	86.41	82.12	80.28	78.09	82.51	85.89	81.43	88.38
175	Correct K	22	22	20	21	25	31	30	32	17	20
	DR (%)	71.903	68.18	77.11	70.548	72.119	83.34	78.95	76.89	77.06	80.22
	FPR (%)	4.489	3.13	3.002	2.44	3.98	15.98	14.14	13.54	3.096	2.738
	F-measure (%)	81.51	79.58	85.61	81.55	81.88	83.55	81.71	82.48	85.53	87.68
200	Correct K	16	18	18	19	22	21	20	19	20	18
	DR (%)	64.24	71.11	77.11	74.343	72.119	73.34	72.95	74.35	81.66	80.22
	FPR (%)	2.738	3.002	1.376	2.739	9.98	12.436	12.15	13.14	14.096	1.314
	F-measure (%)	76.81	81.67	88.71	83.95	79.16	78.9	78.76	80.32	83.37	88.38
250	Correct K	16	17	15	19	19	16	21	18	18	15
	DR (%)	64.24	70.34	77.11	71.01	82.119	72.245	75.95	79.45	72.66	80.22
	FPR (%)	2.738	2.013	3.91	4.11	15.95	5.86	1.16	3.12	3.101	2.738
	F-measure (%)	76.81	81.61	85.18	81.08	82.85	81.1	85.74	86.83	82.66	87.7
300	Correct K	21	20	14	20	21	18	18	19	17	14
	DR (%)	74.82	88.27	99	88.132	81.44	89.911	90.106	88.34	94.109	100
	FPR (%)	10.314	9.12	17.352	9.19	11.209	17.33	24.51	26.93	16.91	9.117
	F-measure (%)	80.74	89.36	91.44	89.28	84.5	86.59	83.86	81.14	88.71	95.64
350	Correct K	21	25	26	22	23	23	26	25	20	26
	DR (%)	77.22	90.122	99	88.668	88.44	95.22	92.20	93.67	97.109	100
	FPR (%)	12.38	16.981	9.676	10.254	9.209	9.164	12.12	11.39	7.454	6.809
	F-measure (%)	81.4	86.96	94.84	89.1	89.45	93.13	90.19	90.83	94.91	96.71
400	Correct K	16	21	25	19	21	28	28	26	27	27
	DR (%)	77.22	90.122	99	92.55	95.29	94.005	96.20	94.23	97.077	100
	FPR (%)	12.38	16.981	17.998	10.45	6.45	15.45	13.12	14.67	14.968	1.847
	F-measure (%)	81.37	86.95	90.89	91.21	94.64	89.82	91.92	88.45	91.76	98.99
500	Correct K	23	24	21	22	25	31	33	33	27	21
	DR (%)	77.22	90.122	99	96.68	94.29	96.005	96.78	96.15	96.807	100
	FPR (%)	12.738	7.672	19.368	8.018	16.45	17.45	17.94	17.63	12.216	12.379
	F-measure (%)	81.25	91.09	90.59	94.43	89.42	89.88	90.01	90.03	92.54	94.17

A. If it gets assigned to class B by the proposed classification method in the second phase, class B is an incorrect class/category for data object d. Hereby, the formed cluster belongings to class B is assumed to be an abnormal cluster for the data object d. In contrast, if data object d is closer to a cluster labeled class A (we called it normal cluster), the outlier distance should be calculated. Then, according to the detection/classification phase of the proposed method, both classification and outlier values are sent to the fuzzy module. If the crisp output is smaller than the predefined threshold, data object d seems normal instance (correct classification); otherwise, it seems anomalous instance (incorrect classification). The results have been summarized in Table

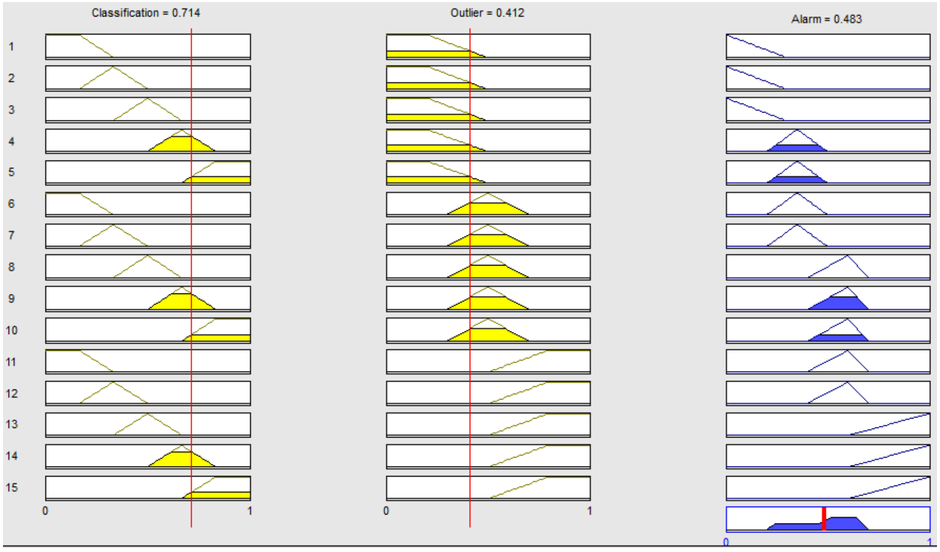


Figure 3: The sample solution area (fuzzy inference) of proposed fuzzy detection system

3. It can be seen in the table that our proposed fuzzy method tends to obtain a more accurate classification rate (Ave.) and lower standard deviation (S.D.) as compared to other methods.

9.3. Feature Construction

We employed simple features that can be extracted by inspecting the headers of the network packets. These intrinsic features are the duration of the connection, source host, destination host, source interface, and destination interface [65]. We also used the following features in each 2 seconds time interval:

1 *Total number of packets* sent from and to the given interface in the considered time interval,
2 *Total number of bytes* sent from and to the given interface in the considered time interval, and
3 *Number of different source-destination pairs* matching the given hostname-interface that being observed in the considered time interval.

The motivation of the first two features is that the number of packets and bytes allow to detect anomalies in traffic volume, and the third feature allows to detect network and interface scans as well as distributed attacks, which both result in increased number of source-destination pairs [66].

9.4. Training Phase

Since there is no reference data for content-centric networks as well as real Internet traffic, we used the

Table 5: CCNx Traffic Generation

Type of traffic	Applied tools
Normal (5240 records)	(1) *ccnsendchunks* with *ccncatchunks2* (2) *ccnputfile* with *ccngetfile* (3) *ccnchat*
Attack (530 records)	(1) *ccndsmoketest* for (distributed) *Interest flooding* attack (2) make abnormal traffics to saturate channels by sending very small contents (decreasing buffer size) from owner of origin, called *Abnormal Source Behavior* (3) do not forward contents deliberately to requester(s), called *Abnormal Unreachable Content Behavior*

Table 6: Rules Matrix

Outlier	Classification (Cls.)				
	Very close	Close	Average	Far	Very far
Close	Normal	Normal	Normal	Low prone	Low prone
Average	Low prone	Low prone	High prone	High prone	High prone
Far	High prone	High prone	Abnormal	Abnormal	Abnormal

CCNx software of PARC (www.ccnx.org) to run a scenario for generating of CCN traffics in a local testbed. This local testbed includes 13 Linux (Ubuntu) machines, three of them acting as servers (content origins) and the other ones as clients. Then, we ran wireshark tool to capture CCNx packets. We performed the following experiments with the main tools in CCNx: ccnsendchunks (to upload objects/files into the CCN repository), ccncatchunks2 (to receive desired contents and to write them to stdout), ccnputfile (to publish a local file in the CCNx repository), ccngetfile (to retrieve published content and writes it to the local file), ccndsmoketest (to send the large number of Interests - Interest flooding attacks- toward a host/network), and ccnchat (to run a chat channel). We conducted three attack instances for both training and detection phases including Interest flooding attacks, flooding a victim router by sending too many small contents from owner of origin content (we called it *Abnormal Source Behavior*) and making content unreachable for requesters (we called it *Abnormal Unreachable Content Behavior*). We also carried out an anomaly instance in the detection phase as serving fake response (we called it *Abnormal Forwarder Capacity Behavior*) which does not appear in the training data set. The structure of the generated traffics are shown in Table 5 for training and Tables 8 and 9 for testing data sets.

For the PSO algorithm, we used swarm size of 25 particles, the number of iterations set to 1000, and other parameters set according to subsection 8.1. The proposed hybrid method was implemented by the MATLAB software on an Intel Pentium 2.13 GHz CPU, 4 GB RAM running Windows 7 Ultimate.

Table 7: Some fuzzy rules in proposed fuzzy system

IF *Cls.=Average* and *Outlier=Close* **THEN** *Alarm=Normal*
IF *Cls.=Close* and *Outlier=Average* **THEN** *Alarm=LowProne*
IF *Cls.=High* and *Outlier=Average* **THEN** *Alarm=HighProne*
IF *Cls.=Very far* and *Outlier=Far* **THEN** *Alarm=Abnormal*

9.5. Detection Phase

We use MATLAB fuzzy logic toolbox for fuzzy rule based intrusion detection. The detection phase is structured with the following components:

1 Two fuzzy set of input variables: Classification and Outlier;
classification membership: *Very Close, Close, Average, Far, Very Far*; outlier membership: *Close, Average, Far*.

2 A fuzzy set of output variable: Alarm; alarm membership: *Normal, Less Prone, High Prone, Abnormal*.

3 Fuzzy membership functions: see section 9.7.

4 Fuzzy rules: 15 rules (Tables 6 and 7).

5 Inference: Mamdani fuzzy inference by fuzzy set operations as *max* and *min* for *OR* and *AND*, respectively.

6 Defuzzifier: Center of Gravity algorithm:

$$Center\ of\ Gravity = \frac{\int_{min}^{max} u\ \mu(u)\ d(u)}{\int_{min}^{max} \mu(u)\ d(u)} \quad (18)$$

Where, u denotes the output variable, μ is the membership function after accumulation, and *min* and *max* are lower and upper limit for defuzzification, respectively.

A sample solution area (fuzzy inference) of proposed fuzzy detection phase is given in Fig. 3.

Table 8: First scenario of CCNx traffic

Type of traffic	Applied tools
Normal (2110 records)	(1) *HttpProxy* application to run a HTTP proxy that converts HTTP Gets to CCN data. (2) *ccnputfile* with *ccngetfile* (3) *ccnchat*
Attack (866 records)	(1) *ccndsmoketest* for *Interest flooding* attack (2) *Abnormal Source Behavior* (3) make capacity limitation in count of content objects by forwarder/router to discard cached content objects deliberately as *Abnormal Forwarder Capacity Behavior*

Table 9: Second scenario of CCNx traffic

Type of traffic	Applied tools
Normal (1545 records)	(1) *ccnsendchunks* with *ccncatchunks2* (2) *ccnputfile* with *ccngetfile* (3) *HttpProxy* application
Attack (492 records)	(1) *Abnormal Source Behavior* (2) *Abnormal Unreachable Content Behavior* (3) *Abnormal Forwarder Capacity Behavior*

9.6. Results of Training Phase

In this section, the performance of proposed method and preexisting methods from the literature are compared. Since null clusters might appear in the results, these clusters are removed and we count the correct number of K. The experiments on each method were repeated 10 times independently with several K values. The results are summarized in Table 4. The proposed method outperforms other preexisting methods in terms of the DR, the FPR and the F-measure at the same time. The PSO (DBI and MSE) could satisfy DR by 99% when initial K is between 300 and 500. However, it could not satisfy a suitable FPR. By the hybridization of K-means algorithm and PSO (DBI and MSE), we could gain suitable results by very low FPR and very high DR at the same time. In contrast, none of other methods meet very high DR and very low FPR at the same time.

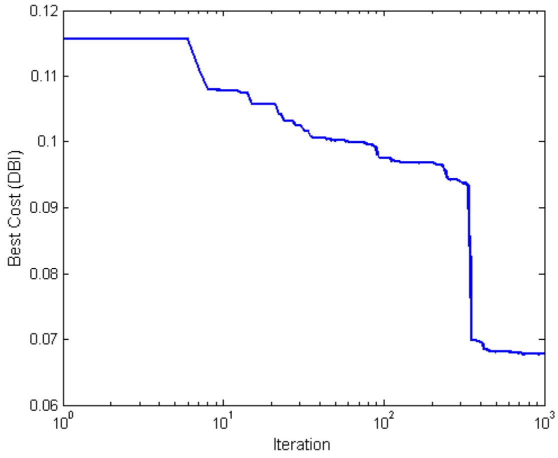


Figure 4: 1st cost function (DBI) in 1000 iterations

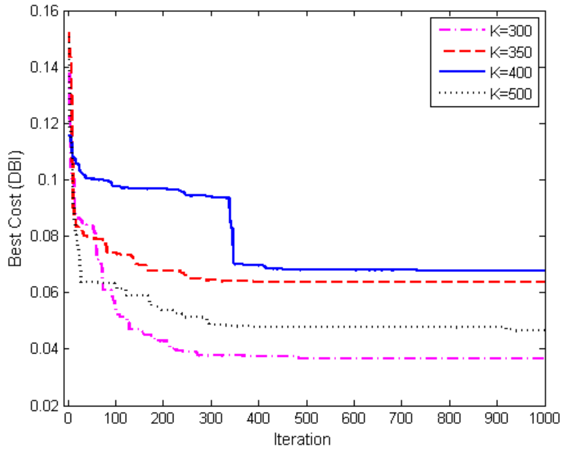


Figure 6: The best cost (DBI) of four clustering results

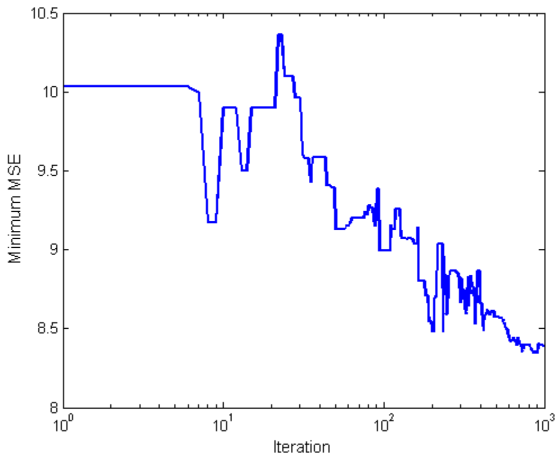


Figure 5: 2nd cost function (MSE) in 1000 iterations

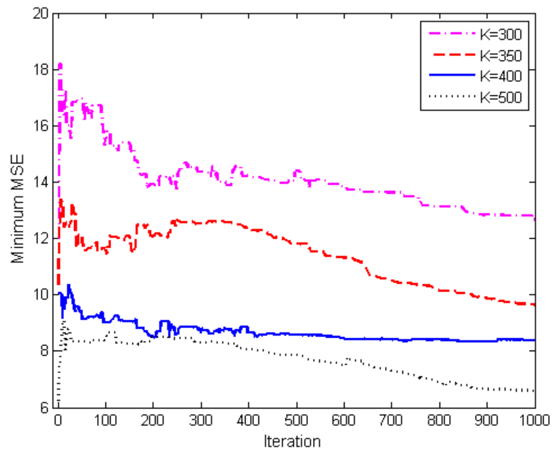


Figure 7: The MSE value of four clustering results

According to the Table 4, by increasing of initial parameter K, results are more efficient with the optimal number of clusters, high detection rate, low false positive rate and greater F-measure at the same time.
The results clearly show that our proposed method offers the best optimized solution in comparison with the other methods when K=400 by DR=100%, FPR=1.847%, F-measure=98.99% and the correct number of K=27. We show the fluctuation of variations of two cost functions during the training phase in Figs. 4 and 5. The results clearly show that by changing of clustering values based on DBI, MSE changes in a irregular manner through the different iterations. For instance, in the last iteration, the minimum MSE is 8.391, but the lowest MSE is in iteration 915 by 8.3458. When DBI is decreasing to find optimal clustering results in the iterations between 100 and 800, there are many fluctuations for MSE value. We also show the trend of changes of DBI and MSE values during the training phase when the DR was 100% and K is between 300 and 500 (Figs. 6 and 7). According to Fig. 6, the best and the worst procedure of reducing the DBI value are for K=300 and 400, respectively. In contrast, the best and the worst procedure of reducing the MSE value are for K=500 and 300 as shown in Fig. 7. The best DBI value for K=300 led to the worst value in MSE. Moreover, the highest changes for minimizing the two applied cost functions during the training phase are for K=400 and

500. These results verify that the MSE parameter cannot be singly used as a good performance criterion for finding the optimal placement of clusters centroids and data objects. We send the optimal outcomes from our proposed method (DR = 100%, FPR = 1.847%, F-measure = 89.99% and K = 27) and the best combination of the DR, the FPR and the F-measure from other methods to the second phase for fuzzy anomaly detection.

9.7. Results of Detection Phase

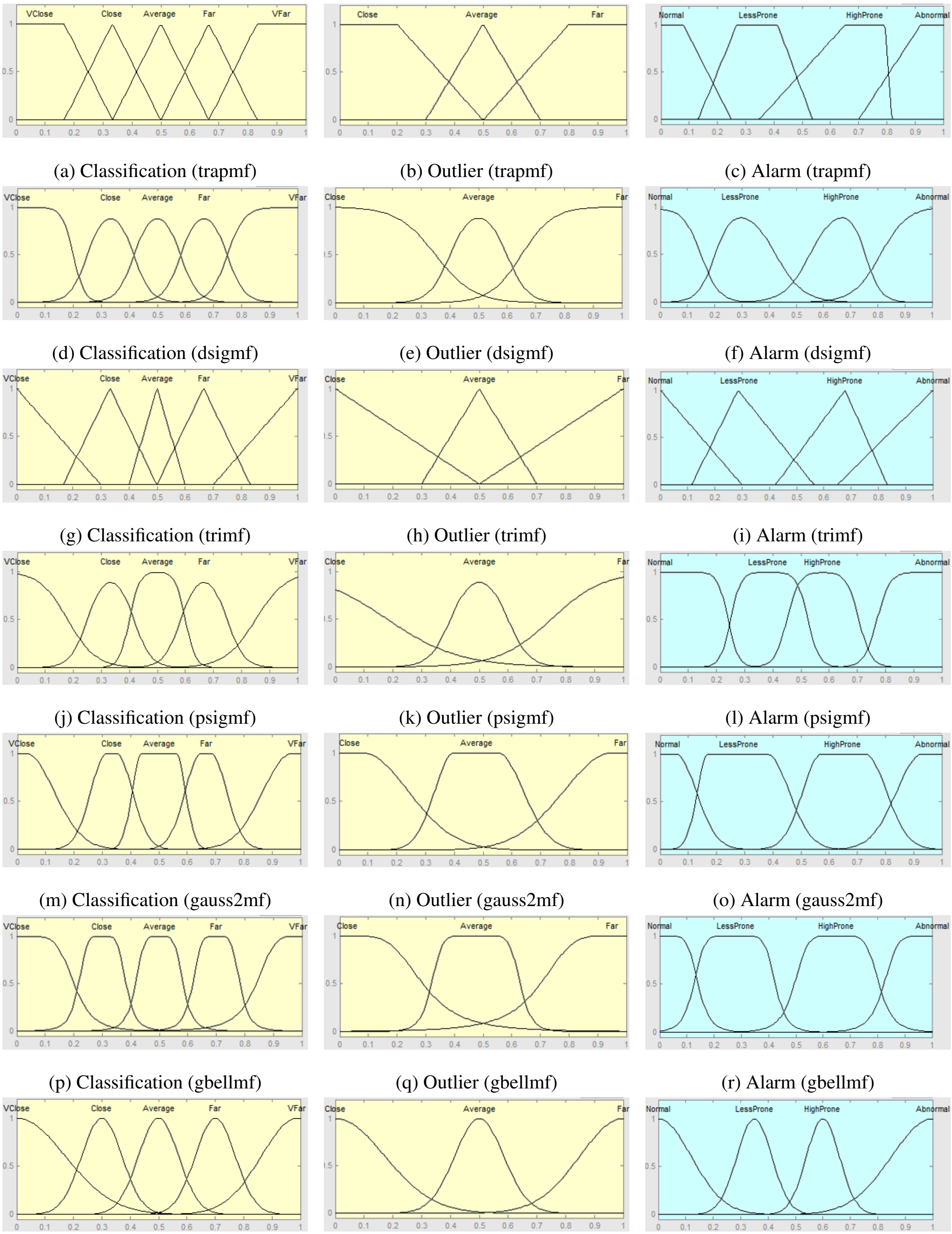
In order to obtain results on how the proposed fuzzy anomaly detection system can perform in real scenarios, we applied it to packet traces recorded at two scenarios with 17 Linux machines (10 clients, 4 servers, and 3 routers). These traces are from CCNx data repository of the University of Politecnica Catalunya (UPC) which are shown in Tables 8 and 9. Each trace file contains about 20 minutes of monitored traffic. According to Tables 8 and 9, there is a new type of normal traffic (*HttpProxy*) and a new type of anomaly traffic (*Abnormal Forwarder Capacity Behavior*) which have not appeared in the training data set. We also define a threshold as $d_{threshold}$=0.5. Each new monitored CCN packet is sent as input to the fuzzy detection phase in order to detect attacks and anomalies. According to the proposed fuzzy anomaly detection system (section 8.2), we calculate the classification distance to find the nearest cluster. If the distance is closer to one of the normal clusters, we calculate the outlier. If the outlier outcome is bigger than a predefined threshold, the packet is treated as an anomaly. In contrast, if the classification distance is closer to one of the attack clusters, it gets treated as an attack packet. Based on the different fuzzy membership functions, the fuzzy detection method produces different results. To find the most ideal system, we apply seven membership functions for each applied methods including trapmf (Trapezoidal-shaped), dsigmf (Difference between two sigmoidal functions), trimf (Triangular-shaped), psigmf (Product of two sigmoidal), gauss2mf (Gaussian combination), gbellmf (Generalized bell-shaped), and gaussmf (Gaussian curve). Fig. 8 illustrates the applied membership functions. We integrated each method by optimal results gained from the training phase (Table 4) with our proposed fuzzy detection method in the second phase. Afterwards, we compare the performance of each method based on the RMSE, minimum and maximum error between target output and predicted output. The comparison results between methods in two applied data sets (Tables 8 and 9) are summarized in Table 10. We found out that the RMSE between target and predicted output is absolutely different. We marked the three best results for each membership function. The most appropriate results based on the RMSE, minimum and maximum error include our proposed method (PSO-Kmeans (DBI, MSE)), PSO (DBI, MSE), methods [36] and [40], respectively. By the integration of DBI (well-separated cost) and MSE (local optimization cost), PSO could considerably improve the results in detection phase. As shown, our proposed method is very well suited for most of the membership functions based on the less RMSE, minimum and maximum error values. Performance of trapmf and gauss2mf MF in our proposed method are better than other MF and applied methods. For anomaly detection performance measurement, we continue our experiment by applying well-performing and preexisting methods from Table 10 on the aforementioned data sets. The performance of fuzzy detection approach is also compared with the non-fuzzy approach. In order to validate the CCNx traffic classification performance of our fuzzy detector, we use the Receiver Operating Characteristic (ROC) curve analysis, Area Under the Curve (AUC), accuracy, specificity and sensitivity (recall). The ROC curve provides a way to visually represent how the trade-off between false positive and detection rate varies for different values of the detection threshold [67]. The AUC summarizes the classification performance of the classifier in the range [0 1] in which the higher the AUC, the easier to distinguish attacks from normal traffic [68]. The other applied performance measures can be summarized as a 2×2 table (confusion matrix in table 11):

1. Accuracy: $(a + d)/(a + b + c + d)$
2. Specificity (true negative rate): $a/(a + b)$
3. Sensitivity (recall): $d/(c + d)$

Table 11: The 2×2 contingency table (confusion matrix)

True label	Predicted label	
	Negative	Positive
Negative	a	b
Positive	c	d

Figs. 9 and 10 present the fuzzy and non-fuzzy ROC curves of our proposed method and the other applied methods for 1st scenario. Figs. 11 and 12 present the ROC curve for both fuzzy and non-fuzzy approaches in 2nd scenario. As it can be seen in these figures, the detection rate and the false positive rate of our proposed method (PSO-Kmeans (DBI, MSE)) are better than in the other methods. This implies a higher number of the correct detection and a lower number of the false



(a) Classification (trapmf) (b) Outlier (trapmf) (c) Alarm (trapmf)

(d) Classification (dsigmf) (e) Outlier (dsigmf) (f) Alarm (dsigmf)

(g) Classification (trimf) (h) Outlier (trimf) (i) Alarm (trimf)

(j) Classification (psigmf) (k) Outlier (psigmf) (l) Alarm (psigmf)

(m) Classification (gauss2mf) (n) Outlier (gauss2mf) (o) Alarm (gauss2mf)

(p) Classification (gbellmf) (q) Outlier (gbellmf) (r) Alarm (gbellmf)

(s) Classification (gaussmf) (t) Outlier (gaussmf) (u) Alarm (gaussmf)

Figure 8: Seven applied membership functions in detection phase (two inputs and one output)

Table 10: Comparison of membership functions for fuzzy anomaly detection purposes

Methods	Data set	Criteria	trapmf	dsigmf	trimf	psigmf	gauss2mf	gbellmf	gaussmf
K-means	Table 8	RMSE	0.1037	0.2397	0.2713	0.2268	0.3039	0.1943	0.1949
		Min error	-0.253	-0.2992	-0.2216	-0.9755	-1.5892	-1.058	-0.4240
		Max error	0.8934	0.8635	0.995	0.9334	1.0023	0.9683	0.9875
	Table 9	RMSE	0.0663	0.1596	0.1211	0.1238	0.2202	0.2703	0.2009
		Min error	-0.8817	-0.2088	-0.432	-0.3606	-1.1779	-0.4503	-0.6663
		Max error	0.9994	0.935	0.6265	0.3563	0.9966	0.9880	1.008
PSO (MSE)	Table 8	RMSE	0.0759	**0.092**	0.103	0.1162	0.0953	0.1046	**0.0865**
		Min error	-0.2625	**-0.7765**	-0.3011	-0.727	-0.6035	-0.6303	**-0.6541**
		Max error	0.4862	**0.7926**	0.4364	0.9918	0.3987	0.8653	**0.8337**
	Table 9	RMSE	0.1295	0.1592	0.2129	0.2604	0.1665	0.1785	0.1728
		Min error	-0.9444	-0.2385	-0.2004	-1.0268	-0.3541	-1.2154	-0.4445
		Max error	0.8943	0.8267	1.0337	0.9501	0.8683	0.4131	0.9616
PSO (DBI, MSE)	Table 8	RMSE	0.6525	0.1817	0.1541	0.1432	0.2024	**0.0723**	0.1587
		Min error	-0.7457	-0.276	-0.6548	-0.4627	-0.2643	**-0.584**	-0.9233
		Max error	0.937	0.8859	0.4301	0.9398	0.9489	**0.5771**	0.8303
	Table 9	RMSE	**0.0524**	0.0892	0.1251	0.1225	**0.0669**	0.25	0.0925
		Min error	**-0.5833**	-0.5382	-0.7248	-0.2865	**-0.6324**	-0.9254	-0.4052
		Max error	**0.6592**	0.8299	0.9487	0.7618	**0.5671**	0.9618	0.8465
PSO-Kmeans (MSE)	Table 8	RMSE	0.1096	0.1381	0.2582	0.2608	0.3255	0.1737	0.1931
		Min error	-0.5418	-0.2839	-0.3055	-1.173	-1.0158	-0.1510	0.8461
		Max error	0.854	0.9903	1.1168	0.915	0.9992	0.9425	0.8425
	Table 9	RMSE	0.2002	0.1597	**0.0979**	0.1466	0.2331	0.2647	0.168
		Min error	-1.1255	-1.1157	**-0.5717**	-1.3077	-1.005	-0.198	-0.4575
		Max error	0.9525	0.6084	**0.5921**	0.1089	0.998	1.043	0.9459
Method [36]	Table 8	RMSE	0.0927	0.1093	**0.0722**	**0.1135**	0.0935	**0.0763**	**0.0581**
		Min error	-0.3177	-0.5658	**-0.3461**	**-0.5126**	-0.092	**-0.6623**	**-0.6063**
		Max error	0.4688	0.8788	**0.8808**	**0.8765**	1.003	**0.5867**	**0.6139**
	Table 9	RMSE	0.1156	0.3435	0.1826	0.2317	0.2817	0.23	0.2393
		Min error	-0.5278	-0.6531	-0.8078	-0.982	-0.9648	-0.1718	-0.565
		Max error	0.8821	0.9217	0.7279	0.825	1.0119	0.9886	1.032
Method [37]	Table 8	RMSE	0.1507	0.2584	0.1868	0.2916	0.2523	0.1115	0.2968
		Min error	-0.4221	-0.6492	-0.8722	-0.3394	-1.074	-0.4625	-1.038
		Max error	0.9439	0.7947	0.78	0.836	1.008	0.3892	0.9654
	Table 9	RMSE	0.1919	0.2442	0.0971	0.1749	0.1374	0.1288	0.1163
		Min error	-0.2277	-0.6492	-0.3084	-0.5541	-0.6253	-0.7965	-0.3109
		Max error	1.0243	0.8691	0.8129	0.8973	0.9699	0.9148	0.8623
Method [38]	Table 8	RMSE	0.0917	0.1971	0.2805	0.2059	0.2891	0.1737	0.1568
		Min error	-0.5883	-0.494	-0.9252	-0.7737	-0.8936	-0.9185	-0.6149
		Max error	0.7866	0.9858	0.9913	1.4086	1.479	1.007	0.6044
	Table 9	RMSE	0.1749	0.13	0.2525	0.1282	0.2481	0.209	0.1788
		Min error	-0.5433	-0.5966	-0.6027	-0.3625	-0.9461	-1.139	-0.902
		Max error	0.9719	0.4311	0.7168	1.0516	1.085	1.005	0.391
Method [39]	Table 8	RMSE	0.0921	0.201	0.2612	0.2112	0.2761	0.1872	0.1691
		Min error	-0.593	-0.5143	-0.8982	-0.8754	-0.9012	-0.9218	-0.6241
		Max error	0.7957	0.9936	0.9984	1.4148	1.502	1.019	0.6502
	Table 9	RMSE	0.1791	0.1256	0.2485	0.1432	0.2516	0.215	0.1889
		Min error	-0.5553	-0.6041	-0.6081	-0.3702	-0.9333	-1.114	-0.924
		Max error	0.9784	0.4394	0.7221	1.0464	1.094	1.055	0.403
Method [40]	Table 8	RMSE	0.1442	**0.0948**	0.1206	**0.0811**	0.0961	**0.0848**	0.1106
		Min error	-0.3528	**-0.5687**	-0.6512	**-0.5823**	-0.209	**-0.5186**	-0.3415
		Max error	1.0159	**0.872**	0.556	**0.7106**	0.8354	**0.8223**	0.8651
	Table 9	RMSE	0.2885	0.1871	0.2245	0.2043	0.1849	0.1968	0.3799
		Min error	-1.391	-1.005	-0.8121	-1.1521	-0.803	-0.2025	-1.3634
		Max error	1.0382	0.805	1.0565	0.4807	0.9676	0.9299	0.8228
Our Method	Table 8	RMSE	**0.0617**	0.2525	0.1191	**0.0653**	**0.0664**	0.1176	0.3219
		Min error	**-0.4157**	-1.0143	-1.0819	**-0.5434**	**-0.581**	-0.3657	-1.0182
		Max error	**0.6002**	0.9994	0.6676	**0.5124**	**0.4562**	0.8798	1.003
	Table 9	RMSE	**0.0531**	**0.0738**	**0.0691**	0.2165	**0.0657**	0.1491	**0.0519**
		Min error	**-0.5215**	**-0.5281**	**-0.671**	-0.5261	**-0.5759**	-0.7349	**-0.5331**
		Max error	**0.5208**	**0.5365**	**0.488**	0.8954	**0.6468**	0.8061	**0.5982**

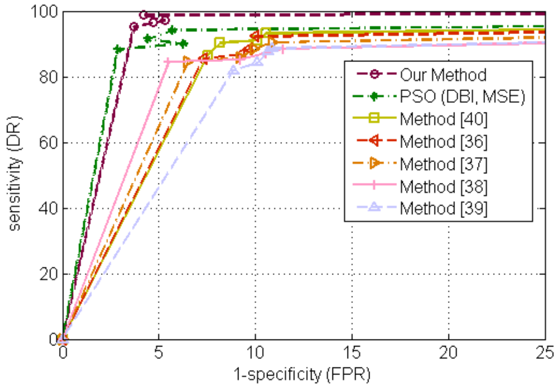


Figure 9: ROC curves corresponding to the proposed method and other applied methods for 1st scenario (fuzzy approach)

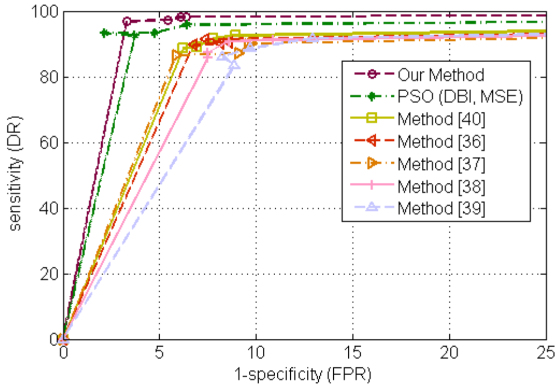


Figure 11: ROC curves corresponding to the proposed method and other applied methods for 2nd scenario (fuzzy approach)

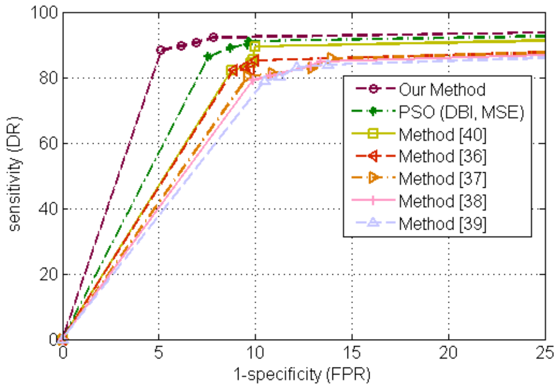


Figure 10: ROC curves corresponding to the proposed method and other applied methods for 1st scenario (non-fuzzy approach)

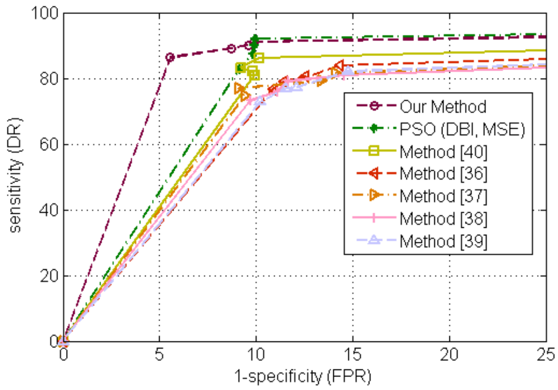


Figure 12: ROC curves corresponding to the proposed method and other applied methods for 2nd scenario (non-fuzzy approach)

positives. Table 12 shows the results of fuzzy and non-fuzzy (crisp) anomaly detection for two applied testing data sets. As shown in this table, our proposed method classifies data objects better than the other approaches based on AUC, accuracy, sensitivity and specificity. In addition, the non-fuzzy anomaly detection approach is often not sufficient in detecting many types of attacks as compared to a fuzzy detection method.

9.8. *Computational Order*

The computational order of standard PSO algorithm is $O(I \cdot S \cdot Cost)$, where I is the required generation number, S is the population size, and $Cost$ is the cost function. The computational complexity of evaluating the cost function depends on the particular cost function under consideration. The applied cost functions in preexisting methods ([36, 37, 38, 39, 40]) are $O(N \cdot K)$, where N is the number of data samples and K is the number of clusters. The computational order of K-means algorithm is $O(T \cdot N \cdot K)$, where T is the number of iterations. The computational order of proposed training method and preexisting methods from the literature are shown in Table 13.

9.8.1. *Time Complexity*

We compare the computational time of algorithms on the training data set. Table 14 shows the computational time and the times of increment on computational time of the six methods. Table 14 demonstrates that the proposed method (PSO+Kmeans (DBI, MSE)) seems to be less time consuming than the other methods except methods [38] and [39] due to the application

Table 12: fuzzy (non-fuzzy) anomaly detection for two applied testing data sets

Method	AUC	Accuracy		Sensitivity (recall)		Specificity	
		mean	S.D.	mean	S.D.	mean	S.D.
Data set 1: **Table 8**							
Our Method	97.44 (93.26)	94.48 (89.07)	0.97 (2.35)	96.88 (90.15)	1.54 (1.41)	95.52 (93.51)	0.79 (1.02)
PSO (DBI, MSE)	95.36 (91.41)	91.38 (87.3)	1.34 (2.48)	91.02 (89.15)	2.45 (2.03)	94.18 (91.12)	1.51 (1.29)
Method [40]	92.39 (89.87)	89.61 (81.74)	2.73 (3.9)	89.2 (82.76)	2.83 (2.97)	91.4 (88.4)	1.28 (1.37)
Method [36]	91.92 (87.37)	88.18 (81.64)	2.84 (3.71)	88.21 (83.33)	2.89 (3.7)	90.98 (87.73)	1.94 (1.17)
Method [37]	91.37 (87.14)	89.29 (81.18)	2.98 (3.88)	87.07 (82.13)	3.04 (3.57)	90.11 (87.61)	2.08 (2.21)
Method [38]	90.87 (86.78)	88.63 (80.51)	3.02 (3.76)	87.1 (82.21)	3.12 (3.85)	90.01 (87.15)	2.18 (2.4)
Method [39]	89.4 (86.12)	87.74 (80.2)	3.01 (3.58)	86.63 (81.68)	3.31 (3.72)	89.41 (87.05)	2.15 (2.31)
Data set 2: **Table 9**							
Our Method	97.41 (92.29)	94.45 (88.14)	0.99 (2.84)	97.65 (89.15)	0.67 (2.03)	96.7 (91.57)	0.99 (1.36)
PSO (DBI, MSE)	95.91 (90.98)	92.01 (86.8)	1.01 (2.68)	93.81 (88.18)	1.43 (3.96)	94.93 (90.3)	1.8 (1.39)
Method [40]	92.92 (88.64)	89.84 (81.06)	2.83 (3.49)	88.49 (82.3)	2.19 (3.19)	91.58 (86.32)	1.74 (1.83)
Method [36]	92.18 (86.67)	89.14 (80.19)	2.78 (3.9)	87.3 (81.82)	0.75 (3.09)	90.43 (85.55)	1.14 (1.98)
Method [37]	91.71 (86.11)	87.11 (80.1)	2.74 (3.99)	87.21 (81.9)	0.8 (3.18)	90.1 (85.33)	1.22 (2.05)
Method [38]	91.47 (85.61)	86.98 (80.06)	2.86 (3.92)	87.17 (81.76)	0.91 (3.41)	90.02 (85.3)	1.34 (2.03)
Method [39]	90.08 (85.86)	85.49 (80.01)	3.03 (3.99)	86.66 (80.54)	1.03 (3.68)	89.43 (85.11)	1.53 (2.61)

Table 13: The computational order of the six methods

Methods	Cost function	Algorithm
Our Method	$O(MSE) + O(DBI) = O(N \cdot K) + O(K^2)$	$O(PSO) + O(K - means)$
Method [40]	$O(MSE) = O(N \cdot K)$	$O(PSO) \times O(K - means)$
Method [36]	$O(MSE) = O(N \cdot K)$	$O(PSO) \times O(K - means)$
Method [37]	$O(MSE) = O(N \cdot K)$	$O(PSO) \times O(K - means)$
Method [38]	$O(MSE) = O(N \cdot K)$	$O(PSO) + O(K - means)$
Method [39]	$O(MSE) = O(N \cdot K)$	$O(PSO) + O(K - means)$

of a single cost function. But the proposed method can find the better solution with less times of increment on computational time than the other five methods due to its fast convergence speed. The results show that the proposed method with the new strategy of cost function -application of two simultaneous cost functions-can yield high accuracy as compared to other methods without very much computational cost.

Table 14: The computational time of the six methods

Methods	Computational time (sec)	Increment time (sec)
Our Method	791.412	92.381
Method [40]	1348.297	478.146
Method [36]	1203.459	401.678
Method [37]	1301.763	424.829
Method [38]	711.359	207.412
Method [39]	723.286	289.764

9.9. Discussion

In this paper, a fuzzy anomaly detection system has been proposed for content-centric networks. This system applies a new hybrid approach with PSO and K-means in two phases: training and detection (Fig. 2). In the training phase, we propose an hybridization of Particle Swarm Optimization (PSO) and K-means algorithm with two simultaneous cost functions as well-separated clusters by DBI and local optimization by MSE. The algorithm utilizes the iteratively global search ability of PSO to find optimal or near optimal cluster centroids and local search ability of K-means to avoid being trapped in a local optimal solution. A new boundary handling approach is also utilized in the PSO to not only select linearly the best set of parameters but fulfill also exploration and exploitation issues. When the optimal placement of clusters centroids and objects are defined, they are sent to the second phase. In the detection phase, we employ a fuzzy approach by the combination of two distance-based methods as classification and outlier to detect anomalies in new monitoring data.

Convergence of the proposed fuzzy anomaly detection system is studied for finding the global and optimal results and measuring the suitable performance over different CCN traffic flows (Table 4 from training phase and Tables 10 and 12 from detection phase). Experimental results show that the applied CCN traffic flows could be used well for both training and detection phase as well as preexisting methods from the literature.

Convergence of the proposed method is also studied for finding global classification of different benchmarking data sets as Iris, Glass, Wine, Ionosphere and Zoo. Experimental results (Table 3) show the accuracy and the robustness of our proposed method based on the average of correct classification and lower standard deviation as compared to other methods.

The feasibility and efficiency of proposed system in training phase compared to nine different approaches. Table 4 depicts the final results using K-means, PSO (MSE), PSO (DBI, MSE), PSO-Kmeans (MSE), methods [36], [37], [38], [39], [40], and our proposed method as PSO-Kmeans (DBI, MSE). The proposed training phase outperforms other methods based on the optimal results as DR = 100%, FPR = 1.847% and F-measure = 98.99 %. In the training phase, future work is needed in the application of multi-objective optimization techniques. Moreover, detection phase results are very capable for anomaly detection purposes. The various membership functions are employed to demonstrate the effectiveness of our proposed method among applied well-performing methods in Table 10. In the most cases, the proposed anomaly detection method performed better than other methods based on the RMSE, minimum and maximum error between target and predicted output at the same time. Specifically, optimal results gained by trapmf and gauss2mf MF. In the detection phase, future work is needed in the application of non-linear membership functions.

Our proposed method and the other methods use different parameter settings and were repeated 10 times independently to find the global results in the training phase; therefore, the effect of tuning parameters on performance of the methods are studied.

We continue our anomaly detection performance measurements by applying well-performing and preexisting methods (from Table 10) and our proposed method over two applied data sets (Tables 8 and 9). As shown in Figs. 9-12 and Table 12, the proposed fuzzy and non-fuzzy anomaly detection phase can outperform other methods. In addition, the times of increment on computational time of proposed method is relative smaller than the other considered methods (Table 14).

10. Conclusion

In this paper, we proposed a novel fuzzy anomaly detection system based on the hybridization of PSO and K-means clustering algorithms over Content-Centric Networks (CCNs). This system consists of two phases: the training phase with two simultaneous cost functions as well-separated clusters by DBI and local optimization by MSE, and the detection phase with two combination-based distance approaches as classification and outlier. Experimental results and analysis show the proposed method in the training phase is very effective in determining the optimal number of clusters, and has a very high detection rate and a very low false positive rate at the same time. In the detection phase, the proposed method clearly outperforms other applied method in terms of AUC (area under the ROC curve), accuracy, sensitivity and specificity. In addition, the times of increment on computational time of proposed method is relative smaller than the other considered methods.

We are currently working on several improvements of the presented approach with the application of computational intelligence methodologies (such as multi-objective optimization techniques) to propose a robust method to improve the accuracy of detection rate and reduce false positive rate over different CCNs traffics.

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