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A Critical Review on the Implementation of Static Data Sampling Techniques to Detect Network Attacks

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ABSTRACT Given that Internet traffic speed and volume are growing at a rapid pace, monitoring the network in a real-time manner has introduced several issues in terms of computing and storage capabilities. Fast processing of traffic data and early warnings on the detected attacks are required while maintaining a single pass over the traffic measurements. To alleviate these problems, one can reduce the amount of traffic to be processed using a sampling technique and detect the attacks based on the sampled traffic. Different parameters have an impact on the efficiency of this process, mainly the applied sampling policy and sampling ratio. In this study, we investigate the statistical impact of sampling network traffic and quantify the amount of deterioration that the sampling process introduces. In this context, an experimental comparison of existing sampling techniques is performed based on their impact on several well-known statistical measures.

INDEX TERMS Data sampling, data streams, intrusion detection system (IDS), statistical analysis.

I. INTRODUCTION

With the emergence of new technologies and applications, the speed and volume of Internet traffic are increasing rapidly. Current businesses' needs require the development of advanced information networks integrating various technologies such as distributed storage systems, encryption/decryption mechanisms, and remote and wireless access. Consequently, Internet service providers and network managers are encouraged to better understand network behavior through the analysis and monitoring of traffic inside the network. Hence, there is a need for network-based security systems, such as Intrusion Detection Systems (IDSs) [1].

Network attacks can be caused by external intruders attempting to access the network or from legitimate users trying to misuse their granted permissions and to gain more privileges for which they are not authorized. Such abnormal activities are manifested by a higher consumption of network resources and many undesired requests overloading them. For instance, the main objective of a DoS attack is to deny end-users from benefiting from network services [2].

Usually, Intrusion Prevention Systems (IPSs) can be used first to ensure the safety of the network and protect it from attacks. For instance, a firewall can be used to manage access inside a private network. It prevents end-users inside a protected network from sending or receiving messages forbidden by the predefined network security policy, without any capability of detecting anomalies or any specific pattern among the network traffic data [3]. The network is becoming increasingly complex, and, therefore, more vulnerable to attacks. Hence, IDSs play an important role in ensuring network security, as they observe user activity on the network and detect any security violation based on data patterns.

The success of an IDS is challenged by the network's implementation flaws and the complexity of the attacks, where it also has to deal with the availability and heterogeneity of the traffic data sources to find malicious behaviors. The performance of IDSs is another challenge, as real-time

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network monitoring requires very fast processing and inspection of network traffic. Thus, the amount of data generated in a network represents a major problem. When the traffic is large, the IDS will be unable to inspect every arriving packet.

As defined by the Institute of Electrical and Electronics Engineers (IEEE), the Internet of Things (IoT) is a collection of sensors that form networks connected to the Internet. IDSs designed for IoT environments should be implemented on programmable devices, such as FPGAs, to facilitate adaptation to IoT environments. Confidentiality, integrity, and availability are three important security concepts for applications and services in intelligent IoT-based environments. The implementation of a robust security mechanism in IoT systems depends on the security strength of IoT devices, which in turn depends on several factors, such as power, memory, hardware, software, and choice design. These present security challenges in IoT systems and impact the performance of an IDS [4]. Collaboration between IoT devices and the router to shift the compute load from resource-constrained IoT devices to the resource edge router is necessary to increase the network lifespan and reduce the intrusion detection time.

Because intrusion detection is the process of monitoring the network and detecting attacks, the data exchanged over the network and coming from different sources such as cell phones, computers, etc., as well as all network activities, have to be measured and processed by the IDS. The latter detects anomalies and sends security alerts to the network administrator as soon as an attack is detected [5]. However, the extensive applications of high-speed Internet make it impossible to adopt traditional packet measuring and processing technologies for network traffic. In fact, these technologies are not scalable to high-speed networks. The largest obstacles in high-speed networks are the huge volume of traffic data to deal with, and the rate at which information accumulates [6].

Real-time and fast processing of traffic data is required; the analysis time of an IP packet must be shorter than the packet inter-arrival time while maintaining a single pass over the traffic data. In addition, early warnings on the detected attacks and their sources must be triggered requiring a highly scalable IDS with architecture, storage, and computing capabilities and resources that can support very high throughput. The reason for the inability of current solutions to detect intrusions in high-speed networks is the high cost of using traditional network monitoring schemes. These schemes measure the network parameters of every packet that passes through the network, making it challenging to monitor the behavior of a large number of users in high-speed networks. To keep track of the huge volume of network traffic, one possible solution is to increase the storage and computing resources of the IDS by distributing network packets to multiple IDSs [7], [8]. However, these solutions are expensive.

Applying Machine Learning (ML) approaches in IoT environments is challenging because of the computing and energy constraints of IoT devices. ML algorithms have complexity issues such as memory complexity and computation. They also lack scalability and are limited to low-dimensional problems. Therefore, ML approaches may not be suitable for environments with limited resources. As for intelligent IoT devices, the detection of anomalies and intrusions requires real-time data processing, however, ML approaches are not designed to handle real-time data streams. In addition, ML algorithms assume that the entire data is available for processing during the learning phase, which is not true for IoT data. This poses many challenges when ML approaches have to process a large amount of data, especially, when the data dimensionality is high [9]. This discussion is applicable for security-related functions in IoT where real-time data is processed to identify anomalies, intrusions, etc. Owing to these limitations, it is important to combine ML with streaming solutions, such as sampling algorithms. Therefore, it is necessary to filter the data on the fly and store only those that are relevant by carrying out summaries (samples) before applying ML algorithms.

A. DATA SAMPLING

To address the issues presented above, and help the IDS process the information gathered during the data fusion from the routers, switches, firewalls, etc., network packets may be sampled where the router inspects every n-th packet using a sampling technique, and then, records its associated features [10]. Thus, intrusions are detected based on the sampled data instead of the entire traffic, as shown in Figure 1. Therefore, an IDS can benefit from the available computing and storage resources to analyze network traffic. The challenge is to prevent the intrinsic loss of information during the sampling process, which will lead to low detection accuracy. Over the years, different sampling strategies have been investigated in the literature to improve attack detection accuracy. Researchers have proposed a variety of static and dynamic sampling algorithms for network traffic reduction. With static sampling algorithms, traffic measurements are sampled either periodically or randomly at a specific predefined interval or using a specific rule. Using a static sampling algorithm to reduce the network traffic volume reduces the bandwidth and storage requirements, making this type of sampling algorithm very efficient. In their turn, dynamic sampling algorithms, also called adaptive sampling algorithms, use different sampling intervals and/or rules to sample the data. In this study, we focus on static sampling algorithms.

Selecting a sample of packets from the entire traffic is a challenging task. For instance, if malicious packets are not selected by the sampling algorithm, the attack may not be detected, as the IDS only analyzes the sampled traffic. Therefore, an efficient sampling algorithm must ensure the sampling of packets that carry a malicious payload. Previous research studies have shown that the sampling process can affect, skew, and distort anomaly detection metrics and detection rates [11]–[13]. Therefore, choosing an appropriate sampling algorithm and sampling interval that provides a good representation of the overall and original traffic is very important and delicate when a sampling process is to be applied.

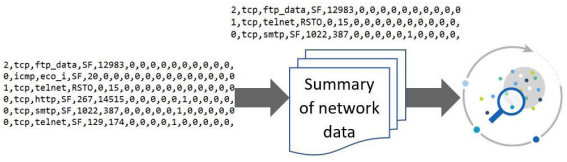


FIGURE 1. Packets sampling of network traffic.

In recent years, the field of sampling network traffic has been widely explored by the research community, which has led to the publication of numerous studies and benchmarking papers. Several studies have examined the impact of data sampling. Mai *et al.* [13] evaluated in their work the effect of sampling the traffic of high-speed IP-backbone networks on the intrusion detection results, especially on port scans and volume anomaly detection. Different sampling algorithms were used to sample the traffic packets. [14], [15] also assessed the impact of packet sampling on the anomaly detection results. Roudiere and Owezarski [16] evaluated the accuracy of the AATAC detector in detecting DDoS attacks over sampled traffic. Different sampling policies were used to sample the traffic. Bartos *et al.* [17] studied the effect of traffic sampling on anomaly detection and proposed a new adaptive flow-level sampling algorithm to enhance the accuracy of the sampling process. Silva *et al.* [18] introduced a framework to evaluate the impact of packet sampling. They discussed the performance of each sampling algorithm and proposed a set of metrics that allows the accurate evaluation of each sampling technique in producing a representative sample of the original traffic. Brauckhoff *et al.* [11] used traces containing the Blaster worm to assess the accuracy of different anomaly detection and data sampling algorithms.

B. PROBLEM DEFINTION AND MOTIVATION

Currently, deploying IDSs inside companies is a common practice to prevent and/or mitigate both internal and external attacks. However, owing to the restricted bandwidth of network links, and the limited storage and computing resources of the IDSs, it has become difficult to efficiently monitor and manage the network. A possible solution to this problem is to apply a sampling strategy to decrease the amount of traffic to be processed. Current research studies are investigating which sampling policy and which parameters provide the best compromise in terms of IDS performance (response time) while having a high attack detection rate.

A sampling policy aims to provide an estimation of a metric of interest from a set of data while reducing the processing cost. This is achieved by selecting a subset of data called ''sample'' and estimating the metric of interest from this subset. The sampling strategy specifies how a subset of data is selected [19]. More specifically, the packet sampling process aims to construct a sample of data on which future analysis tasks will be carried out. Different parameters affect the efficiency of the sampling and the precision of the estimation of the traffic characteristics, mainly the sampling strategy and sampling rate. Thus, given the original set of packets, the most difficult task is to select the correct sampling policy and the relevant parameters.

Packet sampling is involved in large network monitoring, management, and engineering tasks. It provides a dynamic overview of the network by providing detailed information that can be exploited to infer various estimates, statistics, and aggregates of traffic. These include the number of packets, the size of packets, the interarrival delays and protocols of packets, and traffic flows. which can eventually be used to detect particular network problems.

As stated by El Sibai *et al.* [20], a sampling algorithm can be qualified according to the following metrics: (1) Single-pass over the data: since it is almost impossible to store all the traffic packets for further processing, any sampling algorithm must be able to construct the sample by making only one pass over the data. (2) Memory consumption: sample size affects sample quality. The size is usually proportional to the size of the traffic, and it depends on the sampling ratio used. The higher the sampling ratio, the higher the accuracy of the sample, but the larger the sample size. (3) Skewing ability: A sample must represent the entire network traffic. With probabilistic sampling methods, all packets are sampled with the same probability. However, in some cases, some packets should have a higher probability of being sampled (depending on their values, arrival time, etc.). One way to do this is to associate weights to packets and to sample them according to their relative weights. (4) Complexity: Owing to the high traffic arrival rate, a low complexity is required to decrease the execution time of sampling. In many applications, packet sampling can be used to provide accurate results while reducing data processing costs. It can be used to control network congestion, detect broken links, misconfigured devices, and rouge network servers. Packet sampling can also be used to verify the quality of service in the network, build trends, forecast bandwidth, and other resource requirements.

Packet sampling is a class of data sampling techniques that considers packets as basic elements. Therefore, all the packets observed are considered as the original dataset, and the selected packets represent the sample. The target sample size is usually affected by the sampling interval, which is also denoted as the sampling ratio. However, with some sampling algorithms, the obtained sample size can deviate from the target. The sampling decision of a packet can be of three types: count-based, time-based, and content-based. With count-based sampling strategies, the sampling decision of a packet is based on its position in the sequence of packets called stream. With time-based sampling strategies, the sampling decision is based on the packet arrival time. Finally, with content-based sampling strategies, the sampling decision was based on the content of the packet. Content-based sampling strategies are also called filtering algorithms and are outside the scope of this study.

C. OBJECTIVE AND CONTRIBUTIONS

This study aims to check whether summarized (sampled) data are sufficient to detect attacks in high-speed networks. We aim to quantify the robustness of traffic characteristics under different sampling strategies. The sampling process selects some traffic items from the entire received traffic based on the sampling policy used and the chosen sample size. Thus, sampling is considered an approximate method of measurement. Because many packets in the dataset are not sampled, the traffic distribution of the sampled data may deviate from the distribution and statistical characteristics of the original traffic. Taking these sampled data as the input of any attack detection algorithm will inevitably affect the accuracy of the detection algorithm.

An effective sampling policy selects a subset of packets with which the statistical parameters of traffic can be accurately estimated. In this context, we focus on the statistical impact of packet sampling on traffic analysis. The sampling techniques were evaluated and compared in terms of the similarity between the results of the aggregation query evaluated for the original traffic and the sampled traffic. By building a sample of the traffic and performing offline analysis of the sampled packets, several statistical metrics gathered from sampled traffic and non-sampled traffic can be measured and compared to assess the level of degradation introduced by the sampling process. This study was initiated with a survey of the sampling algorithms. Then, an experimental comparison of all these sampling methods was performed.

The recently published benchmarks, cited in Table 1, focus on the most traditional sampling algorithms. However, none of these studies have thoroughly reviewed all data sampling approaches, their impact on detecting a variety of attacks, and the behavior and robustness of the features under different sampling strategies. Even if it is well known that the sampling distorts the statistical measures, it was surprising that few studies have explored how the network characteristics estimation varies according to the sampling method used, sample size, and so on, and how this affects statistical inference from these data.

Pescape *et al.* [14] considered a list of traffic characteristics. Two statistical metrics are used to assess feature distortions, ''Hellinger'' for similarities and ''Fleiss Chi-Square'' for classification. The intersection of the chosen characteristic sets in each database separately formed a robust final feature set. Various sampling techniques were applied to assess robust feature sets. The results showed that sampling techniques have a slight impact on reducing the degradation behavior of the anomaly detection process and that the characteristics of many packets are most affected by distortion. Data sampling depends on the data measurement method. Therefore, sampling is subject to a certain variance in the total traffic distribution, which affects the accuracy of the anomaly detection results. To address this problem, Pan *et al.* [21] suggested a method for measuring packet sampling based on IP flow. The sampling rate is variable and depends on the arrival process sequence of the IP flow at both the packet and flow levels, and the flow size. Subsequently, the sampling probability was adjusted based on the number of samples in the stream. Two evaluation metrics were used; RMSE to measure volume anomalies in the size of the IP stream and the hit detection rate to measure the sequence of variance in the stream. The results showed that for a sample rate of 1%, the proposed solution detected 27 out of 30 worm and DDoS attacks, while traditional random sampling only detected three. Singh *et al.* [22] studied the statistical impact of data sampling on traffic analysis by calculating the statistical parameters for an unsampled dataset and then for sampled data. Subsequently, a comparative analysis of the unsampled and sampled datasets was performed. The following sampling algorithms were used to sample the data: Simple Random Sampling (SRS), Systematic sampling, and under-over sampling. The following attributes from the NSL KDD dataset were considered: duration, src_bytes, dst_bytes, wrong_fragment, num_compromised, num_file_ creations, and srv_count. The statistical parameters used to compare the network characteristics before and after sampling were: the mean, range including the minimum and maximum values for each attribute, and the standard deviation showing the distribution of the network. Silva *et al.* [18] developed a data-sampling framework based on a multilayered design. The framework selects the characteristics and sampling techniques based on the measurement task. The implementation of the framework is based on a sampling taxonomy that determines the granularity, selection scheme, and selection trigger.

A comparison between the above papers and our work is summarized in Table 1.

In this study, the impact of sampling is studied in terms of well-known statistical metrics, such as the mean, standard deviation, median, etc. from the perspective of determining the characteristics of the traffic before and after sampling. Our main objective is to provide an up-to-date survey of static sampling algorithms and evaluate the impact of data sampling on network traffic analysis. Different sampling algorithms and a variety of parameters were considered in our study. Our contributions in this study can be summarized as follows. (1) Presenting an exhaustive survey of existing data stream sampling algorithms, (2) Elaborating on the following critical question: Given the network traffic, what are the suitable sampling policies and parameters to be applied to reduce the network volume? (3) Evaluating the behavior and robustness of various features characterizing the network, under different sampling strategies and parameters, (4) Determining which attacks are more robust to the sampling process, (5) Determining whether there exists a family of features that are more robust to the sampling process, and (6) Exposing, based on the obtained results, the research challenges and possible solutions to handle them.

D. SUMMARY AND OUTLINE

The remainder of this paper is organized as follows. Section I-B discusses the motivation and introduces the

TABLE 1. Comparison of this and similar works, where C1 shows whether the benchmark evaluated all sampling algorithms, C2 represents whether the benchmark studied the appropriate sampling policy and parameters, C3 indicates whether the benchmark presented an exhaustive study of the sampling algorithms, C 4 shows if the benchmark evaluated the sampling impact on different types of attacks, C5 shows if the benchmark studied the sampling impact on feature behavior, C6 shows whether the benchmark analyzed sampling performance with respect to accuracy, and C7 shows whether the benchmark assessed sampling distortion.

Reference	Year	C1	C2	C3	C4	C5	C6	C7
Pescape *et al.* [14]	2010	✓	✓	✗	✗	✓	✓	✓
Pan *et al.* [21]	2012	✓	✓	✗	✓	✗	✗	✓
Singh *et al.* [22]	2014	✓	✓	✗	✗	✓	✓	✓
Silva *et al.* [18]	2015	✓	✓	✗	✗	✗	✓	✓
This paper	2021	✓	✓	✓	✓	✓	✓	✓

contribution of our work. This section also shows the differences between our work and the existing ones. Section II presents a survey of existing sampling algorithms. Section III elaborates on the experimental approach and methodology that we apply in our work. Section IV illustrates and discusses the results. Finally, Section V concludes the paper.

II. TAXONOMY OF PACKETS SAMPLING POLICIES

In high-speed networks, network traffic arrives continuously, at a high rate. The IDS receiving this traffic may not be able to store them exhaustively, and/or have sufficient computing resources to process them rapidly. Thus, processing high-speed network traffic requires minimizing the volume of traffic by building, storing, and maintaining a sample of this traffic. An efficient sample should be able to answer, approximately, to any query regardless of the period investigated. The literature shows that most sampling techniques share the following main components: sampling function, the temporal aspect of packets, windowing model, and sample size [19]. Classifying and evaluating sampling policies according to these components is an important step for achieving better sampling accuracy.

Figure 2 presents our taxonomy that classifies the sampling policies into four components: the sampling function, the temporal aspect of packets, the windowing model, and the sample size. Table 2 classifies the existing sampling policies according to the proposed taxonomy.

- Sampling function: This identifies the policy defining which packets will be added to the sample. This policy may follow a static or dynamic approach. A static approach can be either deterministic or random.
- Temporal aspect of packets: It can be physical or logical (sequential). The physical aspect depicts the arrival time of the packet, and the logical aspect describes the index of the packet in the traffic stream.
- Windowing model: Sampling techniques use windowing models and divide the traffic into successive windows to limit the number of packets to be analyzed. There are two main windowing models: fixed and sliding [23]. The window boundaries were absolute using a fixed window. The traffic stream is partitioned into non-overlapping windows, and the offset between two consecutive windows is equal to the number of packets in the window. Using the sliding window model, the window boundaries are updated over time: when a new packet arrives, it is added to the window and the oldest one will be removed. In this case, the shift between two consecutive windows is less than the window size, and most often equals 1. In this benchmark, two types of estimations are considered: total traffic statistics and instantaneous traffic statistics estimation. The overall traffic behavior was predicted using, the total traffic statistics estimation. The traffic stream is divided into successive fixed (non-overlapping) windows, and, the sample of the traffic stream is constructed by combining all the sub-samples built over all the fixed windows. Network behavior was analyzed based on the final sample. However, with instantaneous traffic statistics estimation, the sample is built over the most recent packets of the stream. Thus, the network behavior is analyzed over each sliding window, during the measurement process. In our work, the sampling policies used to estimate the overall traffic statistics are called ''non-stream sampling algorithms'', while the sampling policies used to estimate instantaneous traffic statistics are called ''stream sampling algorithms''.
- Sample size: The sample size is most often proportional to the length of the traffic and depends on the sampling ratio. The higher the sampling rate, the higher the accuracy of the sample; nevertheless, this requires more computational resources. Note that some sampling policies have a fixed and bounded sample size independent of the sampling ratio. In this work, and without loss of generality, all the algorithms will be adapted to provide a sample with a ratio-dependent size.

In the following, we discuss in detail each one of these sampling policies.

A. SIMPLE RANDOM SAMPLING (SRS) OVER A SLIDING WINDOW (SRSSW)

The SRS algorithm [24] aims to construct a random sample. It samples packets randomly and all packets have the same

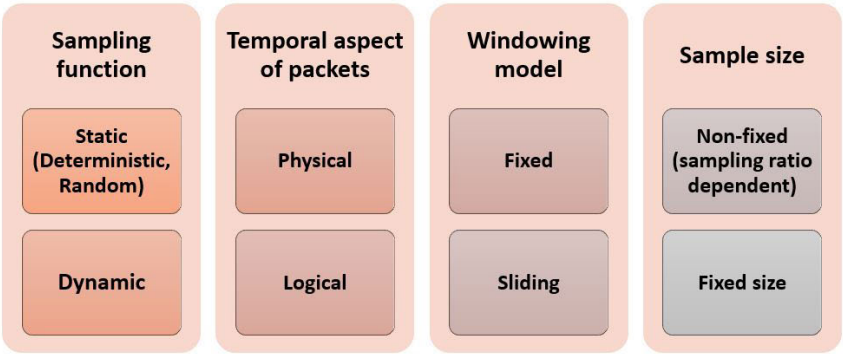


FIGURE 2. Taxonomy of sampling policies.

TABLE 2. Classification of static sampling policies.

Sampling policy	Sampling function		Temporal aspect		Windowing model		Sample size	
	Deterministic	Random	Physical	Logical	Fixed	Sliding	Fixed	Ratio-dependent
SRSFW		✓		✓	✓			✓
SRSSW		✓		✓		✓		✓
DETFW	✓			✓	✓		✓	
DETSW	✓			✓		✓	✓	
Chain-sample		✓		✓		✓		✓
Chain+		✓		✓		✓		✓
Stratified		✓		✓	✓			✓
Systematic	✓			✓	✓		✓	
Reservoir		✓		✓		✓	✓	
Backing		✓		✓		✓		✓
Priority		✓	✓			✓		✓
Random Pairing		✓		✓		✓		✓
WRS-N-P		✓		✓	✓			✓
WRS-N-W		✓		✓	✓			✓
StreamSamp		✓		✓	✓		✓	

probability p of being sampled. SRS can be performed with and without a replacement. When applying SRS with replacement, the sample will contain redundant packets because each packet may be selected at least once. However, with SRS without replacement, each packet can be sampled only once. In this study, we were concerned with SRS without replacement.

B. SIMPLE RANDOM SAMPLING (SRS) OVER A FIXED WINDOW (SRSFW)

The SRS without replacement algorithm can also be applied to build a sample over a fixed window. This is done by constructing a sample over each window of the traffic stream and removing the samples constructed on the former windows. To sample k packets from a window of size n, each packet is selected with a probability p equal to the sampling ratio k/n. This step must be repeated until k distinct packets are selected [20].

C. DETERMINISTIC SAMPLING OVER A FIXED/SLIDING WINDOW

The deterministic algorithm is a non-probabilistic sampling algorithm that constructs a sample without randomness. It consists of constructing a sample of size k by selecting one packet from every x packet of the traffic stream. Assuming that the traffic stream consists of packets with an always-increasing index, to construct a sample of distinct packets among the n most recent packets of the traffic, and given the sampling ratio p, each $1/x$ packet is sampled. The value of x is equal to $100/p$. For instance, if p equals 20%, then, the value of x will be equal to $100/20 = 5$, and thus, every $1/5$ packet will be selected exactly. The selection of

one packet from every x packets depends on the packet index. If the packet index equals $\alpha \times n/k$, where α is a positive integer, the packet will be selected.

D. SYSTEMATIC SAMPLING

Let k be the sample size and n the window size, the systematic sampling algorithm partitions the traffic into x groups, each of size $x = n/k$. Thereafter, it selects a random value $j \in [1, x]$ and adds the packets to the sample at the following indices: j, $j + x, j + 2x, j + 3x$, etc. [24].

Deterministic and systematic sampling algorithms have several advantages; the samples are easy to build and are faster than the SRS algorithm. However, the drawback of these algorithms is that the sample lacks randomness. The packets wer sampled periodically. If the periodicity of the traffic stream is close to the size of sample k, the constructed sample will be skewed and not representative of the original traffic.

E. STRATIFIED SAMPLING

The stratified sampling algorithm [24] divides the traffic into homogeneous subgroups and then randomly builds a sample from each subgroup. Compared to SRS, the stratified sampling algorithm enhances the sampling accuracy because it ensures a high level of representativity of the entire traffic. Using the stratified sampling algorithm is beneficial in many cases, especially, when it is required to highlight a specific set of packets within the traffic. Stratified sampling can also be applied to ensure the representation of extreme or rare groups of packets in the sample.

F. WEIGHTED RANDOM SAMPLING WITHOUT REPLACEMENT

An effective sample must represent the entire traffic stream. However, this requirement may not be satisfied: some packets may be oversampled or undersampled. Consequently, the statistical information inferred from the constructed sample will not be reliable. To deal with the lack of representativeness of some packets in the sample, a correction of the sample is required. This can be done using the Weighted Random Sampling (WRS) algorithm by sampling each packet with a probability based on the packet's weight [25], [26].

Efraimidis *et al.* [25], [26] proposed two WRS algorithms. WRS-N-P adds each element e_k to the sample with a probability proportional to the weight w_k of the element, as follows:

$$p_k = \frac{\alpha \times w_k}{\sum_{i=1}^{k} w_i} \tag{1}$$

where α is the sample size.

In turn, WRS-N-W adds each packet e_k to the sample with a probability proportional to the item's weight w_k and relative to the weights of the non-sampled items. The sampling probability p_k is calculated as follows:

$$p_k = \frac{w_k}{\sum_{i \in v-S} w_i} \tag{2}$$

where S represents the sample.

G. RESERVOIR SAMPLING

The reservoir sampling algorithm [27], [28] retains a uniform and random sample of a fixed size of k from the whole stream. First, the algorithm selects the first k received elements of the stream and adds them to the sample. Subsequently, when a new element arrives, it is sampled with a probability $p = k/i$, where i is the index of the element in the stream, and an element is randomly removed from the sample.

H. BACKING SAMPLING

Backing sampling [29], [30] samples the data as follows: First, the first k elements of the stream are added to the sample. Thereafter, a random number of elements is skipped and the next element is added to the sample with a probability equal to k/n. Another random number of elements is ignored, and so forth.

I. CHAIN-SAMPLE

The chain-sample algorithm [31] provides, at any time, a random sample of size k selected from the last elements of the stream. It constructs a sample containing one element selected from the last sliding window of the stream. First, the algorithm samples one element from the first window with a probability equal to $\frac{min(i,n)}{n}$, where n is the window size, and i is the index of the element in the window. Once selected, a successor's index j is chosen at random for the i^{th} element from the elements with indexes $\in [i+1, i+n]$. When the element with index j arrives at the window, a random successor will also be chosen for it. When the element with index i is removed from the window, it will be removed from the sample and substituted by its successor j. To build a sample containing $k > 1$ elements, all the previous steps must be repeated k times.

J. Chain+ SAMPLING

To build a sample containing k elements, the Chain+ sampling algorithm [32] builds one sample of size k instead of constructing and maintaining k independent samples, each of size equal to 1. The algorithm samples each element in the first sliding window with a probability equal to $\frac{min(i,n)}{n}$, where n is the window size and i is the index of the element in the window, if and only if it was not present in the sample. This process is repeated until k distinct elements are sampled.

K. PRIORITY SAMPLING

Babcock *et al.* [31] introduced the priority sampling algorithm that constructs and maintains a random sample over a physical sliding window. To construct a sample containing one element, the priority sampling algorithm assigns a random priority $p \in [0, 1]$ for each element, then selects the element with the highest priority in the sliding window. To construct a sample containing k elements, the process must be repeated k times. In the old version of the priority sampling algorithm, the weights are assigned randomly without inspecting the arrival time of the element.

In addition, this algorithm suffers from all the problems of the chain-sample algorithm. These problems are presented in section IV. Therefore, in this work, we implemented a new version of the priority sampling algorithm proposed in [33]. The modified version of the Priority sampling algorithm alters the traditional algorithm by assigning weights to the packets according to their arrival time, their contents, and their impact on the sample accuracy.

L. RANDOM PAIRING SAMPLING

The Random Pairing (RP) sampling algorithm [34], [35] constructs and retains a random sample over the most recent sliding window of the stream. To achieve this, three values are calculated for each window: the number of expired elements present in the sample (denoted by c_1), the number of expired elements not present in the sample (denoted by c_2), and the number of all expired elements (denoted by d). When a sampled element expires, it is deleted from the sample. Each new element was added to the sample based on the value of d. If $d = 0$, sampling the new element follows the reservoir sampling algorithm [28]. However, if $d > 0$, the new element is added to the sample with a probability equal to $\frac{c_1}{c_1+c_2}$.

M. StreamSamp

StreamSamp [36] algorithm is a progressive sampling technique based on the Simple Random Sampling algorithm. Once received, stream elements are sampled with a predefined sampling ratio. When the sample size is reached, the sample is stored with an order equal to 0, and a second sample of the same size will be constructed. As the number of stream elements increases, the number of samples of order 0 also increases. When this number exceeds a certain limit, StreamSamp merges the two old samples of order 0 into a single sample by performing a simple random sampling of rate $p = 0.5$. The new sample obtained is of order 1, and so on.

A comparison of the presented algorithms is provided by Table 3.

III. METHODOLOGY

This study focuses on existing static sampling techniques. The efficiency of a sampling policy depends on its capability to balance its precision with the computational resources required. This study investigates the statistical effect of sampling the traffic stream and the execution time required to sample the traffic. Our methodology consists of using the sampling algorithms presented to summarize a real traffic dataset. This allows us to understand the behavior of these algorithms. To quantify the distortion introduced by the sampling procedures, we compared different statistical metrics. The overall quantification of statistical changes between sampled and unsampled traffic is defined by the Overall Statistic (OS) calculated as follows [37], [38]:

$$OS = \frac{|(\mu_0 - \mu)|}{\mu_0} + \frac{|(med_0 - med)|}{med_0} + \frac{|(std_0 - std)|}{std_0} \quad (3)$$

where μ_0 is the real average value estimated before sampling the traffic, μ is the estimated average value of the traffic calculated after sampling, med_0 and med are the median values of a traffic parameter estimated before and after sampling respectively, and std_0 and std are the standard deviation values of the traffic estimated before and after sampling respectively.

Our experiment in Section IV can be thus summarized as follows:

- Scenario 1 - Without sampling: In this scenario, the mean, standard deviation, and median of the unsampled dataset were calculated.
- Scenario 2 - With sampling: In this scenario, the mean, standard deviation, median, and OS were calculated based on the sampled data. Different sampling strategies with different parameters are considered. The computational resources and execution time needed for sampling were also calculated. Finally, a comparative analysis of both scenarios is carried out.

The dataset used in this work is NSL-KDD [39], which was developed to enhance the KDD CUP 99 dataset. The main concern with the KDD CUP 99 is the huge number of duplicate records in the training and testing subsets, which leads to inaccurate intrusion detection results [39]. In the NSL-KDD dataset, all redundant records have been removed. The obtained dataset contains approximately $150K$ records divided into training and testing subsets. The NSL-KDD dataset consists of 41 attributes and includes 22 attack types.

IV. EXPERIMENTS AND RESULTS

In this section, we investigate the impact of different sampling policies and sampling rates to measure the distortion introduced by the sampling process. We aim to isolate a set of features that are more robust (less distorted) to sampling. The specifications of our machine are RAM: 8 GB, System disk: 450 GB, and processor: 2.7 GHz Intel Core $i7$.

A. COMPUTATIONAL RESOURCES

The traffic scenario used to evaluate the sampling policies is the training set of the NSL-KDD dataset, which consists of 125.974 records with a size of 18.662 MB. The computational resources of packet sampling techniques are analyzed according to the execution time, which depicts the time spent in summarizing the traffic. A higher sampling ratio leads to the selection of more packets. Thus, intuitively, the computational resources of the sampling algorithms should be proportional to the sampling rates. The execution times of non-stream and stream policies presented in this study are evaluated in Figures 3 and 4 respectively, based on the sampling ratio and window size (for stream sampling algorithms).

Figures 3 and 4 confirm the relationship between the sampling ratio and the computational resources. Since each sampling policy selects the data samples differently, different computations resources are required by each sampling algorithm, even with the same sampling rate. The results

TABLE 3. Advantages and weaknesses of data streams sampling algorithms.

Sampling Algorithm	Advantages	Weak Points
Simple Random (SRSFW [20] and SRSSW [24])	The sample is accurate, convenient, and representative of the entire stream	Biased sample in case of periodicity in the data stream, no skewing ability
Deterministic (DETFW and DETSW) [24], [20]	It provides a sample with an exact size, the sample is representative of the entire stream when no periodicity is displayed	Biased sample in case of periodicity in the data stream, no skewing ability
Chain-sample [31]	It provides a sample with an exact size	Redundant samples, no skewing ability
Chain+ [32]	It provides a representative sample with an exact size without duplication	No skewing ability
Stratified [24]	The use of this algorithm is beneficial when it is desired to high-light a specific subgroup within the data and ensure its presence in the sample, this algorithm is also used to represent the smallest, extreme or rare subgroups of the data in the sample	Unbounded sample size, no policy to choose the sample size, no skewing ability
Systematic [24]	The sample is easy to be built, The sampling process is fast and accurate since sampled data are spread over the entire stream	Unbounded sample size, biased sample in case of data stream periodicity, no skewing ability
Reservoir [27], [28]	This algorithm is simple and suitable for streaming environments since it is executed in one pass	Recent elements have less chance of being sampled, no skewing ability
Backing [29], [30]	This algorithm is suitable for streaming environments since it is executed in one pass	Performs several passes over the data, no skewing ability
Priority [31]	It provides a sample with an exact size	No policy for the determination and revision of the weights
Random Pairing [34], [35]	The algorithm builds and maintains a uniform sample of fixed size	No skewing ability
StreamSamp [36]	The algorithm maintains a sample of a fixed size	No policy for the determination and revision of the weights

in Figure 3 show that the deterministic and systematic sampling algorithms have the lowest execution time. Based on the SRSFW and stratified sampling algorithms, the sample may contain duplicated elements. This redundancy occurs when the sampling rate is > 0.1, and it arises when an element is sampled many times in the same jumping window. This problem becomes more serious when the values k (sample size) and n (window size) are close to each other. To deal with the redundancy problem, and to sample exactly k distinct elements from each window, the sampling process on each window should be repeated until an element is selected that is not present in the sample. This process adds significant overhead in terms of runtime, mainly when the values of k and n are close to each other. Figure 5 shows the collision rate of the SRSFW and stratified sampling algorithms and the theoretical probability of collision for sampling k elements

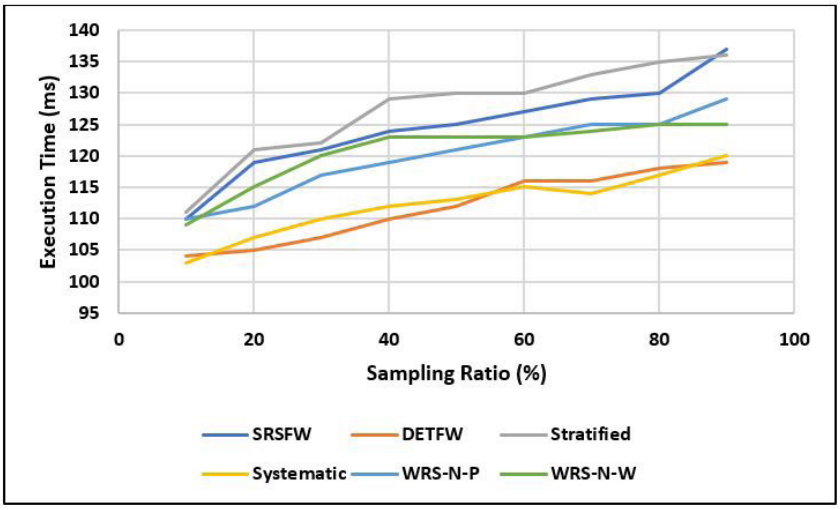


FIGURE 3. Execution time of non-stream sampling algorithms.

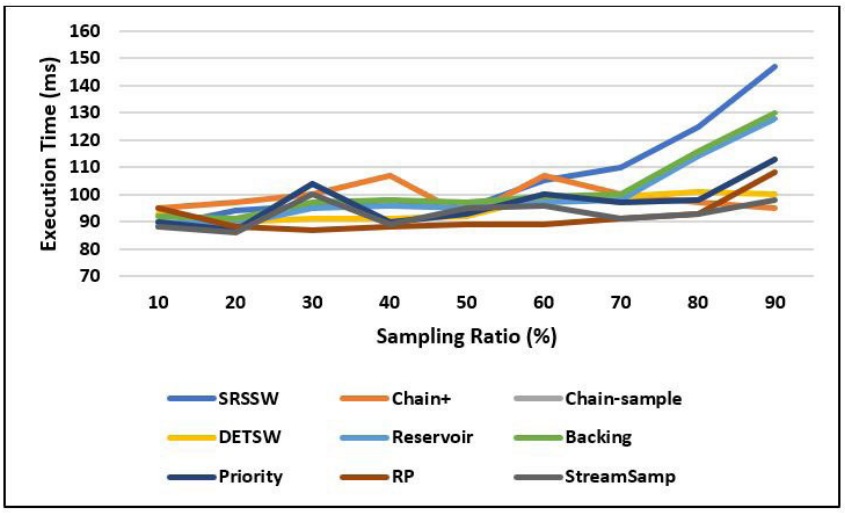


FIGURE 4. Execution time of stream sampling algorithms, using a window size = 10.

from a window of size n. Different sampling rates k/n are used. The window size was fixed to 10 packets. The theoretical probability of collision $P_{collision}$ is computed as follows:

$$\begin{aligned} P_{collision} &= 1 - P_{Selecting\ k\ distinct\ items} \\ &= 1 - \frac{n!}{n^k(n-k)!} \end{aligned} \tag{4}$$

Figure 5 shows that when the sampling ratio (k/n) is equal to 50%, 30% of the packets in the constructed sample are redundant, which will greatly affect the accuracy of the sample. Thus, the need to remove the duplicated elements. Figure 5 and Equation 4 show that for a given sampling ratio, when the values of k and n increase, the collision rate also increases. Figure 5 also shows that the collision rate of the SRSSW algorithm is a little bit higher than that of the stratified sampling algorithm. In fact, with the

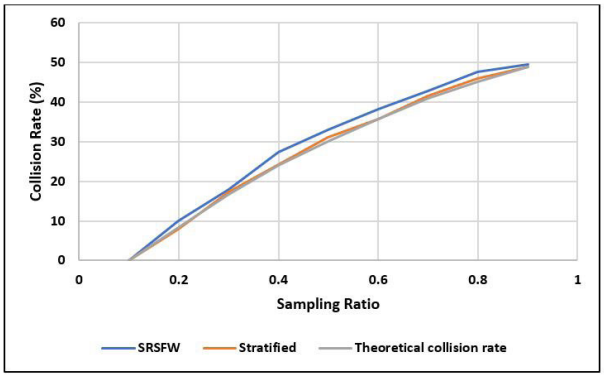


FIGURE 5. Collision rate of the SRSFW and stratified sampling algorithms.

stratified sampling algorithm, each packet in the traffic stream must be added to the subgroup before sampling. After the

subgroups were formed, some elements of each subgroup were selected. Thus, the collision rate was lower. Because of this process, building the sample using the stratified sampling algorithm is more expensive than using the SRSWF algorithm.

Figure 4 shows the execution times of the stream sampling algorithms described in this study. The window size was fixed at 10 packets. The results show that, similar to SRSFW, the execution time of the SRSSW increases when the sample size k and the sliding window size n are close to each other, mainly, when the value of k/n is close to 1. This problem also occurs because of the redundancy issue that arises when the sampling rate is > 0.1. Similar to SRSFW algorithm, and in order to avoid duplication in the sample, the SRSSW selection process is repeated until an element is selected that is not present in the current sample. Therefore, a possible additional cost in terms of execution time is added, mainly, when the value of k/n is high. Even if the SRSSW and Chain+ sampling algorithms use very similar sampling procedures, the results in Figure 4 show that the difference in execution time for these two algorithms increases as k/n increases, and becomes clearer when k/n is > 0.5. In fact, the Chain+ sampling algorithm minimizes the collision rate to be equal to that of $k/n = k/n - 0.5$, when k/n is > 0.5, as proven in [32], which decreases the execution time of this algorithm. It should be noted that the priority and chain-sample algorithms have almost the same execution time.

Figure 6 presents the execution time of the stream sampling algorithms for various sampling rates and sliding window sizes. Three window sizes were considered: 10, 100, and 1000. The results show a clear trade-off between the execution time of all these algorithms and the window size: the execution time becomes longer for a larger window. In fact, varying the window size leads to different sample sizes and, therefore, to different computational requirements, even at the same sampling rate. For instance, to sample 20% of the most recent traffic leads to a data volume equal to 2/10, 20/100, and 200/1000 for a window size equal to 10, 100, and 1000 respectively, the required execution times using the SRSSW are 88, 95, and 111 ms, respectively. This behavior was observed for all stream sampling policies. It is also observed that there is a stabilization of the execution time for the DETSW algorithm, as shown in Figure 7. This algorithm has less variation in the execution time regardless of the sampling ratio, whereas the SRSSW exhibits the highest variation.

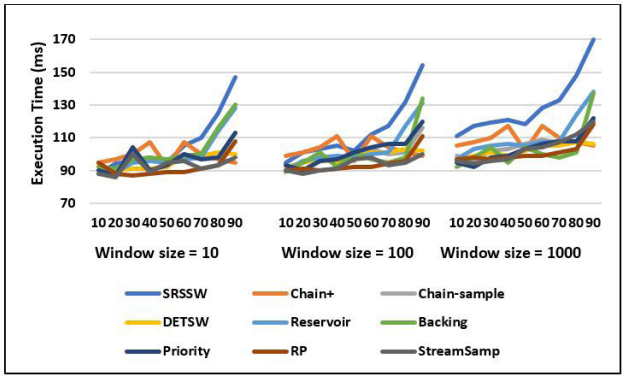


FIGURE 6. Execution time of stream sampling algorithms for different window sizes.

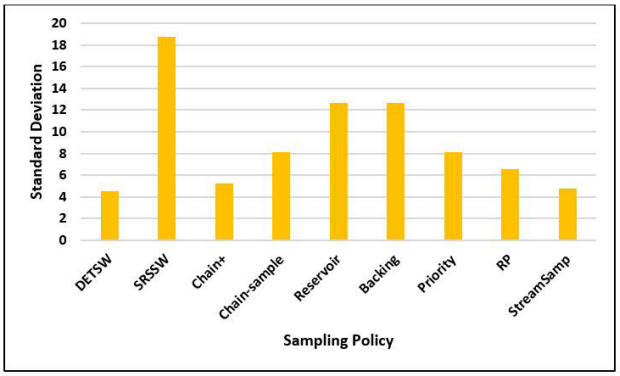


FIGURE 7. Variation of the execution time of stream sampling algorithms, using a window size equal 10.

B. ESTIMATING TOTAL TRAFFIC STATISTICS

Several monitoring and management activities were conducted using the measurement of the network. Therefore, the sampling policy should describe the behavior of the network accurately despite the importance of reducing the execution time of the sampling process. In this section, we analyze and compare the ability of each sampling policy to provide accurate estimations of traffic characteristics. Our work in this section consists of reducing the size of the traffic using all the sampling policies described previously and then, evaluating the statistical measures of the traffic. Our benchmarking study considers the accuracy of the sampling process regarding the unsampled (original) traffic stream, while also comparing each sampling policy with the others. All sampling policies are evaluated based on their ability to provide samples that accurately represent traffic behavior. The methodology adopted in this section is to sample the NSL-KDD traffic using all the sampling techniques described previously, and then calculate several statistical measures to assess the accuracy of the sampling estimates for the unsampled traffic while comparing each sampling policy with the others. To achieve this goal, the mean, standard deviation, and median of the traffic stream were estimated before and after sampling, as shown in Figures 8 and 9. The sampling accuracy is also evaluated through the Overall Statistic (OS), which represents the relative error of the estimated mean, median, and standard deviation of the original traffic, as detailed in section III.

Table 4 presents the most important numeric features of the NSL-KDD dataset that can be used to detect DoS, Probe, R2L, and U2R attacks, according to Ao *et al.* [40].

TABLE 4. Relevant features for each attack type in the NSl-KDD dataset.

Attack	Features names	Features numbers
DoS	source bytes, land, wrong fragment	5, 7, 8
Probe	source bytes, srv error rate, diff srv rate, src port rate	5, 28, 30, 36
R2L	destination bytes, failed logins, count, dst host error rate	6, 11, 23, 39
U2R	root shell, srv count, src port rate	14, 24, 36

FIGURE 8. Traffic statistics estimation for unsampled data.

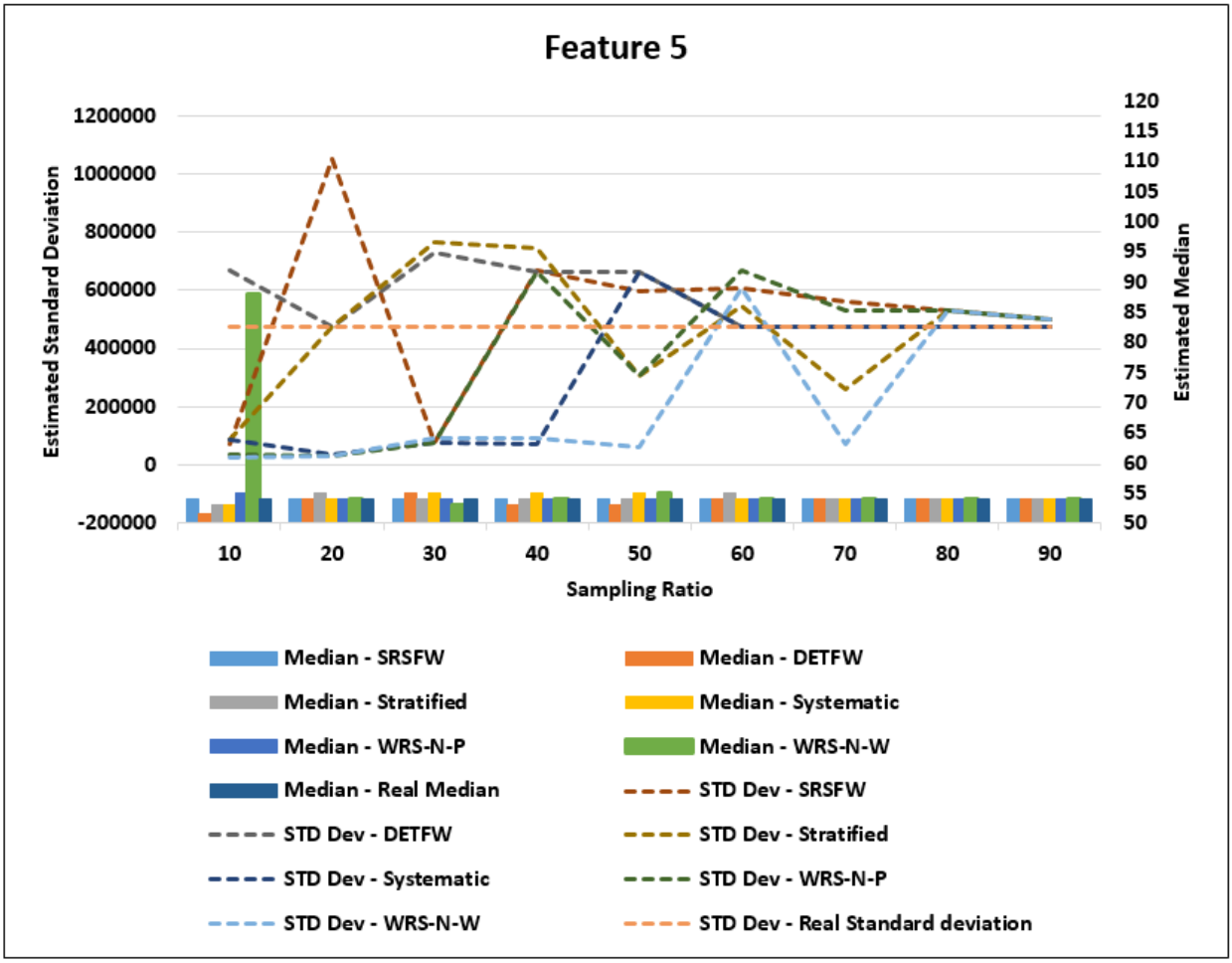
FIGURE 9. Traffic statistics estimation for sampled data.

1) DoS ATTACK

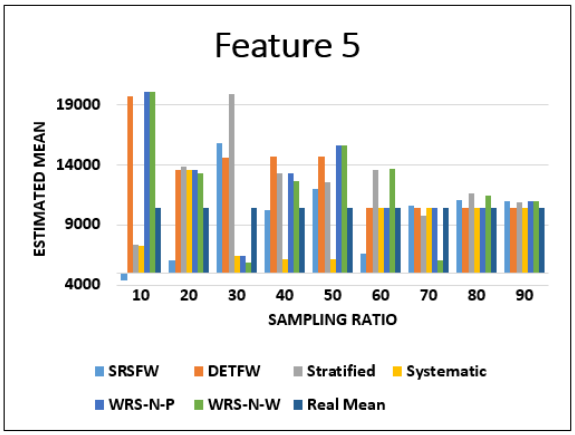
Figures 10.c, 11.c, and 12.c show the variation of the OS metric based on the estimated mean, standard deviation, and median values of features 5, 7, and 8, respectively. Different non-stream sampling policies and various sampling rates $\in [10, 90]$ were considered. The results in these figures show that, regardless of the non-stream sampling policy used, the level of distortion introduced by the sampling process decreases significantly when the sampling ratio increases. In fact, when the interval in which packets are sampled from the network increases, significant periods of network activity are considered by the sampling process. The results also show that, for a given sampling strategy, the estimated OS metric for features 7 and 8 does not vary significantly when the sampling ratio was $\in [70, 90]$. For feature 5, the variation in the OS metric was small when the sampling ratio was $\in [80, 90]$. All these results demonstrate that sampling fewer packets (less than 90%) does not lead to a less accurate estimation. Thus, it is possible to save computational resources by collecting fewer packets and achieving high sampling accuracy. Figures 10, 11, and 12 show in detail the accuracy of the estimated mean, standard deviation, and median of the features 5, 7, and 8, according to the sampling strategy and sampling ratio. The results in Figure 10 show that when the sampling ratio is $\in [80, 90]$, the accuracy of the mean and standard deviation metrics is approximately the same and very close to the real mean and standard deviation values of the unsampled traffic. Figure 11 shows that for a sampling ratio $\in [60, 90]$, the level of distortion introduced by the sampling process using deterministic and systematic sampling is null. In addition, for a given sampling ratio of less than 50%, the estimation accuracy of all algorithms is highly variable. The results also show that WRS-N-W is the worst sampling strategy because it gives the highest OS value, regardless of the sampling ratio. According to Figures 11.c, one can notice that like feature 5, and for a sampling ratio $\in [60, 90]$, the level of distortion introduced by the sampling process using deterministic and systematic sampling is null. For a given sampling ratio of less than 50%, the estimation accuracy of all algorithms is also highly variable. According to Figure 12.c, one can notice that like features 5 and 7, and for a sampling ratio $\in [60, 90]$, the level of distortion introduced by the sampling process using the deterministic and systematic sampling is null. For a given sampling ratio of less than 50%, the estimation accuracy of all algorithms is highly variable. The results also show that the SRSFW and WRS-N-W are the worst sampling strategies because they provide the highest OS value, regardless of the sampling ratio. Based on the above discussion, one can conclude that to estimate the values of features 5, 7, and 8 needed to detect the DoS attack, the best sampling strategy, and sampling ratio to apply in order to achieve the lowest distortion level is the deterministic/systematic sampling with a sampling ratio of 60%. Because the deterministic and systematic strategies require the lowest execution time and computational resources, there is a possibility of saving computational resources by collecting fewer packets and achieving a very high sampling accuracy when using these strategies.

2) PROBE ATTACK

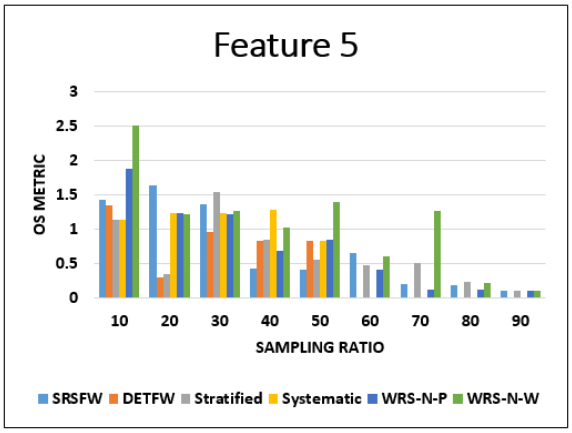
Figures 10.c, 13.c, 14.c, and 15.c show the variation of the OS metric based on the estimated mean, standard deviation, and median values of features 5, 28, 30, and 36 using sampled data while considering different non-stream sampling policies and various sampling rates $\in [10, 90]$. The results show that regardless of the non-stream sampling policy used, the level of distortion introduced by the sampling process does not vary significantly when the sampling ratio is $\in [70, 90]$. The results also show that for a given sampling strategy, the estimated OS metric for feature 28 does not vary significantly when the sampling ratio is $\in [60, 90]$. For feature 5, the variation in the OS metric was small when the sampling ratio was $\in [80, 90]$. All these results show that sampling fewer packets will not lead to a less precise estimate. Thus, there is a possibility to save computational resources by collecting fewer packets and achieving high sampling accuracy.



(a) Standard deviation and median estimation



(b) Mean estimation

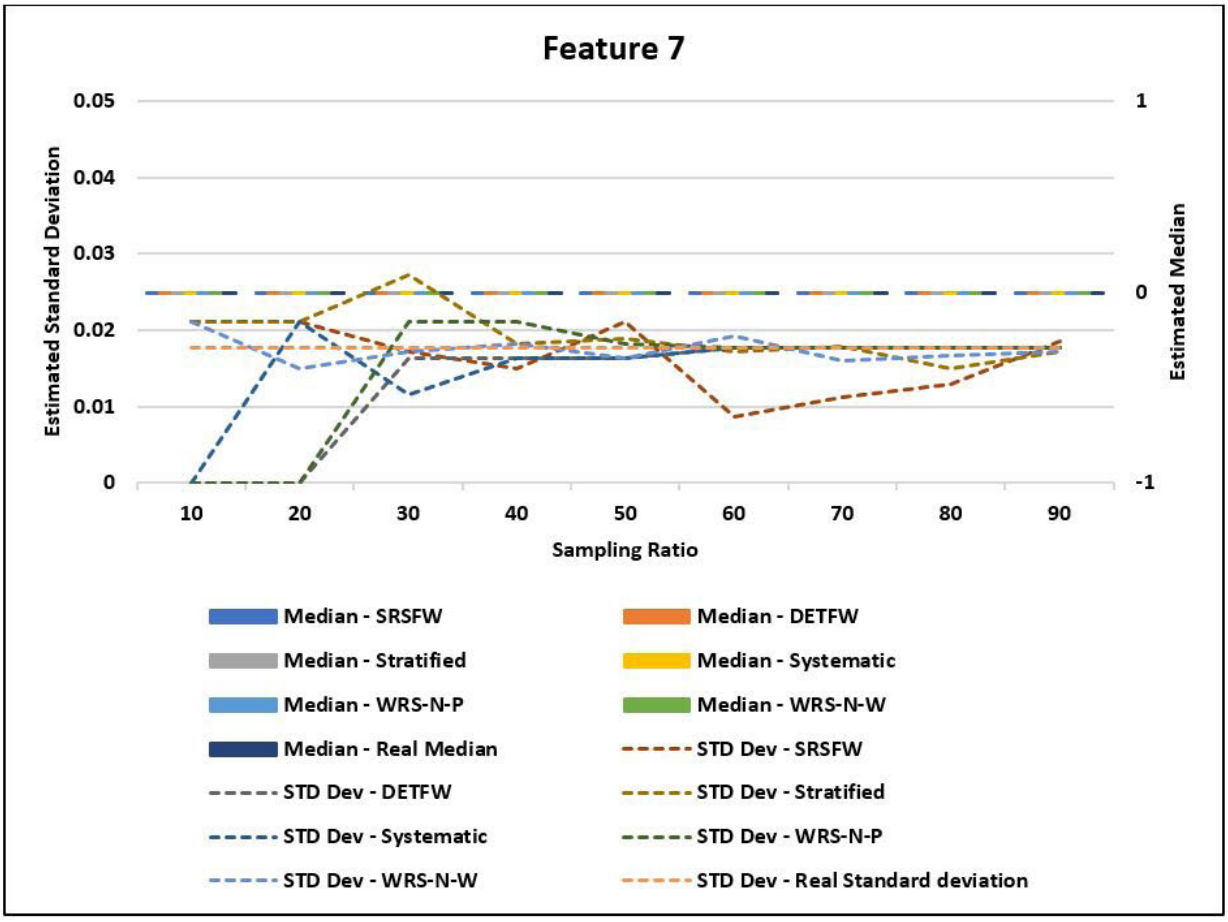


(c) OS metric.

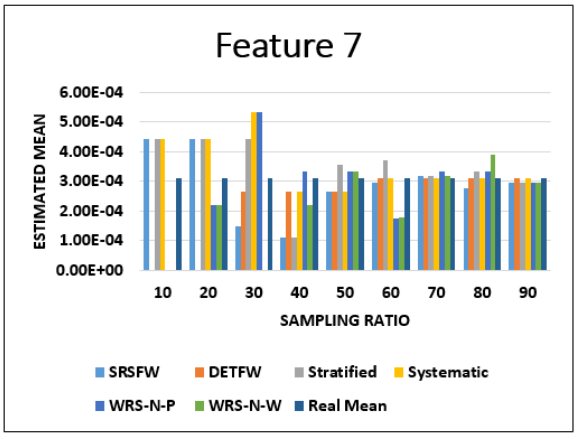
FIGURE 10. Statistical metrics estimation of feature 5 using non-stream sampling policies.

3) R2L ATTACK

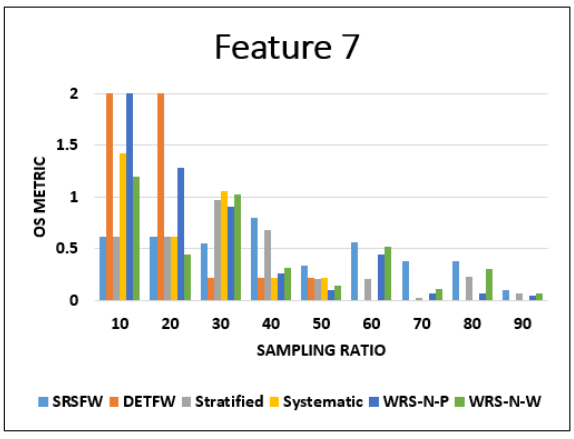
Figures 16.c, 17.c, 18.c, and 19.c show the variation of the OS metric based on the estimated mean, standard deviation, and median values of features 6, 11, 23, and 39 using sampled data while considering different non-stream sampling policies and various sampling rates $\in [10, 90]$. The results also show that regardless of the non-stream sampling policy used, the level of distortion introduced by the sampling process does not vary significantly when the sampling ratio is $\in [70, 90]$.



(a) Standard deviation and median estimation



(b) Mean estimation

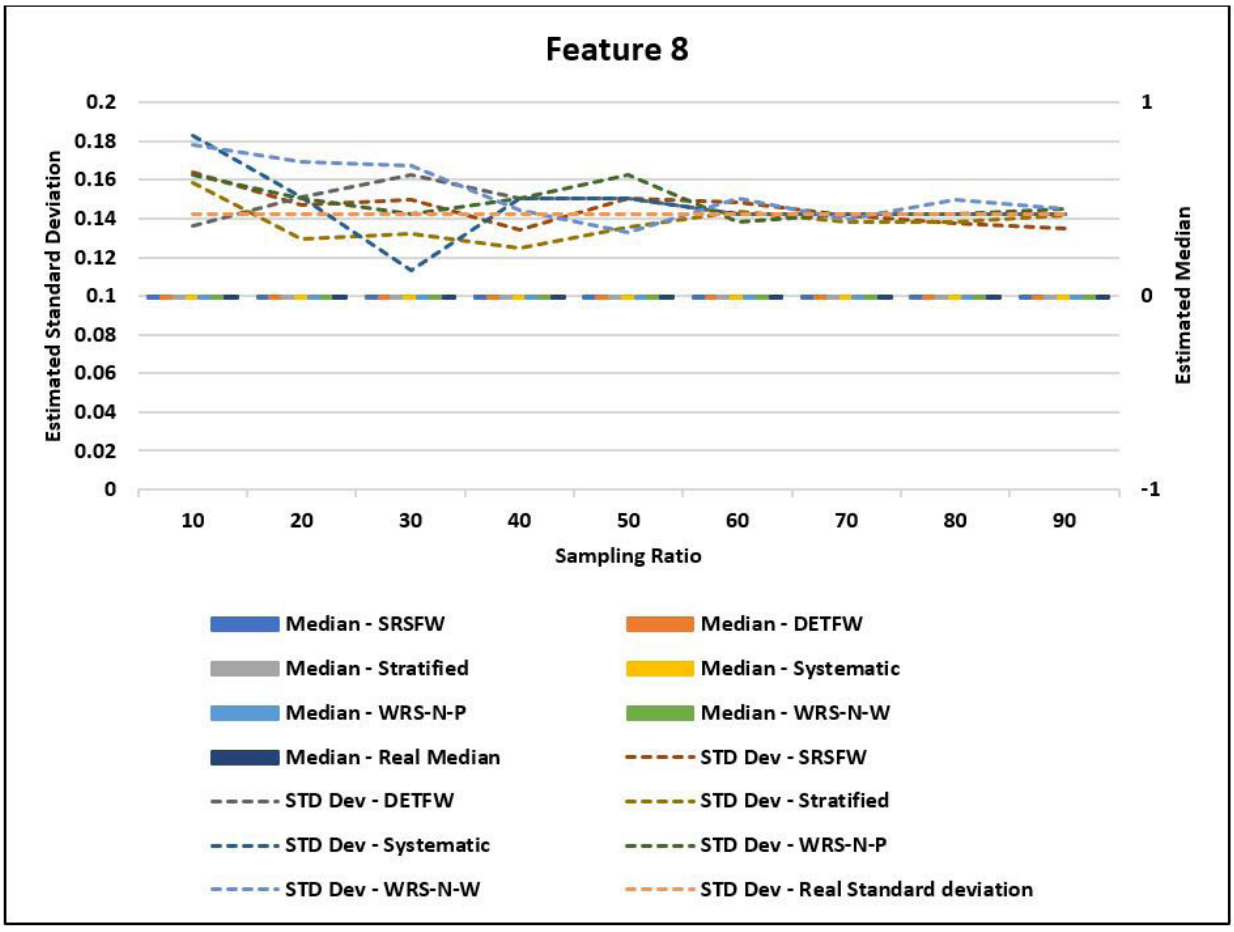


(c) OS metric.

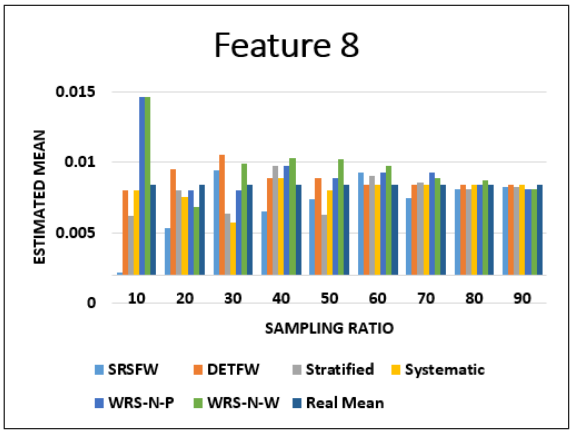
FIGURE 11. Statistical metrics estimation of feature 7 using non-stream sampling policies.

4) U2R ATTACK

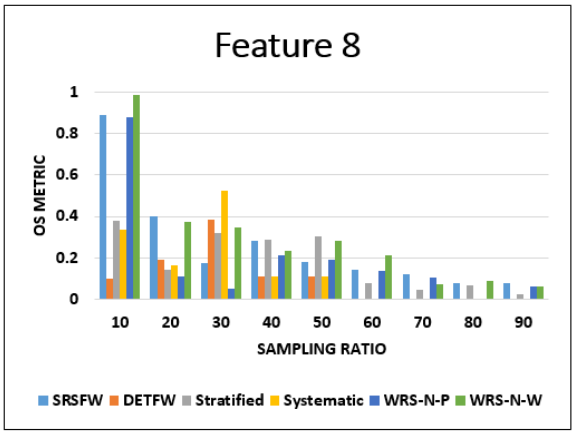
Figures 20.c, 21.c, and 15.c show the variation of the OS metric based on the estimated mean, standard deviation, and median values of features 14, 24, and 36 using sampled data while considering different non-stream sampling policies and various sampling rates $\in [10, 90]$. The results also show that regardless of the non-stream sampling policy used, the level of distortion introduced by the sampling process does not vary significantly when the sampling ratio is $\in [70, 90]$. A comparison of the different sampling algorithms shows that in general, the sampling precision is high and less variable when the sampling ratio is $\in [50, 90]$.



(a) Standard deviation and median estimation



(b) Mean estimation



(c) OS metric.

FIGURE 12. **Statistical metrics estimation of feature 8 using non-stream sampling policies.**

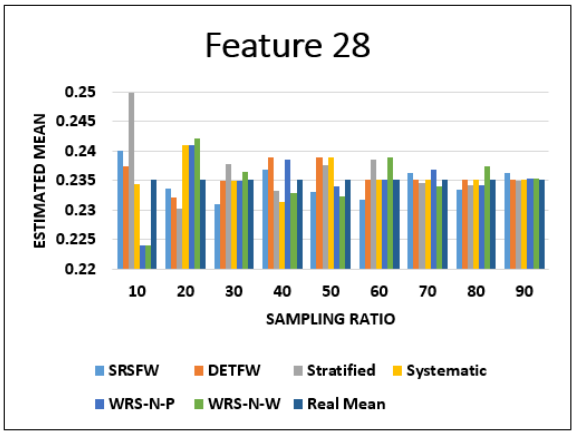
C. ESTIMATING INSTANTANEOUS TRAFFIC STATISTICS

A common way to understand the traffic behavior is to estimate the traffic statistics instantaneously, in a time interval. Thereby, the accuracy in estimating the traffic behavior over time is analyzed through instantaneous mean, median, standard deviation, and OS metric constantly calculated during the measurement process.

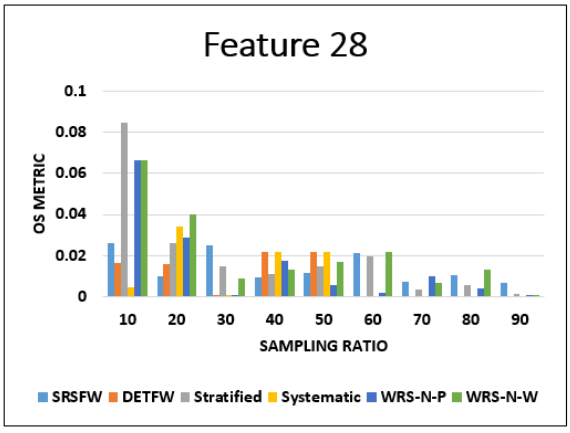
1) DoS ATTACK

Figures 22.c, 23.c, and 24.c show the variation of the OS metric based on the estimated mean, standard deviation, and median values of features 5, 7, and 8 using sampled data. Different stream sampling policies, various sampling rates $\in [10, 90]$, and various window sizes were considered. The results in these figures show that the chain-sample

(a) Standard deviation and median estimation



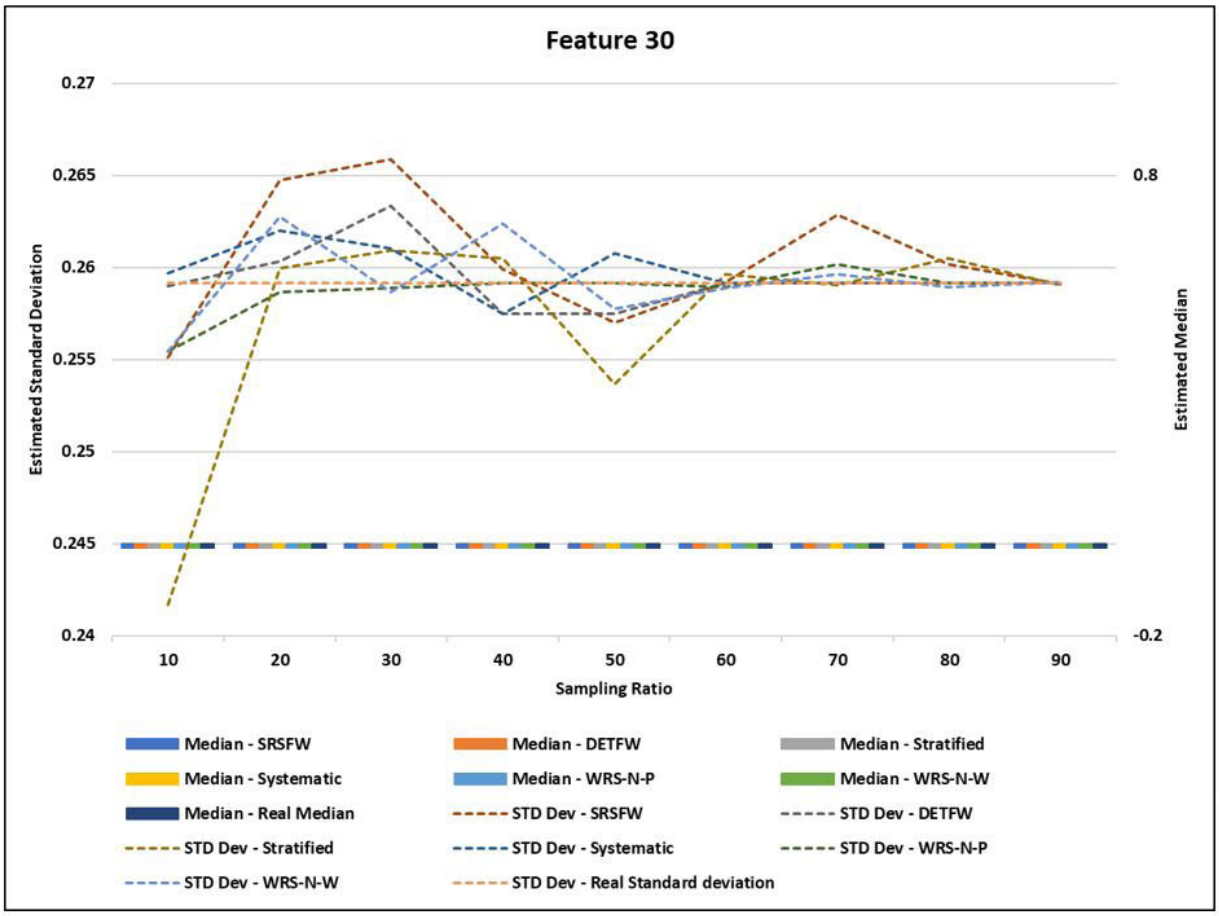
(b) Mean estimation



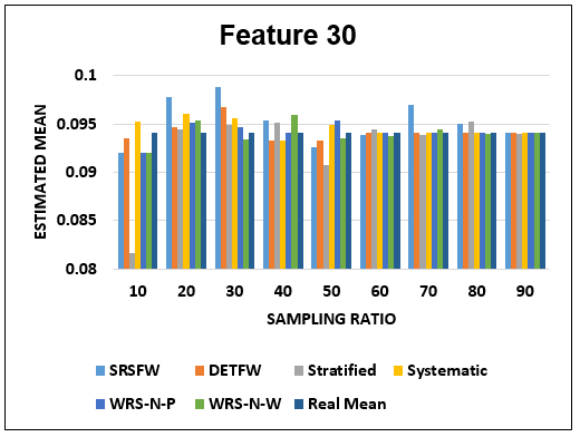
(c) OS metric.

FIGURE 13. Statistical metrics estimation of feature 28 using non-stream sampling policies.

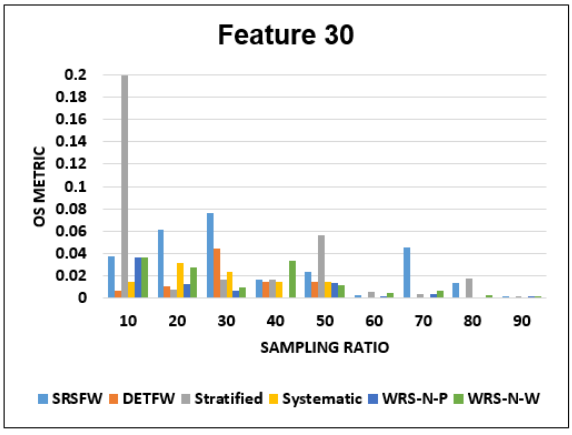
algorithm has the highest OS value, regardless of the sampling rate ($\in [20\%, 90\%]$) and window size, and the performance of this algorithm in terms of the OS value decreases when the sampling rate increases and/or when the window is large. This is because of the poor quality of the constructed sample because the number of collisions increases when the value of k/n increases. It should be noted that for a sampling rate equal to 10% and window size equal to 10, the OS value of the chain-sample algorithm is very close to that of the SRSSW algorithm since the collision rate, in this case,



(a) Standard deviation and median estimation



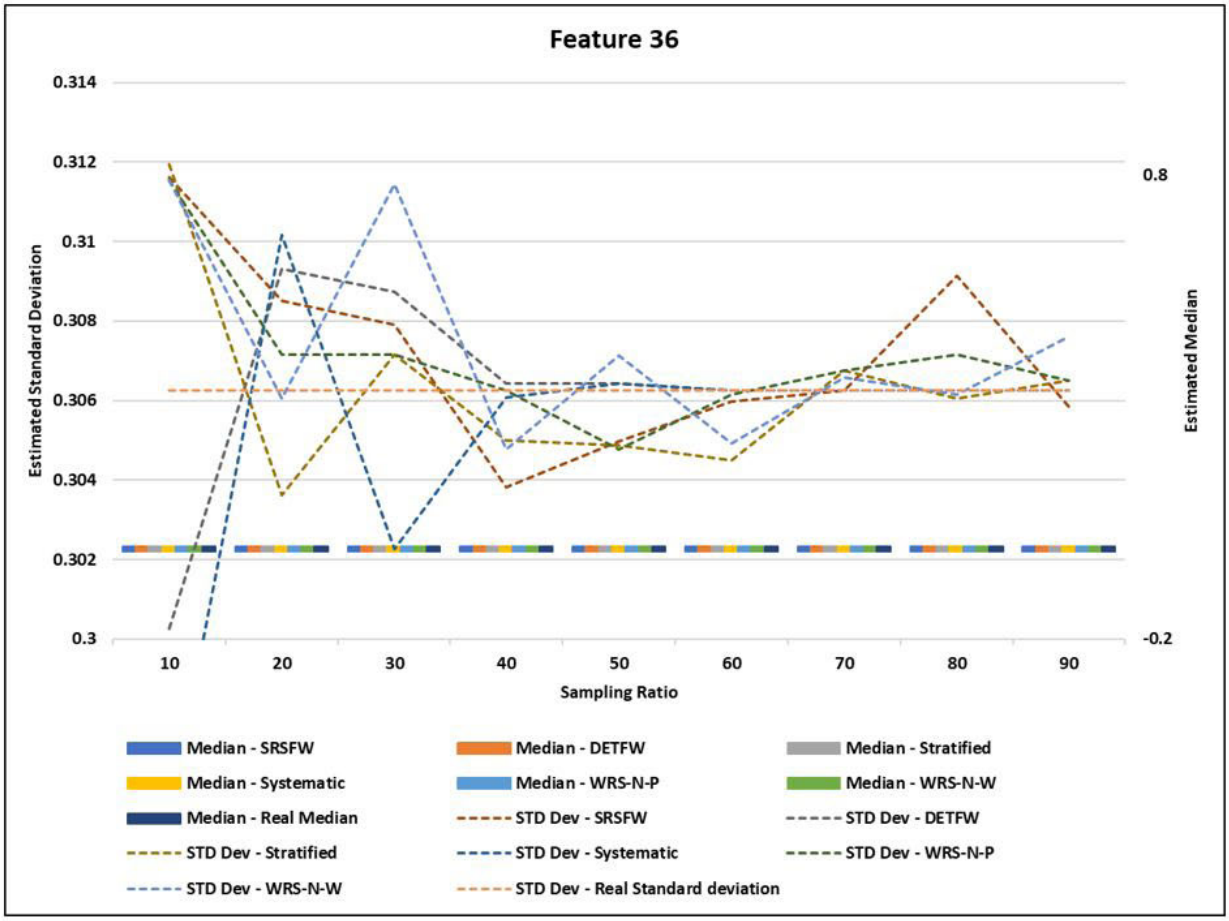
(b) Mean estimation



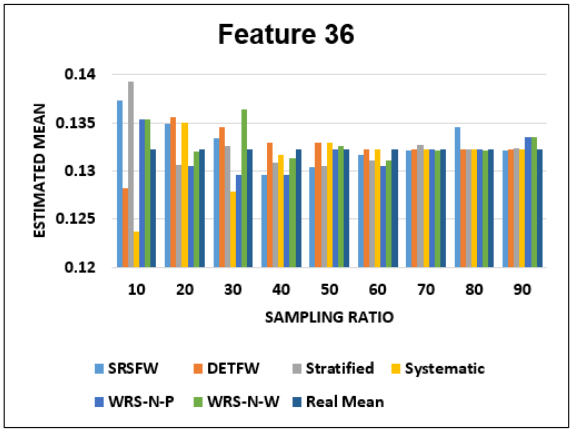
(c) OS metric.

FIGURE 14. **Statistical metrics estimation of feature 30 using non-stream sampling policies.**

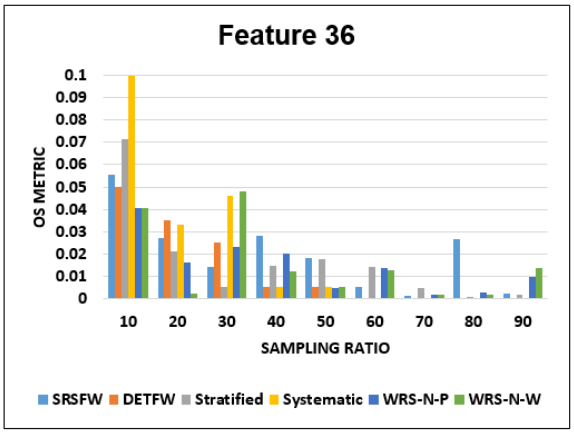
is equal to 0%. When the sampling rate increases or when the window size increases, the collision rate will be higher, thus, leading to a higher OS metric. Figures 22, 23, and 24, and Tables 5, 6, and 7 show that for all the stream algorithms, except the DETSW the chain-sample algorithms, the window size has no considerable impact on the OS value of features 5, 7, and 8. Changing the window size did not change the OS value. This can be explained by the fact that the elements are selected in a deterministic manner. Regarding the chain-sample algorithm, the OS value increases when the value of the window increases because of the collision problem. The results also show that the OS value of the



(a) Standard deviation and median estimation



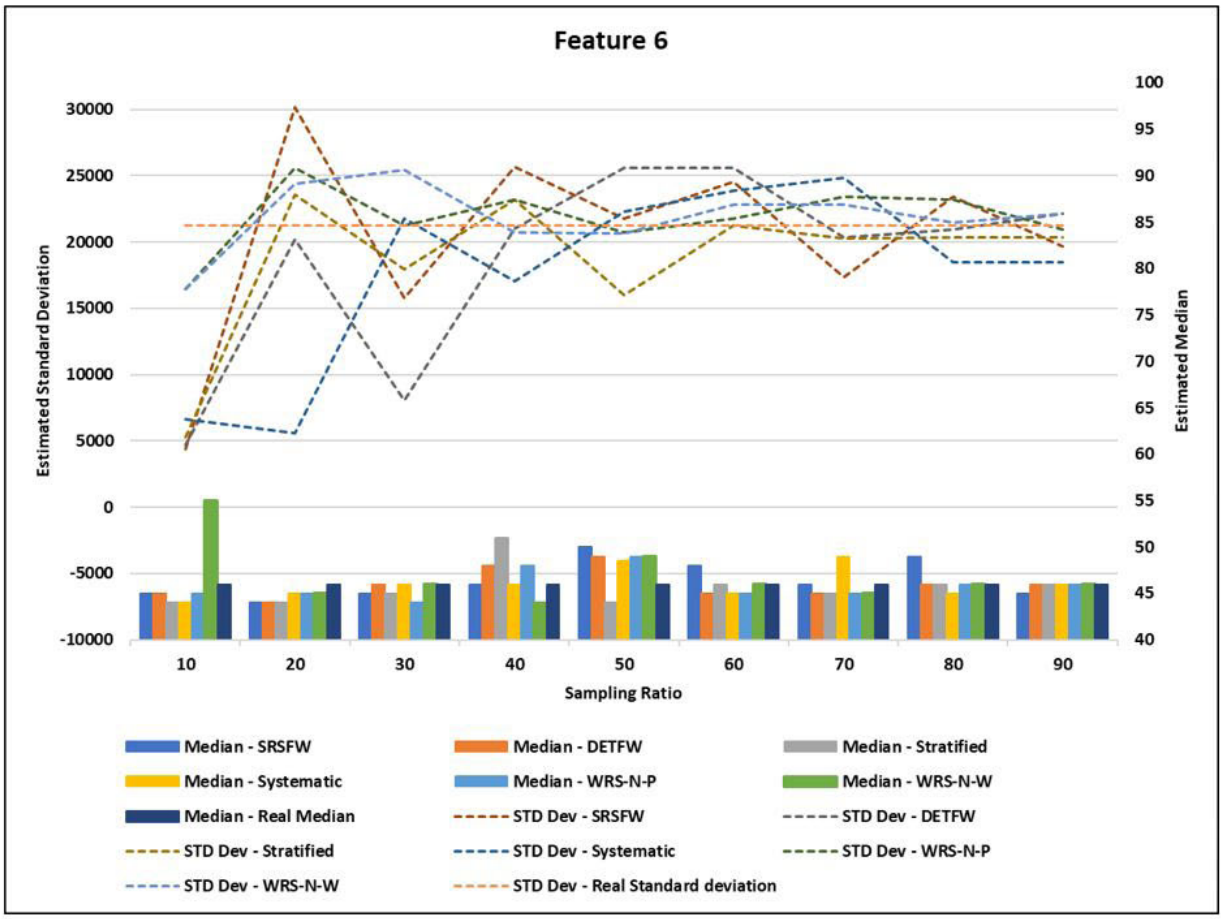
(b) Mean estimation



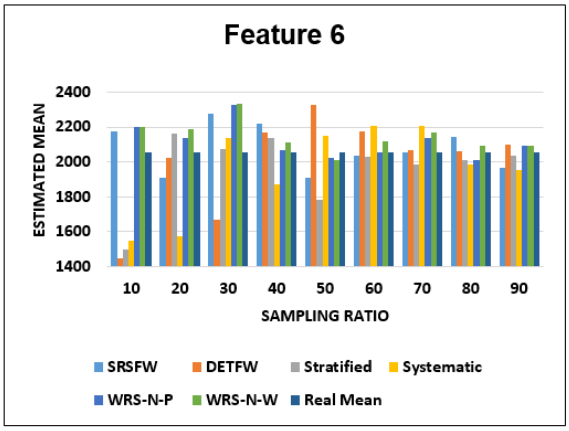
(c) OS metric.

FIGURE 15. Statistical metrics estimation of feature 36 using non-stream sampling policies.

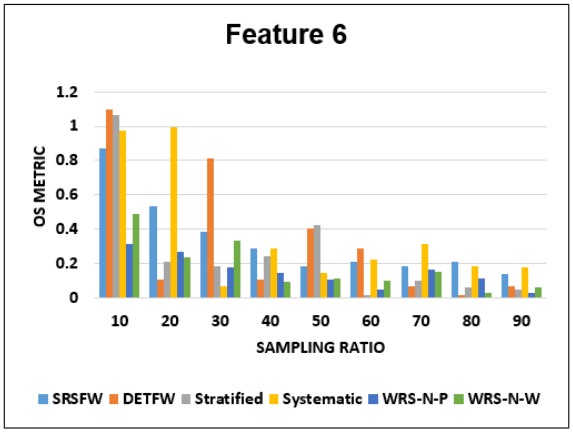
priority sampling algorithm is almost zero when the sampling rate is $\in [60, 90]$. The results also show that the OS value of the DETSW algorithm is stable and very close to 0 when the sampling ratio is $\in [60\%, 90\%]$. The results in Figure 22 show that while for all the stream algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value's variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, reservoir, and RP sampling algorithms, the minimum OS value is achieved when the sampling rate is equal to 80%. For the backing algorithms, it was achieved for a sampling rate equal to 60%. For the StreamSamp algorithm,



(a) Standard deviation and median estimation



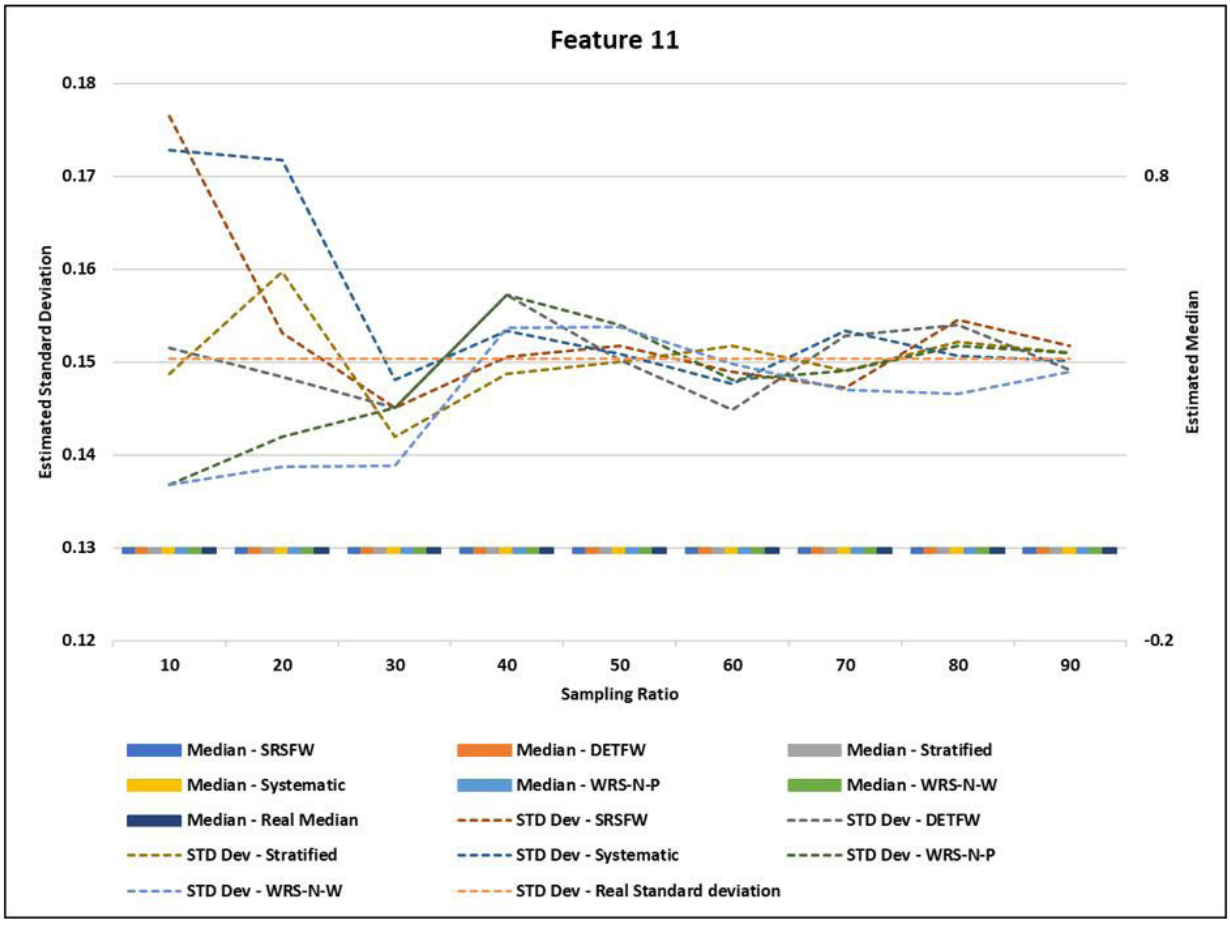
(b) Mean estimation



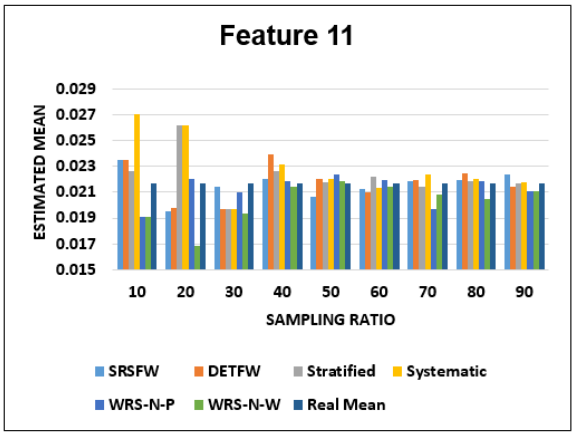
(c) OS metric.

FIGURE 16. **Statistical metrics estimation of feature 6 using non-stream sampling policies.**

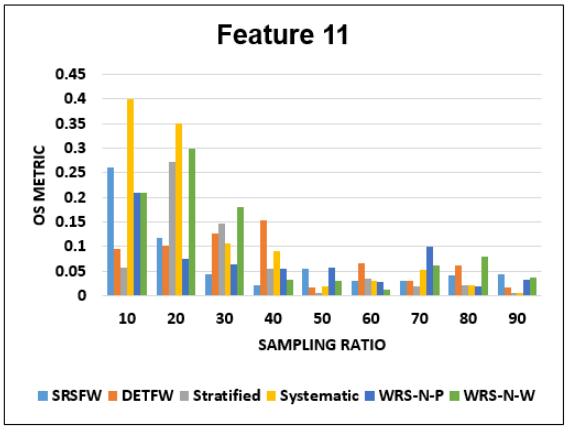
it was achieved for a sampling rate equal to 70%. The results in Figure 23 show that while for all the stream algorithms the OS value reaches almost its minimum when the sampling rate is equal to 90%, and the variation in the OS value according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, and RP sampling algorithms, the minimum OS value was achieved when the sampling rate is equal to 80%. For the reservoir algorithm, it was achieved for a sampling rate equal to 60%. For the backing algorithm, it was achieved for a sampling rate equal to 20%. For the StreamSamp algorithm, it was achieved for a sampling rate equal to 30%. The results in Figure 24 show



(a) Standard deviation and median estimation



(b) Mean estimation

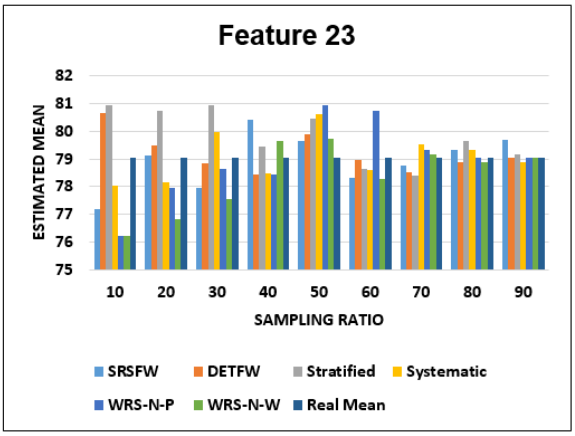


(c) OS metric.

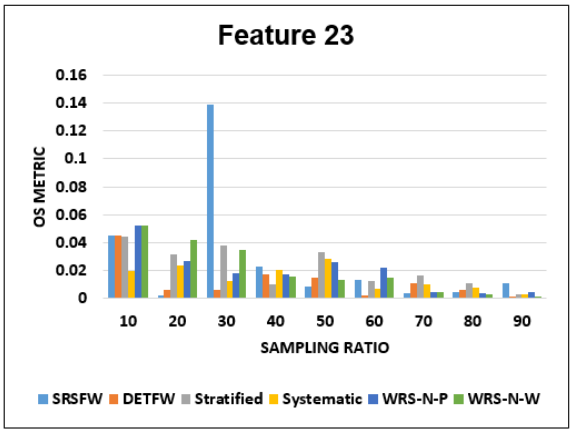
FIGURE 17. Statistical metrics estimation of feature 11 using non-stream sampling policies.

that, for all stream algorithms, the OS value reaches almost its minimum when the sampling rate is equal to 90%, and the variation in the OS value according to the sampling ratio is dependent on the sampling policy. For instance, for SRSSW and Chain+ sampling algorithms, the minimum OS value was achieved when the sampling rate was equal to 70%. For the reservoir and StreamSamp algorithms, it was achieved for a sampling rate equal to 80%. For the backing algorithm, it was achieved for a sampling rate equal to 30%. For the RP algorithm, it was achieved for a sampling rate equal to 60%.

(a) Standard deviation and median estimation



(b) Mean estimation



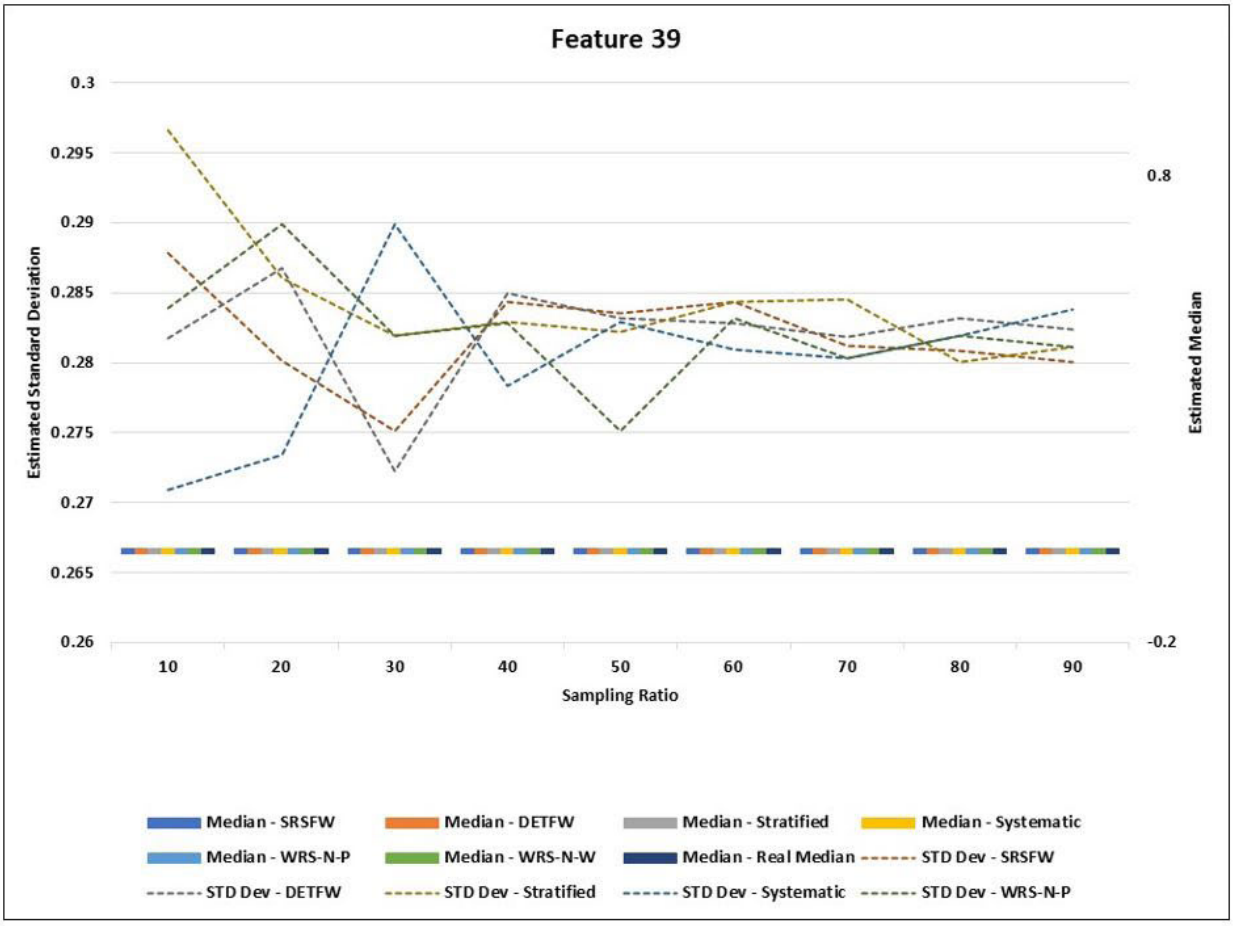
(c) OS metric.

FIGURE 18. Statistical metrics estimation of feature 23 using non-stream sampling policies.

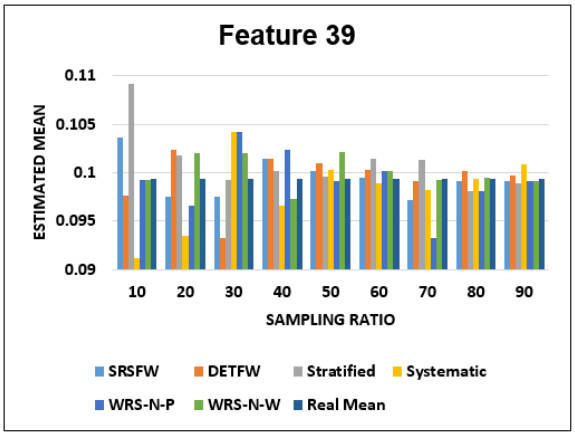
In conclusion, Table 8 shows the stream sampling policies and the corresponding sampling rates ($\in [10\%, 80\%]$) that can be used to achieve low OS values for features 5, 7, and 8.

2) PROBE ATTACK

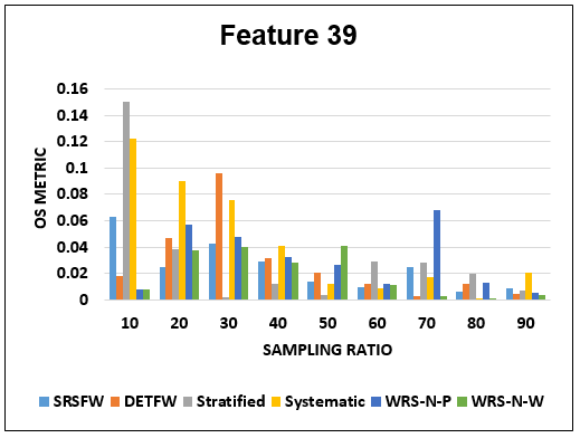
Figures 22, 25, 26, 27, and Tables 5, 9, 10, and 11 show that for all the stream algorithms, except the DETSW the chain-sample algorithms, the window size has no considerable impact on the OS value for features 5, 28, 30, and 36. Regarding the DETSW, the OS value remains the same when the window size changes. This can be explained by the fact that the elements are selected in a deterministic manner. Regarding the chain-sample algorithm, the OS value increases when the value of the window increases. The results



(a) Standard deviation and median estimation



(b) Mean estimation

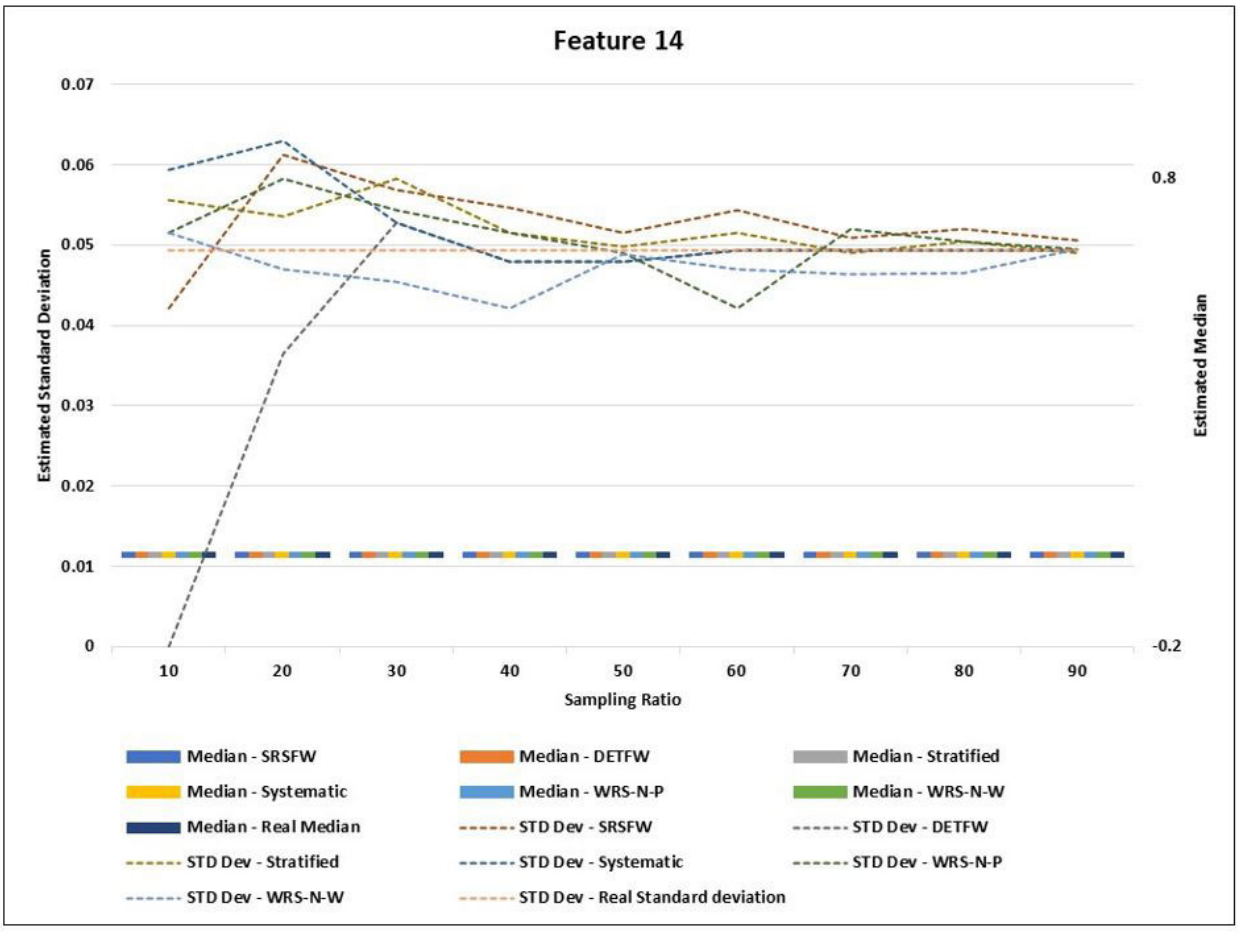


(c) OS metric.

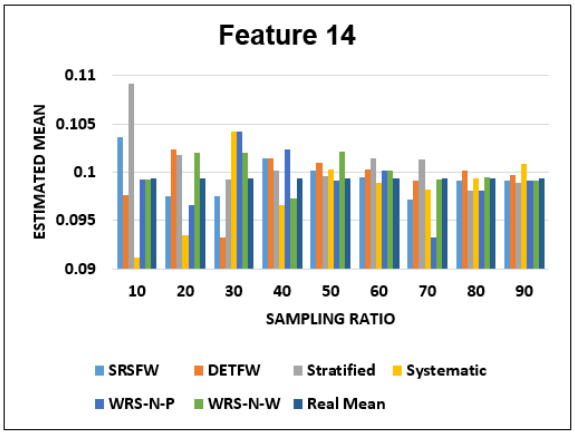
FIGURE 19. Statistical metrics estimation of feature 39 using non-stream sampling policies.

TABLE 5. Variation of the OS value of feature 5 for stream algorithms for different window sizes.

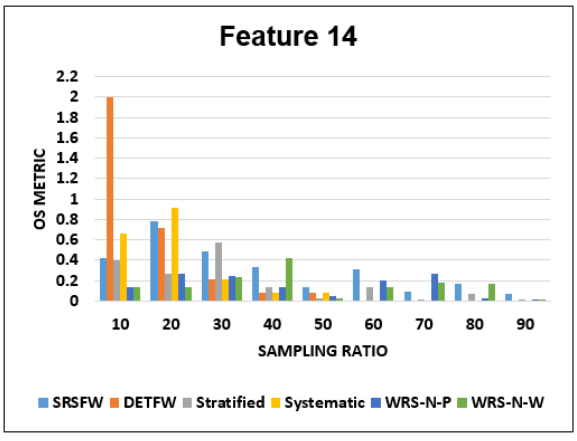
	SRSSW	Chain	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.899	2.027	0.720	0.643	0.741	0.540	0.568	0.766	0.772
n = 100	0.826	2.376	0.626	0.643	0.982	0.540	0.665	1.045	0.693
n = 1000	0.773	2.865	0.638	0.643	0.825	0.534	0.634	0.976	0.730
OS Average	0.833	2.422	0.661	0.643	0.849	**0.538**	0.622	0.929	0.732



(a) Standard deviation and median estimation



(b) Mean estimation

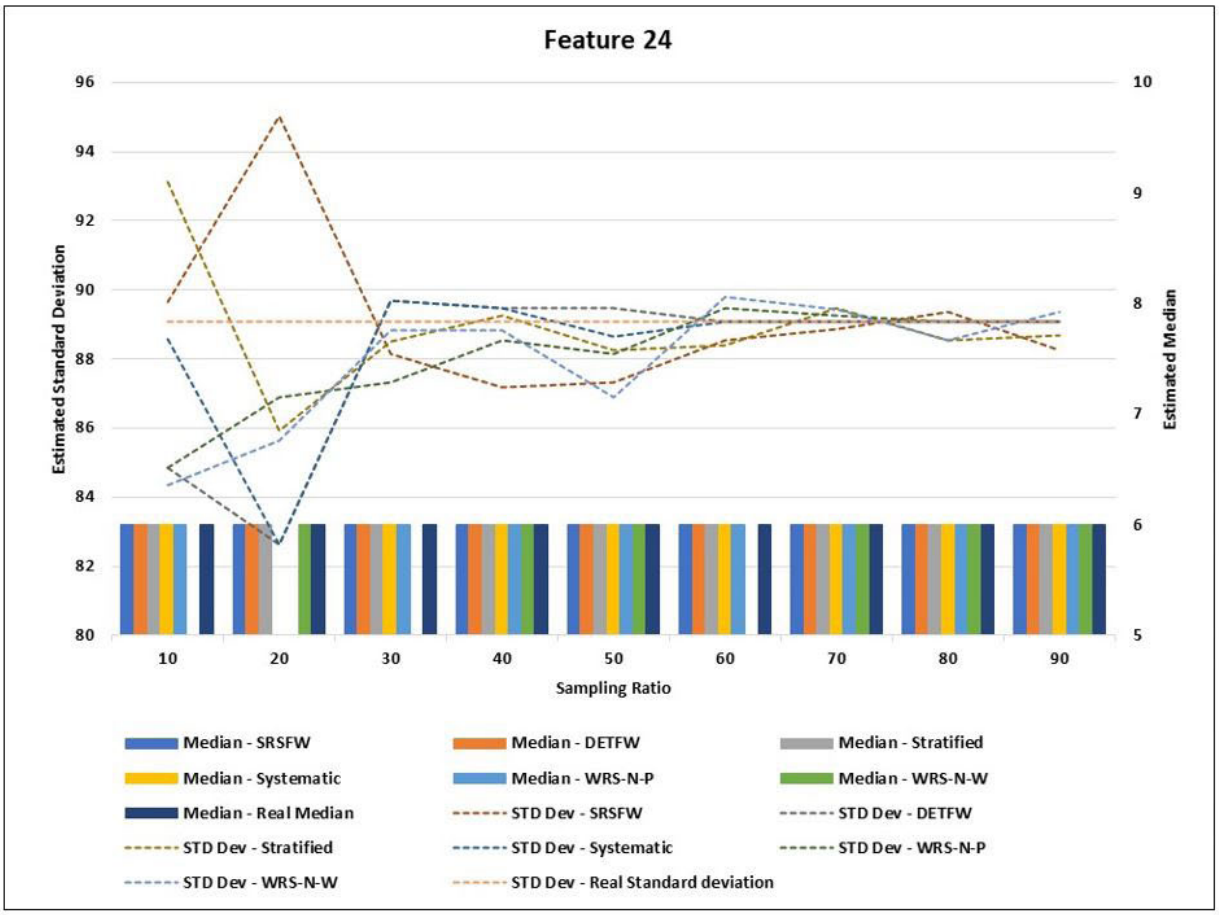


(c) OS metric.

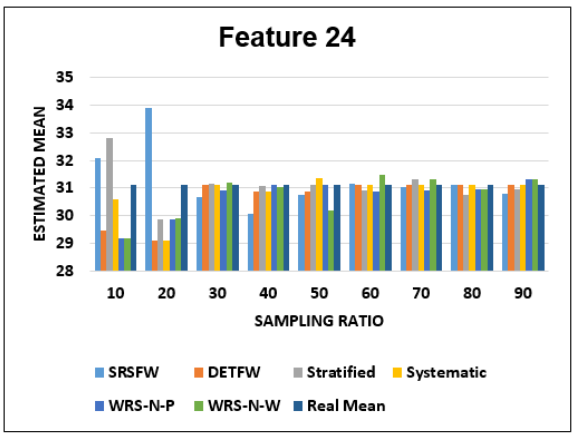
FIGURE 20. Statistical metrics estimation of feature 14 using non-stream sampling policies.

TABLE 6. Variation of the OS value of feature 7 for stream algorithms for different window sizes.

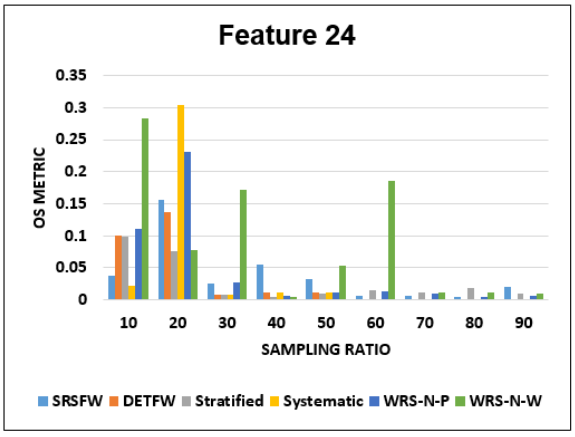
	SRSSW	Chain	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.382	1.530	0.332	0.298	0.674	1.117	0.210911657	0.629	0.607
n = 100	0.687	2.552	0.657	0.298	0.929	1.117	0.280	0.925	0.388
n = 1000	0.866	3.381	0.826	0.298	0.710	1.117	0.437	0.757	0.598
OS Average	0.645	2.488	0.605	**0.298**	0.771	1.117	0.309	0.770	0.531



(a) Standard deviation and median estimation



(b) Mean estimation

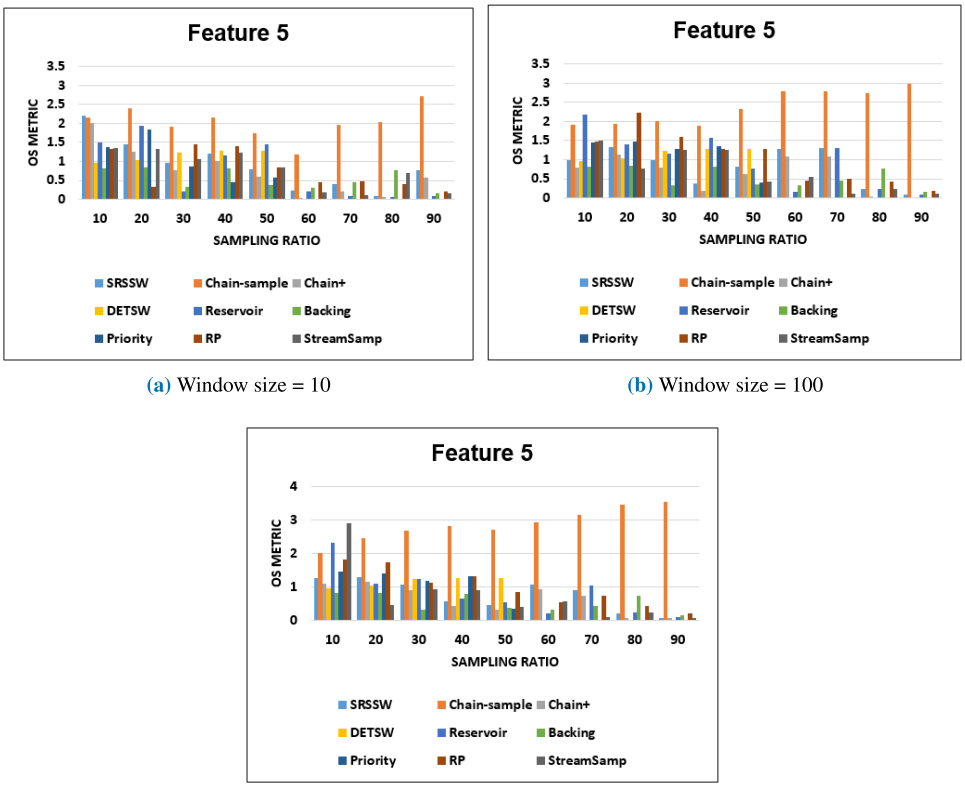


(c) OS metric.

FIGURE 21. Statistical metrics estimation of feature 24 using non-stream sampling policies.

TABLE 7. Variation of the OS value of feature 8 for stream algorithms for different window sizes.

	SRSSW	Chain	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.201	0.568	0.181	0.122	0.207	0.406	0.138	0.269	0.239
n = 100	0.260	0.606	0.240	0.122	0.194	0.4184	0.073	0.181	0.133
n = 1000	0.193	0.432	0.183	0.122	0.146	0.404	0.138	0.111	0.185
OS Average	0.218	0.535	0.202	0.122	0.182	0.409	**0.116**	0.187	0.186



(a) Window size = 10

(b) Window size = 100

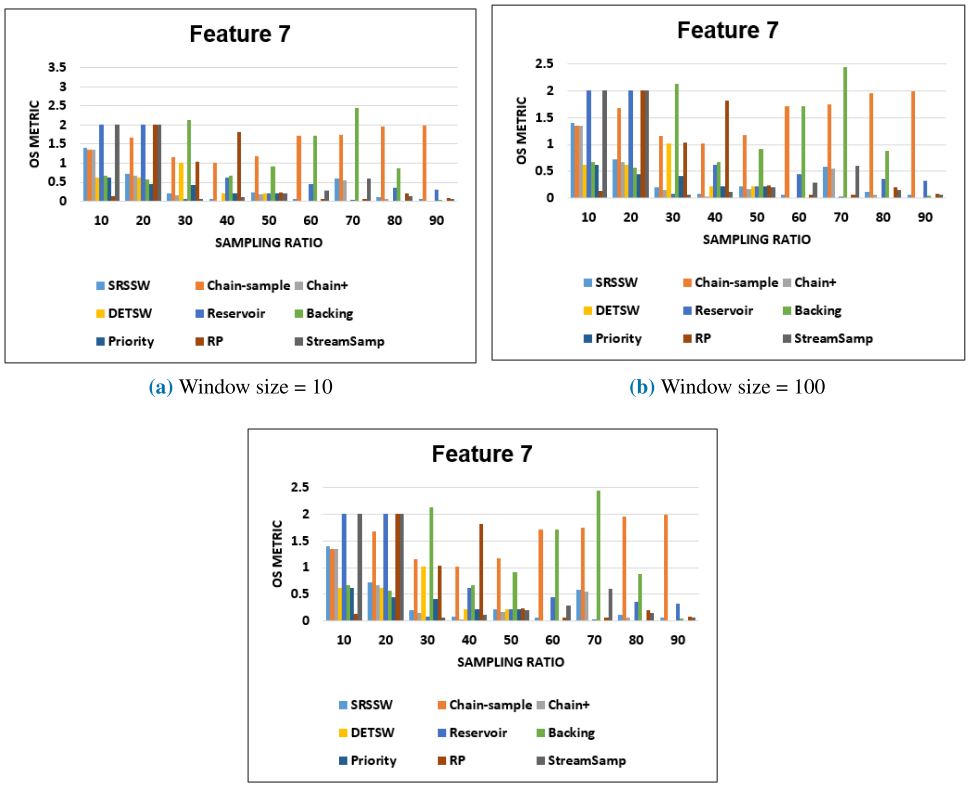
(c) Window size = 1000

FIGURE 22. Statistical metrics estimation of feature 5 using stream sampling policies.

TABLE 8. Lowest achieved OS values according to the stream policies and sampling rates, for DoS attack features.

Feature	Sampling Policy								
	SRSSW	Chain	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
5	**80%**	**10%**	**80%**	**60%**	**80%**	**60%**	**60%**	**80%**	**70%**
	0.137	1.245	0.067	0.0004	0.171	0.318	**0**	0.421	**0.104**
7	**80%**	**10%**	**80%**	**60%**	**60%**	**20%**	**60%**	**80%**	**30%**
	0.197	2.06	0.161	0.0002	0.264	0.574	**0**	0.446662	0.070885
8	**70%**	**10%**	**70%**	**60%**	**80%**	**30%**	**60%**	**60%**	**80%**
	0.047	0.455	0.028	**0.0006**	0.076	0.101	**0**	0.068	0.048

also show that the OS value of the priority sampling algorithm is almost zero when the sampling rate is $\in$ [60, 90]. The results in Figures 22, 25, 26, and 27 show that the OS value of the priority sampling algorithm is almost zero when the sampling rate is $\in$ [60, 90]. The results also show that the OS value of the DETSW and priority algorithms is stable when the sampling ratio is $\in$ [60%, 90%]. The results in Figure 25 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the variation in the OS value according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW and Chain+ sampling algorithms, the minimum OS value was achieved when the sampling rate is equal to 70%. For the reservoir and RP algorithms, it was achieved for a sampling rate equal to 80%. For the backing and StreamSamp algorithms, it was achieved for a sampling rate equal to 40%. The results in Figure 26 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate was equal 90%, the OS value's variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, and StreamSamp sampling algorithms, the minimum OS value was achieved when the sampling rate is of 80%. For the reservoir algorithm, it was achieved for a sampling rate of 40%. For the backing algorithm, it was achieved for a sampling rate of 60%. For the RP it was achieved for a sampling rate equal to 70%. The results in Figure 27 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value's variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW and Chain+ sampling algorithms, the minimum OS value is achieved when the sampling rate is equal to 70%. For the reservoir algorithm, it was achieved for a sampling rate of 80%. For the backing and StreamSamp



(a) Window size = 10

(b) Window size = 100

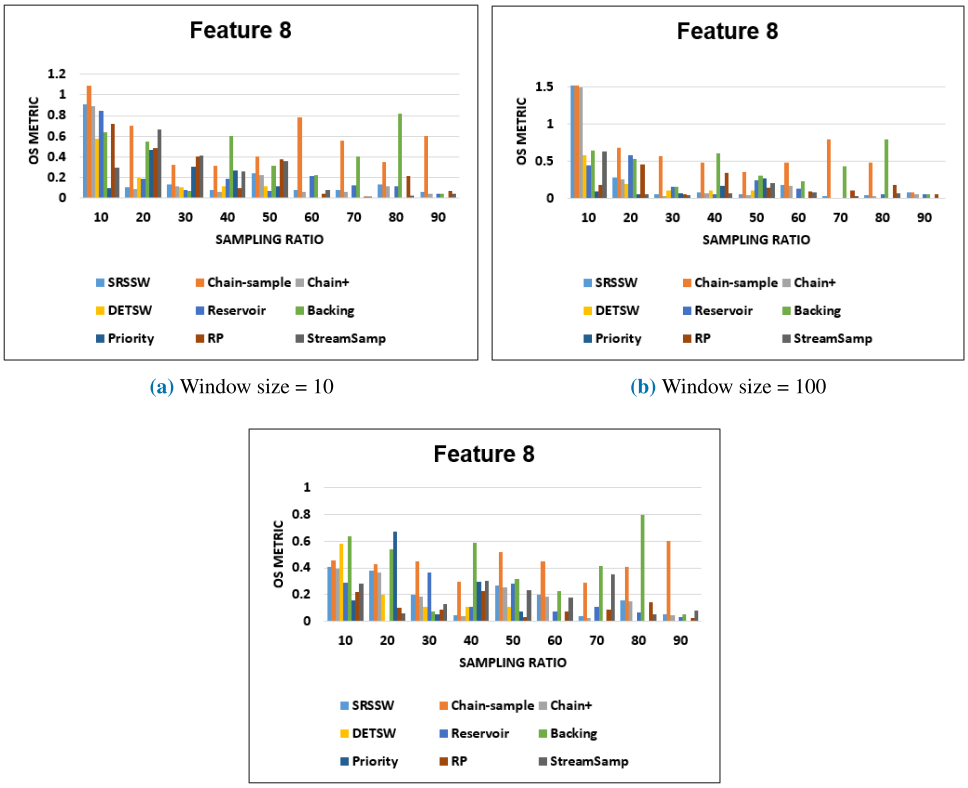
(c) Window size = 1000

FIGURE 23. Statistical metrics estimation of feature 7 using stream sampling policies.

algorithm, it was achieved for a sampling rate of 50%. For the RP it was achieved for a sampling rate equal to 40%. In conclusion, Table 12 shows the stream sampling policies and the corresponding sampling rates ($\in$ [10%, 80%]) that can be used to achieve low OS values for features 5, 28, 30, and 36.

3) R2L ATTACK

Figures 28, 29, 30, and 31, and Tables 13, 14, 15, and 16 show that for all the stream algorithms, except the DETSW the chain-sample algorithms, the window size has no considerable impact on the OS value for features 6, 11, 12, and 39. Regarding the DETSW, the OS value remains the same when the window size changes. This can be explained by the fact that the elements are selected in a deterministic manner. Regarding the chain-sample algorithm, the OS value increases when the value of the window increases. The results also show that the OS value of the priority sampling algorithm is almost zero when the sampling rate is $\in$ [60, 90]. The results also show that the backing sampling algorithm presents the highest OS value regardless of the sampling ratio. The results in Figures 28, 29, 30, and 31 show that the OS value of the priority sampling algorithm is almost zero when the sampling rate is $\in$ [60, 90]. The results also show that the OS value of the DETSW and priority algorithms is stable when the sampling ratio is $\in$ [60%, 90%]. The results in Figure 28 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value's variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW and Chain+ sampling algorithms, the minimum OS value is achieved when the sampling rate was equal to 70%. For the reservoir and backing algorithms, it was achieved for a sampling rate equal to 60%. For the RP and StreamSamp algorithms, it was achieved for a sampling rate equal to 80%. The results in Figure 29 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value's variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, and backing sampling algorithms, the minimum OS value is achieved when the sampling rate is equal to 60%. For the reservoir sampling, it was achieved for a sampling rate equal to 80%. For the RP and StreamSamp sampling algorithms, it was achieved for a sampling rate equal to 70%. The results in Figure 30 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value's variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, and reservoir sampling algorithms, the minimum OS value is achieved when the sampling rate is equal to 80%. For the backing sampling, it was achieved for a sampling rate



(a) Window size = 10

(b) Window size = 100

(c) Window size = 1000

FIGURE 24. Statistical metrics estimation of feature 8 using stream sampling policies.

TABLE 9. Variation of the OS value of feature 28 for stream algorithms for different window sizes.

	SRSSW	Chain-sample	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.013	0.088	0.009	0.008	0.011	0.006	0.009	0.020	0.021
n = 100	0.0122	0.065	0.007	0.008	0.0154	0.006	0.009	0.020	0.027
n = 1000	0.010	0.083	0.006	0.008	0.017	0.006	0.012	0.016	0.017
OS Average	0.011	0.079	0.007	0.008	0.014	**0.006**	0.010	0.019	0.022

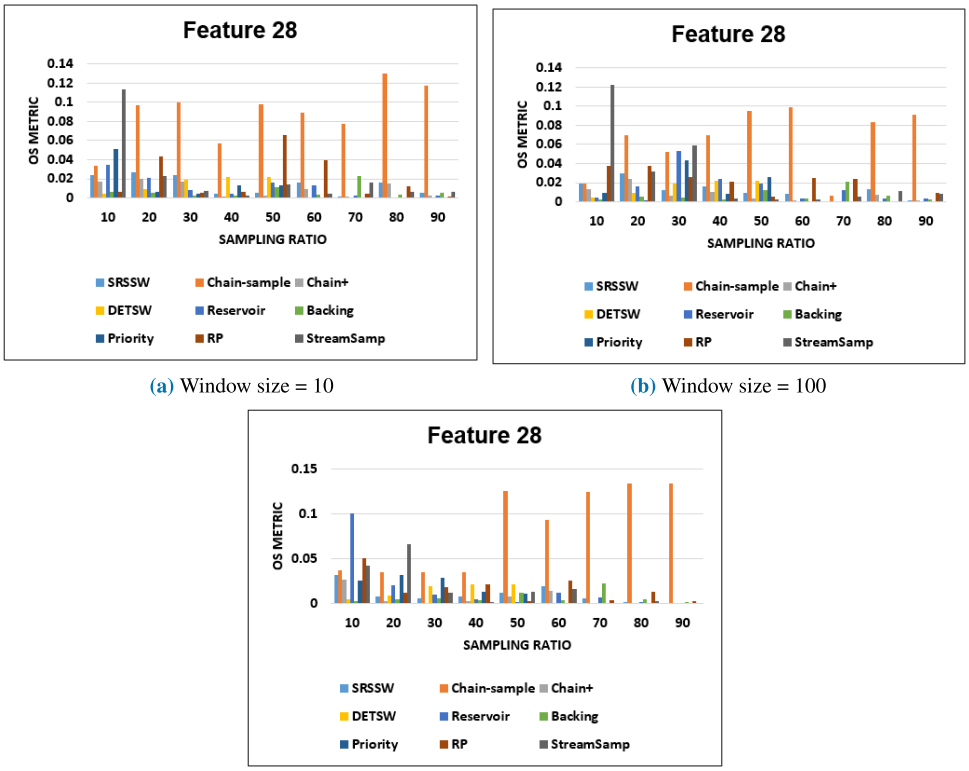
TABLE 10. Variation of the OS value of feature 30 for stream algorithms for different window sizes.

	SRSSW	Chain-sample	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.014	0.275	0.012	0.020	0.020	0.030	0.020	0.024	0.020
n = 100	0.036	0.497	0.029	0.020	0.020	0.029	0.014	0.031	0.013
n = 1000	0.029	2.829	0.026	0.020	0.028	0.030	0.019	0.028	0.038
OS Average	0.026	1.200	0.023	0.020	0.022	0.030	**0.018**	0.027	0.024

TABLE 11. Variation of the OS value of feature 36 for stream algorithms for different window sizes.

	SRSSW	Chain-sample	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.021	0.891	0.018	0.015	0.0177	0.067	0.018	0.023	0.023
n = 100	0.025	1.475	0.015	0.015	0.024	0.069	0.021	0.025	0.022
n = 1000	0.021	2.471	0.015	0.015	0.029	0.069	0.016	0.017	0.025
OS Average	0.022	1.612	0.016	0.015	0.024	0.068	**0.019**	0.022	0.023

equal to 50%, for the RP sampling, it was achieved for a sampling rate equal to 60%, for the StreamSamp sampling, it was achieved for a sampling rate equal to 70%. The results in Figure 31 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value's variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, and StreamSamp sampling algorithms, the minimum OS value is achieved when the sampling rate is equal to 70%. For the reservoir and RP sampling algorithms, it was achieved for a sampling rate equal to 80%. For the backing sampling, it was achieved for a sampling rate equal to



(a) Window size = 10

(b) Window size = 100

(c) Window size = 1000

FIGURE 25. Statistical metrics estimation of feature 28 using stream sampling policies.

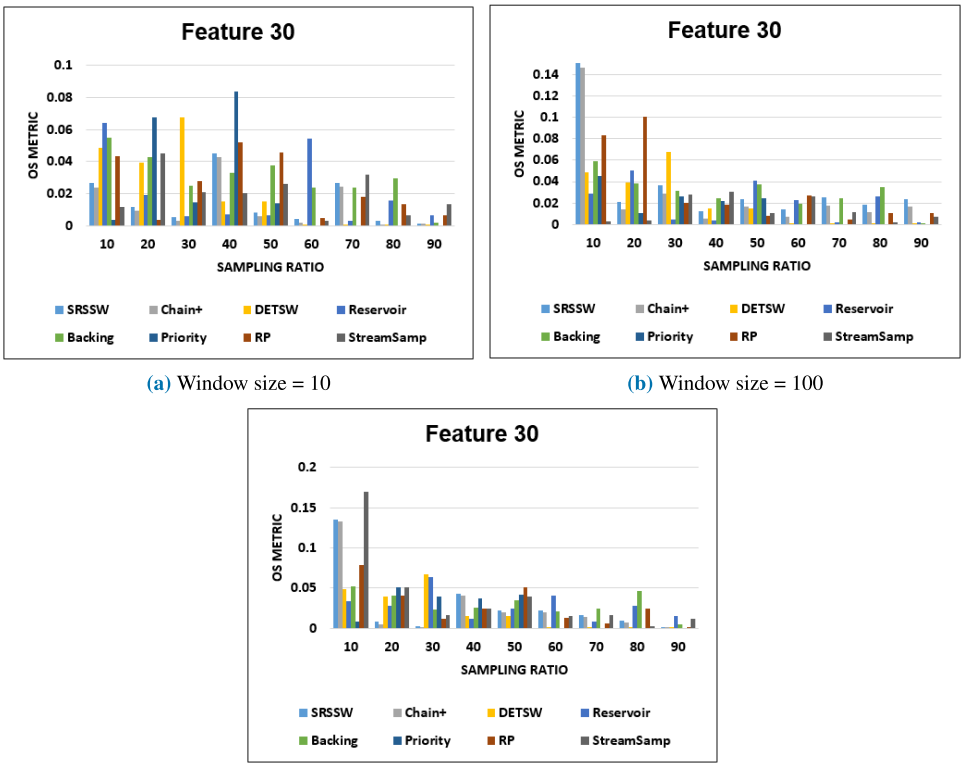
TABLE 12. Lowest achieved OS values according to the stream policies and sampling rates, for Probe attack features.

Feature	Sampling Policy								
	SRSSW	Chain-sample	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
5	**80%**	**10%**	**80%**	**60%**	**80%**	**60%**	**60%**	**80%**	**70%**
	0.137	1.245	0.067	**0.0004**	0.171	0.318	**0**	0.421	0.003
28	**70%**	**10%**	**70%**	**60%**	**80%**	**40%**	**60%**	**80%**	**40%**
	0.002	0.037	0.002	**0.0001**	0.001	0.002	**0**	0.008	0.002
30	**80%**	**10%**	**80%**	**60%**	**40%**	**60%**	**60%**	**70%**	**80%**
	0.01043	2.935	0.014	**0.0001**	0.007	0.02127	**0**	0.009	0.003
36	**70%**	**10%**	**70%**	**60%**	**80%**	**50%**	**60%**	**40%**	**50%**
	0.007	2.463	0.014	**0.00004**	0.003	0.0193	**0**	0.003	0.008

30%. In conclusion, Table 17 shows the stream sampling policies and the corresponding sampling rates ($\in$ [10%, 80%]) that can be used to achieve low OS values for features 6, 11, 23, and 39.

4) U2R ATTACK

Figures 32, 33, 27, and Tables 18, 19, and 11 show that for all the stream algorithms, except the DETSW the chain-sample algorithms, the window size has no considerable impact on the OS value for features 14, 24, and 36. Regarding the DETSW, the OS value remains the same when the window size changes. This can be explained by the fact that the elements are selected in a deterministic manner. Regarding the chain-sample algorithm, the OS value increases when the value of the window increases. The results also show that the OS value of the priority sampling algorithm is almost zero when the sampling rate is $\in$ [60, 90]. The results also show that the backing sampling algorithm presents the highest OS value regardless of the sampling ratio. The results in Figures 32, 33, and 27 show that the OS value of the priority sampling algorithm is almost zero when the sampling rate is $\in$ [60, 90]. The results also show that the OS value of the DETSW and priority algorithms is stable when the sampling ratio is $\in$ [60%, 90%]. The results in Figure 32 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, and RP sampling algorithms, the minimum OS value is achieved when the sampling rate is equal to 80%. For the StreamSamp algorithm, it was achieved for a sampling rate equal to 50%. For the reservoir and backing sampling, it was achieved for a

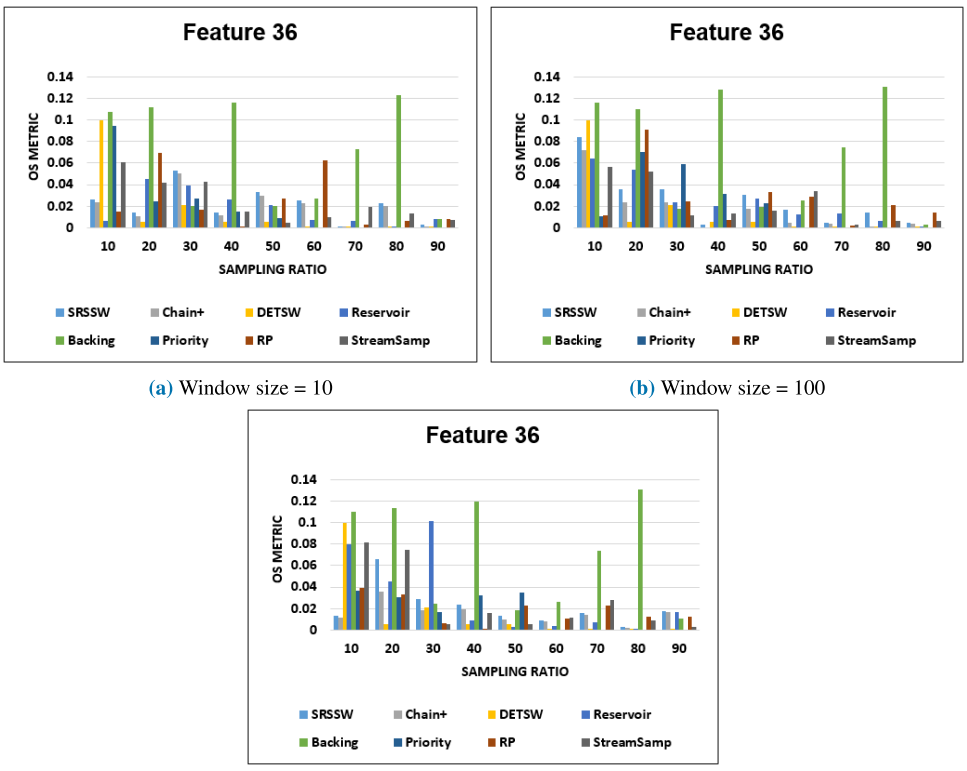


(a) Window size = 10

(b) Window size = 100

(c) Window size = 1000

FIGURE 26. Statistical metrics estimation of feature 30 using stream sampling policies.

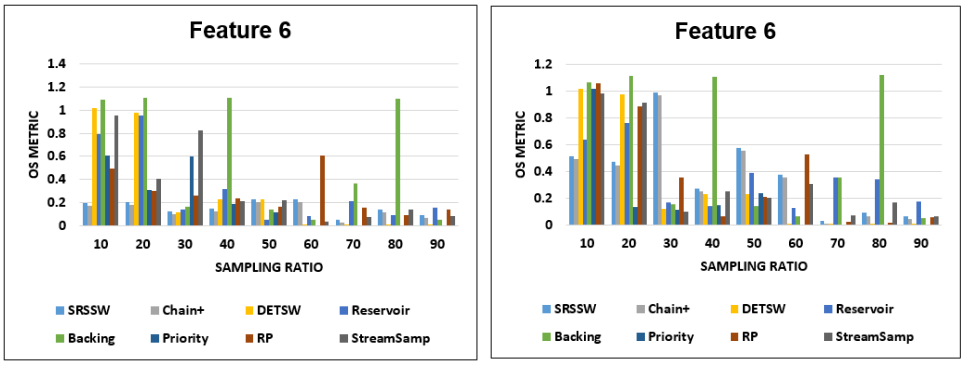


(a) Window size = 10

(b) Window size = 100

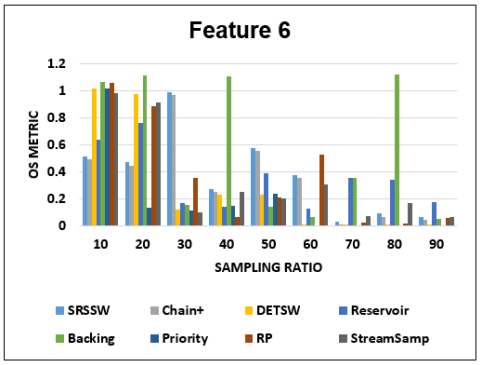
(c) Window size = 1000

FIGURE 27. Statistical metrics estimation of feature 36 using stream sampling policies.



(a) Window size = 10

(b) Window size = 100



(c) Window size = 1000

FIGURE 28. Statistical metrics estimation of feature 6 using stream sampling policies.

TABLE 13. Variation of the OS value of feature 6 for stream algorithms for different window sizes.

	SRSSW	Chain-sample	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.155	1.624	0.132	0.286	0.311	0.574	0.202	0.273	0.327
n = 100	0.376	2.698	0.353	0.286	0.343	0.575	0.182	0.356	0.340
n = 1000	0.263	3.568	0.240	0.286	0.277	0.572	0.182	0.244	0.354
OS Average	0.265	2.630	0.242	0.286	0.310	0.574	**0.189**	0.291	0.341

TABLE 14. Variation of the OS value of feature 11 for stream algorithms for different window sizes.

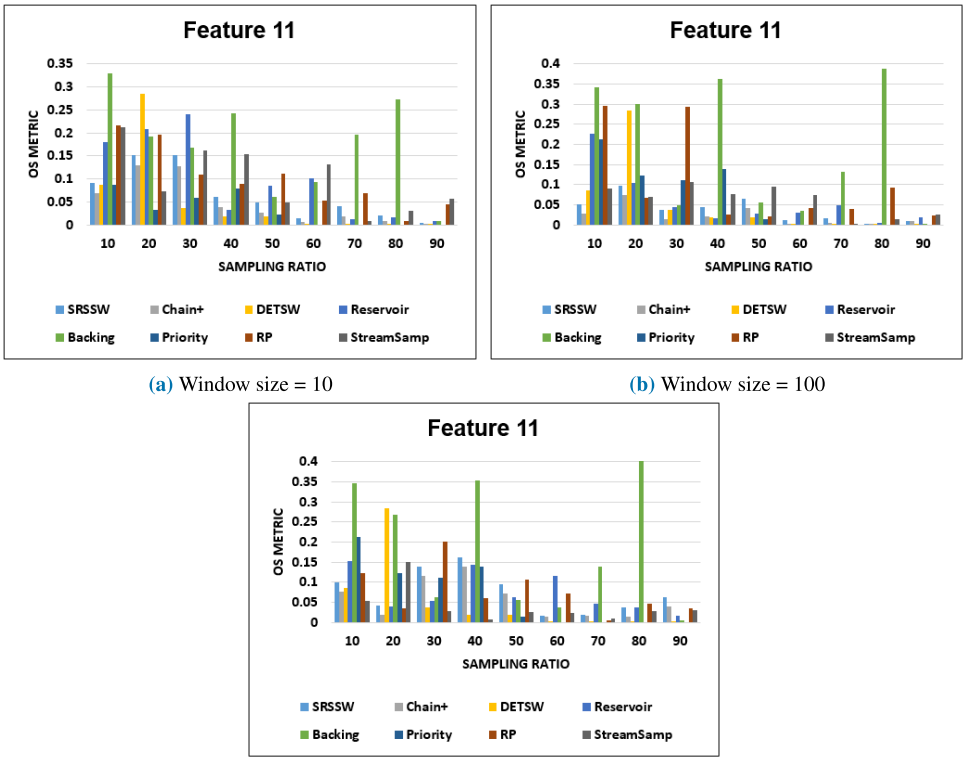
	SRSSW	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.065	0.047	0.049	0.098	0.173	0.031	0.099	0.098
n = 100	0.037	0.021	0.049	0.058	0.185	0.066	0.100	0.061
n = 1000	0.074	0.056	0.049	0.074	0.187	0.066	0.076	0.040
OS Average	0.059	**0.041**	0.049	0.077	0.182	0.054	0.092	0.066

TABLE 15. Variation of the OS value of feature 23 for stream algorithms for different window sizes.

	SRSSW	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.012	0.008	0.015	0.020	0.108	0.018	0.012	0.018
n = 100	0.032	0.028	0.015	0.050	0.092	0.038	0.069	0.031
n = 1000	0.0207	0.019	0.015	0.030	0.107	0.038	0.015	0.035
OS Average	0.021	0.018	**0.015**	0.0335	0.102	0.0315	0.0327	0.0284

TABLE 16. Variation of the OS value of feature 39 for stream algorithms for different window sizes.

	SRSSW	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.022	0.018	0.019	0.033	0.027	0.027	0.018	0.019
n = 100	0.018	0.017	0.019	0.029	0.027	0.018	0.022	0.029
n = 1000	0.021	0.019	0.019	0.013	0.032	0.018	0.027	0.020
OS Average	0.020	0.0187	**0.019**	0.025	0.028	0.021	0.022	0.023

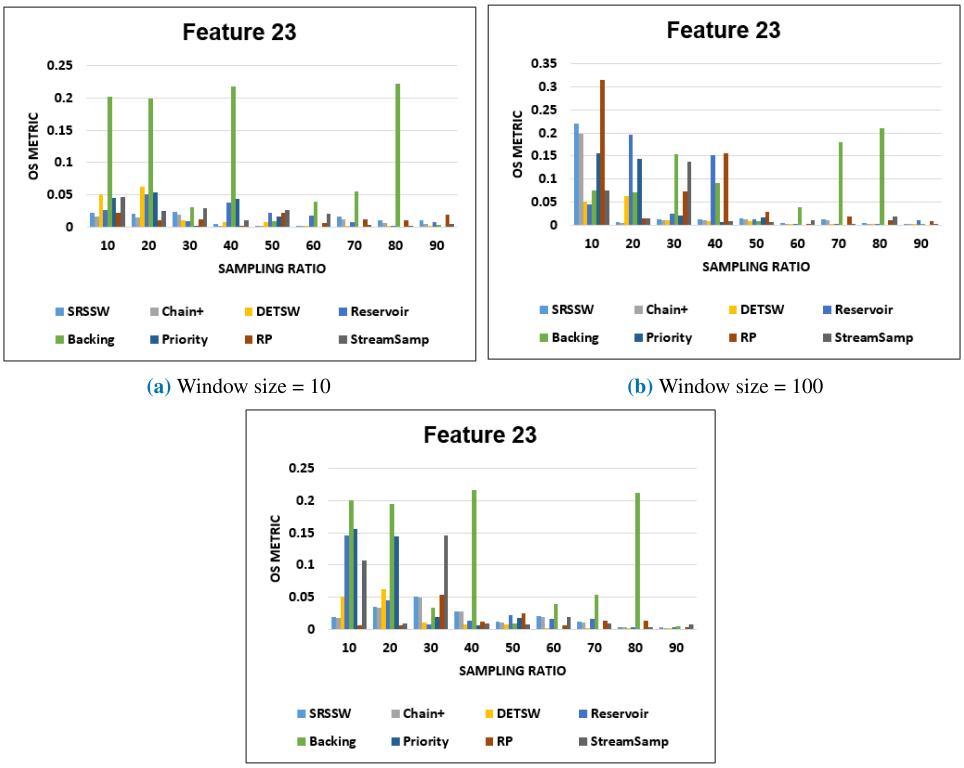


(a) Window size = 10

(b) Window size = 100

(c) Window size = 1000

FIGURE 29. Statistical metrics estimation of feature 11 using stream sampling policies.

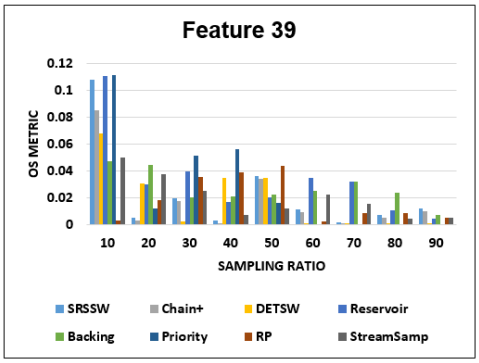


(a) Window size = 10

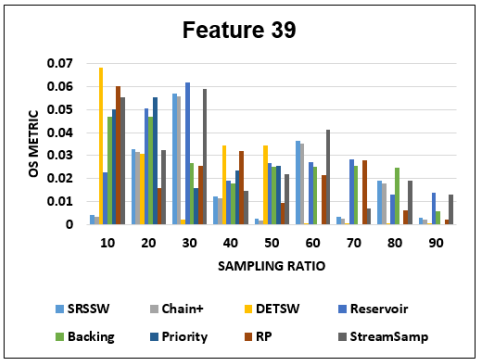
(b) Window size = 100

(c) Window size = 1000

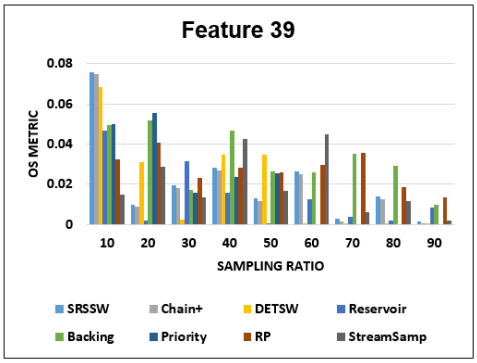
FIGURE 30. Statistical metrics estimation of feature 23 using stream sampling policies.



(a) Window size = 10

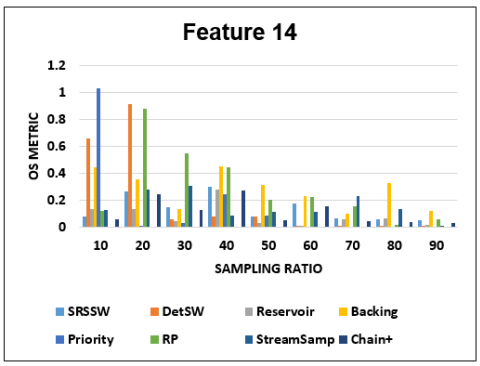


(b) Window size = 100

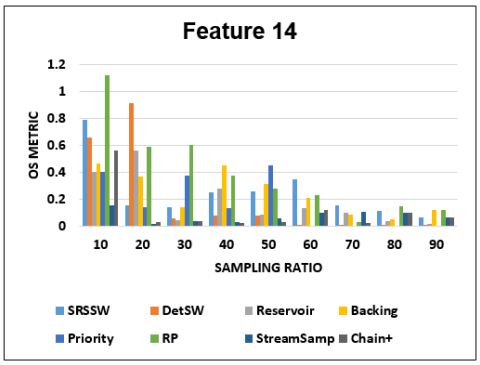


(c) Window size = 1000

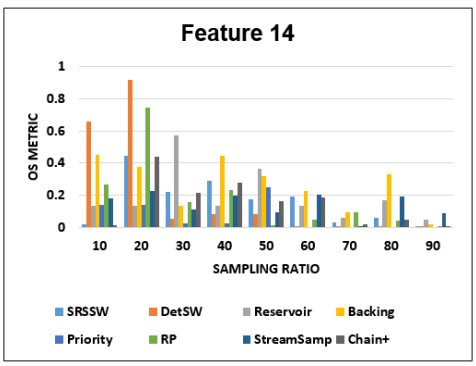
FIGURE 31. Statistical metrics estimation of feature 39 using stream sampling policies.



(a) Window size = 10

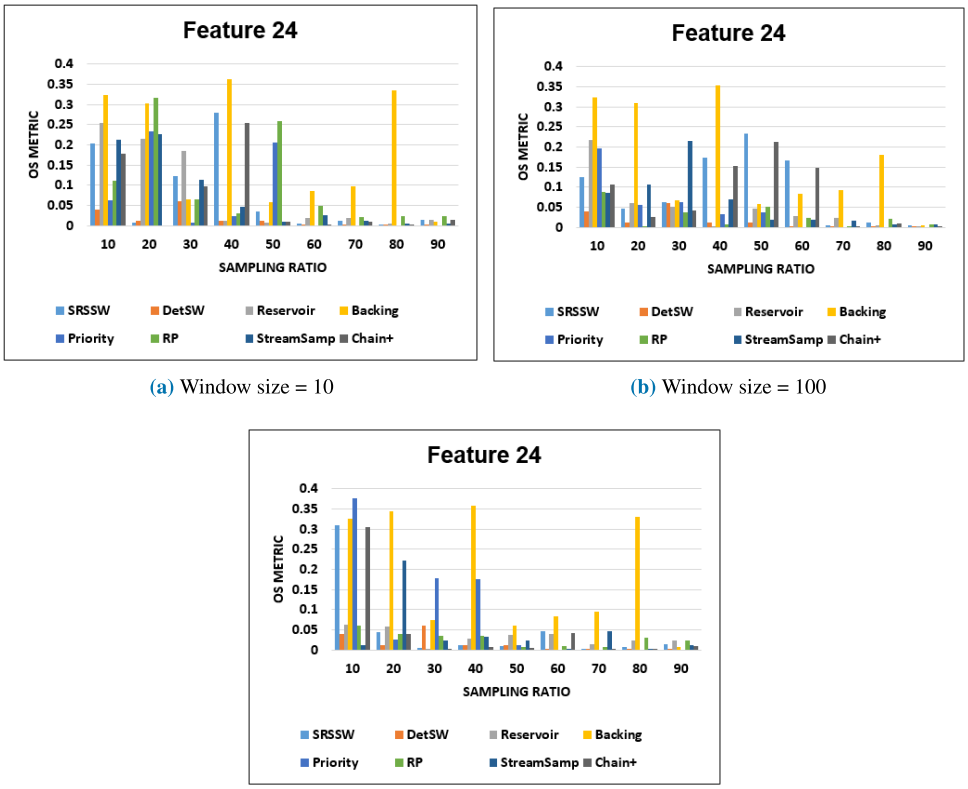


(b) Window size = 100



(c) Window size = 1000

FIGURE 32. Statistical metrics estimation of feature 14 using stream sampling policies.



(a) Window size = 10

(b) Window size = 100

(c) Window size = 1000

FIGURE 33. Statistical metrics estimation of feature 24 using stream sampling policies.

TABLE 17. Lowest achieved OS values according to the stream policies and sampling rates, for R2L attack features.

Feature	Sampling Policy								
	SRSSW	Chain-sample	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
6	**70%**	**10%**	**70%**	**60%**	**60%**	**60%**	**60%**	**80%**	**80%**
	0.066	3.092	0.097	**0.0003**	0.099	0.058	**0**	0.105	0.109
11	**60%**	**10%**	**60%**	**60%**	**80%**	**60%**	**60%**	**70%**	**70%**
	0.014	2.198	0.014	**0.0006**	0.0199	0.055	**0**	0.039	0.007
23	**80%**	**10%**	**80%**	**60%**	**80%**	**50%**	**60%**	**60%**	**70%**
	0.006	2.719	**0.002**	0.0003	**0.002**	0.009	**0**	0.004	0.005
39	**70%**	**10%**	**70%**	**60%**	**80%**	**30%**	**60%**	**80%**	**70%**
	0.002	2.525	0.0015	**0.0006**	0.008	0.021	**0**	0.0111	0.009

TABLE 18. Variation of the OS value of feature 14 for stream algorithms for different window sizes.

	SRSSW	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.136	0.113	0.199	0.084	0.273	0.153	0.293	0.154
n = 100	0.253	0.109	0.199	0.183	0.243	0.166	0.389	0.074
n = 1000	0.159	0.150	0.199	0.194	0.266	0.064	0.178	0.145
OS Average	0.183	**0.124**	0.199	0.154	0.261	0.128	0.287	**0.124**

TABLE 19. Variation of the OS value of feature 24 for stream algorithms for different window sizes.

	SRSSW	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
n = 10	0.075	0.064	0.015	0.081	0.182	0.059	0.100	0.073
n = 100	0.092	0.078	0.015	0.048	0.164	0.042	0.026	0.060
n = 1000	0.050	0.046	0.015	0.032	0.186	0.085	0.02807163	0.042
OS Average	0.072	0.062	**0.015**	0.054	0.177	0.062	0.051	0.058

sampling rate equal to 70%. The results in Figure 33 show that while for all the algorithms the OS value reaches almost its minimum when the sampling rate is equal 90%, the OS value variation according to the sampling ratio is dependent on the sampling policy. For instance, for the SRSSW, Chain+, and RP sampling algorithms, the minimum OS value is achieved

TABLE 20. Lowest achieved OS values according to the stream policies and sampling rates, for U2R attack features.

Feature	Sampling Policy								
	SRSSW	Chain-sample	Chain+	DETSW	Reservoir	Backing	Priority	RP	StreamSamp
14	**80%**	**10%**	**80%**	**60%**	**70%**	**70%**	**60%**	**80%**	**50%**
	0.075	2.112	0.049	**0.0006**	0.071	0.093	**0**	0.069	0.088
24	**70%**	**10%**	**70%**	**60%**	**80%**	**50%**	**60%**	**70%**	**80%**
	0.006	2.104	0.001	**0.0004**	0.011714	0.059	**0**	0.010	0.005
36	**70%**	**10%**	**70%**	**60%**	**80%**	**50%**	**60%**	**40%**	**50%**
	0.007	2.463	0.014	**0.00004**	0.003	0.0193	**0**	0.0030	0.008

when the sampling rate is equal to 70%. For the reservoir and StreamSamp algorithm, it was achieved for a sampling rate equal to 80%. For the backing, it was achieved for a sampling rate equal to 50%. In conclusion, Table 20 shows the stream sampling policies and the corresponding sampling rates ($\in$ [10%, 80%]) that can be used to achieve low OS values for features 14, 24, and 36.

V. CONCLUSION AND OPEN RESEARCH CHALLENGES

In this paper, we investigated the statistical impact of network traffic sampling to quantify the amount of deterioration that the sampling process introduces with respect to non-sampled traffic. By performing an offline analysis of the NSL-KDD dataset, we carried out an experimental comparison of existing sampling techniques and studied their impact on several well-known statistical measures to assess the level of degradation introduced by sampling. Different sampling policies were evaluated, and different features and attacks were considered.

Our study suffers from the following limitations:

- Without loss of generality, in our work, we evaluated the performance of sampling algorithms for intrusion detection using the NSl-KDD database. However, there are other datasets, such as CAIDA [41], CIDDS [42], etc. In our future work, we aim to consider data from other modern networks or even real networks.
- Feature preprocessing and feature selection processes should be conducted prior to intrusion detection. Because the network traffic is enormous, analysis and intrusion detection are difficult. On the other hand, there could be a relationship between the network characteristics. Some of these features may even be redundant or irrelevant. Thus, it is necessary to reduce the volume of traffic data to be processed and analyzed using a feature selection process. This process identifies the relevant characteristics of the traffic and will lead to improved performance of the IDS. In this work, we referred to many recent studies to determine the appropriate features of each form of attack. In our future work, we plan to study different feature selection algorithms to determine the most precise features, and therefore, to select the most relevant features for each attack.
- The NSL-KDD database contains approximately 150K records divided into training and testing subsets. It consists of 41 attributes and includes 22 attack types. These attacks are of four categories: DoS, probe, R2L, and U2R. In our future work, we aim to test the impact of sampling on the detection of many other types of network attacks.

Knowing the traffic parameters, a convenient sampling algorithm with a calculated compromise (accuracy vs. computational cost) can be configured and fine-tuned accordingly. Several open issues that could benefit from further studies can be identified.

- *Static vs. dynamic packet sampling*. The sampling ratio directly affects the accuracy of the built sample [43], [44]. Static packet sampling algorithms have been used for many years. With these algorithms, all items are selected randomly, except for deterministic sampling, with a predefined sampling ratio. Nevertheless, given the dynamic nature of network traffic, static sampling cannot guarantee the estimation accuracy and is, thus, poorly suited for network monitoring. During periods of idle activity or low network loads, a long sampling interval provides sufficient accuracy at minimal overhead. However, bursts of high activity require shorter sampling intervals to accurately measure the network status at the expense of increased sampling overhead. To preserve the accuracy and provide accurate estimations, the sampling policy should adapt to the network state. It is worth noting that network devices have certain limits in terms of resources available for sampling. Some network devices may even stop sampling during traffic bursts. To address these issues, adaptive sampling algorithms can be designed and applied to dynamically adjust the sampling interval and optimize the sampling and traffic classification accuracy. Dynamic sampling algorithms have dynamic sampling rates, which allow them to control the accuracy of the sample by controlling the number of measurements to be sampled. A decision should be made in advance to adjust the sampling ratio before network traffic change.
- *On-the-fly learning*. High-speed network traffic is dynamic and volatile; thus, a responsive packet sampling algorithm is vital for robust and timely anomaly detection. For a sampling algorithm to be responsive, fast traffic feature learning is a prerequisite. Fast and accurate on-the-fly feature learning is an open challenge to be studied, especially with the adequacy of data mining (such as time series) and artificial intelligence algorithms for this task. In this context, various prediction and forecasting techniques can be used to

predict network traffic and any potential changes in its characteristics.

- *Weighted sampling algorithm*. As the benchmarking results showed, not all features were equal in predicting anomalies. Some features are more sensitive to change and thus can be used as an early warning for potential anomalies. In addition, not all packets were equal. Designing a multi-feature weighted sampling algorithm can benefit from sensitivity and accuracy if successfully configured.
- *Data Quality*. The arriving packets can be contaminated (i.e. delayed or distorted) or even lost before reaching the IDS. This is very frequent in the case of network congestion, noisy channels, and unstable changes to the network topology. The missing data can be very random and sporadic, resulting in very distorted measurements by the IDS, following survivor bias. Studying the impact of missing data or, more generally, data quality is also an open issue.

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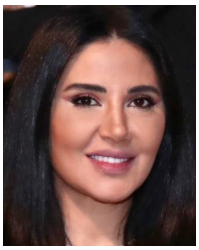

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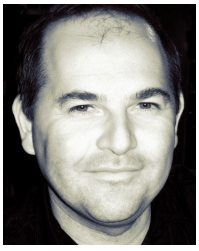

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