Next Generation P2P Botnets: Monitoring Under Adverse Conditions

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Abstract. The effects of botnet attacks, over the years, have been devastating. From high volume Distributed Denial of Service (DDoS) attacks to ransomware attacks, it is evident that defensive measures need to be taken. Indeed, there has been a number of successful takedowns of botnets that exhibit a centralized architecture. However, this is not the case with distributed botnets that are more resilient and armed with countermeasures against monitoring. In this paper, we argue that monitoring countermeasures, applied by botmasters, will only become more sophisticated; to such an extent that monitoring, under these adverse conditions, may become infeasible. That said, we present the most detailed analysis, to date, of parameters that influence a P2P botnet's resilience and monitoring resistance. Integral to our analysis, we introduce BotChurn (BC) a realistic and botnet-focused churn generator that can assist in the analysis of botnets. Our experimental results suggest that certain parameter combinations greatly limit intelligence gathering operations. Furthermore, our analysis highlights the need for extensive collaboration between defenders. For instance, we show that even the combined knowledge of 500 monitoring instances is insufficient to fully enumerate some of the examined botnets. In this context, we also raise the question of whether botnet monitoring will still be feasible in the near future.

1 Introduction

Botnets are networks of infected computers, that can be remotely controlled by malicious entities, commonly referred to as botmasters. Botnets have been historically used for launching a multitude of attacks, ranging from DDoS and blackmailing, to credential theft, banking fraud, etc. Recently, with the emergence of the Internet of Things (IoT), the landscape of vulnerable connected devices has increased significantly. This led to a resurgence of many new botnets infecting weakly protected IoT devices. These IoT botnets are particularly notorious for their high bandwidth DDoS attacks, bringing down even well protected websites and services.

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An approach to remove the botnet threat, is to identify and take down the Command and Control (C2) channel used by the botmasters. For centralized botnets, this has proven to be an effective approach with many being taken down by seizing their respective C2 servers [7]. More advanced botnets overcome this Single Point of Failure (SPoF), by employing a peer-to-peer (P2P) C2 structure, where each bot acts as a server and a client. Hence, defenders have to target the majority of bots to take the botnet down. This requires knowledge about the population and inter-connectivity of the botnet, which is commonly achieved via monitoring. Monitoring mechanisms are commonly developed by reverse engineering and re-implementing the communication protocol of a botnet to gather intelligence. As botnet monitoring poses a threat for the botmasters, many botnets, e.g., GameOver Zeus [3] and Sality [6], implement monitoring countermeasures. These mechanisms increase the difficulty of monitoring operations, but do not prevent them [20]. Nevertheless, recent publications presented sophisticated countermeasures, that further limit or even prevent monitoring activities [2,14,25]. Hence, we argue that it is a matter of time until botmasters introduce such countermeasures to impede monitoring in its current form.

To deal with next-generation botnets, we need to understand the extent at which advanced countermeasures prevent monitoring operations. Investigating each of the countermeasures individually will likely end in a never ending arms race for new monitoring and anti-monitoring mechanisms. To avoid this arms race, we instead introduce a lower boundary for monitoring operations in adverse conditions, i.e., monitoring in the presence of sophisticated countermeasures.

To achieve this, we make the assumption that a botmaster can detect any behavior deviating from that of a normal bot. Therefore, the maximum intelligence that can be gathered with a single monitoring instance is limited to the information that can be obtained by any regular bot itself. As this can vary for different botnets, we analyze several botnet parameterizations to be able to evaluate how much intelligence can be gathered in different botnet designs. This allows us to evaluate the effectiveness of monitoring operations in adverse conditions, based on the parameters of the botnet protocol. To ensure that our simulations accurately replicate the behavior of real bots, we utilize churn measurements taken from live botnets [11]. Moreover, we develop and present a novel botnet churn generator that simulates churn more accurately than the state of the art. At a glance, the two major contributions of this paper are:

– An *extensive analysis* of botnet designs and parameterizations, with an emphasis to their resilience and monitoring resistance.
– A *realistic* and *botnet-focused* churn generator, namely BotChurn (BC).

The remainder of this paper is structured as follows. Sections 2 and 3, introduce the background information and the related work respectively. Section 4, presents our analysis regarding the effectiveness of monitoring in adverse conditions. Section 5, provides a detailed description of our proposed botnet churn generator. Section 6 discusses the evaluation of our churn generator and the effectiveness of monitoring in adverse conditions. Lastly, Sect. 7, concludes our work and presents outlooks with regard to our future work.

2 Background

In the following, we provide background information with regard to P2P botnets and their underlying technologies as well as introductory information regarding common monitoring mechanisms.

2.1 P2P Botnets

The decentralized nature of P2P botnets and the absence of a SPoF, makes them highly resilient against takedown attempts [20]. P2P networks can be categorized into structured and unstructured overlays. *Structured* P2P overlays such as Kademlia [16] use a concept called *Distributed Hash Table (DHT)*. As an example, Kademlia implements a ring structure on which all *peers*, i.e., participants in the P2P network, are placed based on their ID. Peers connect to a set peers, based on their distance in the ring structure. *Unstructured* P2P overlays do not have such a structure but maintain connectivity based on a Membership Management (MM) mechanism. At the core of this MM is a so called Neighborlist (NL). The NL consists of a subset of all existing peers commonly referred to as *neighbors*. To maintain connectivity within the network, peers frequently exchange NL-entries with their neighbors.

For botnets, the major difference between structured and unstructured P2P networks is related to the difficulty of monitoring. For instance, structured botnets, e.g., *Storm* [10], can be monitored efficiently [21]. More recent P2P botnets such as *Sality* [6], *GameOver Zeus* [3] and *ZeroAccess* [18] use unstructured P2P overlays. This makes them more difficult to be monitored, as the lack of a structure prevents the usage of efficient approaches applicable to structured P2P networks. Due to the greater resistance against monitoring attempts, this paper focuses on unstructured P2P botnets.

A major challenge for any P2P overlay is the handling of node churn, i.e., nodes leaving and joining the network. Churn is caused by diurnal patterns or by machines being turned off and on throughout the globe. To ensure that the network remains connected under the effects of churn, P2P overlays leverage the MM system. The MM ensures that inactive peers, in the NL of a node, are replaced with responsive peers. This is usually achieved by probing the activity of all entries in an NL at fixed intervals. Common values for such Membership Management Interval (MMIs) are between *one* second [18] and 40 min [6].

If an entry in the NL of a bot is unresponsive for several consecutive MMIs, it is removed from the NL. To replace removed peers, a node commonly asks their own neighbors for responsive candidates by sending an *NL-request*. A bot's NL can also be passively updated upon receipt of a message from a bot that is not in the bot's NL [3]. This allows the bots to maintain active connections among bots within the P2P overlay despite being affected by churn.

2.2 Botnet Monitoring Mechanisms

To obtain information about the extent of a botnet infection, one has to conduct intelligence gathering by monitoring the botnet. Monitoring a P2P botnet is achieved via the usage of crawlers, sensors or a combination of both. At a glance, crawlers are more of an active approach whereas sensors are more passive.

A *crawler* enumerates the botnet by continuously requesting NL-entries from bots. Given a list of *seed-nodes*, a crawler follows a crawling strategy such as Breadth-First Search (BFS), Depth-First Search (DFS) or Less Invasive Crawling Algorithm (LICA) [12] to discover bots within the botnet. The seed-list is updated between crawls by adding all newly discovered bots into it. This allows crawlers to quickly obtain information about participating bots and their inter-connectivity. The major drawback of crawlers is that they cannot discover bots that are behind Network Address Translation (NAT) or a firewall. Such bots usually cannot be contacted from the Internet, unless they initiate the connection first. Therefore, crawlers underestimate the population of a botnet [20]. Moreover, the aggressive sending of *NL-requests* makes crawlers easy to detect [14].

Sensors can provide more accurate enumerations of botnets by overcoming the aforesaid drawback of crawlers. A sensor imitates the behavior of a regular bot by responding to probe messages from other bots. By remaining active within the botnet for prolonged periods, sensors become popular within the botnet. That is, more bots will add the sensor to their NL and frequently contact it during their MMI. This allows a sensor to accurately keep track of the entire botnet population including those that are behind NAT-like devices. However, a major drawback for sensors is the lack of inter-connectivity information of the botnet. Therefore, sensors are commonly used as an addition to crawlers instead of a replacement. Another drawback of sensors is that they require time to become popular and therefore do not yield results as quickly as crawlers. This can again be surmounted by using a crawler to help spread information about the sensor to speed up the popularization process [27].

3 Related Work

In this section, we discuss the state of the art of: (*i*) P2P botnet monitoring techniques and (*ii*) advanced countermeasures against monitoring.

3.1 P2P Botnet Monitoring

Rossow et al. present an in-depth analysis on the resilience against intelligence gathering and disruption of P2P botnets [20]. They analyze the peer enumeration capabilities of sensors and crawlers on several P2P botnets and provide real world results. Furthermore, they analyze the resilience of these botnets against communication layer poisoning and sink-holing attacks. Their work clearly presents the drawbacks and benefits of crawlers and sensors. The authors also present an analysis of reconnaissance countermeasures implemented by botnets. Most notably, botnets such as Sality and GameOver Zeus implement rate limiting mechanisms on neighborlist replies. In addition, GameOver Zeus implements an automated blacklisting mechanism against aggressive crawlers.

Karuppayah et al. introduce a new crawling strategy called LICA [12]. Their crawling algorithm approximates the minimum vertex coverage by prioritizing nodes with high in-degree. Their approach provides a means to crawl a botnet faster and more efficiently compared to BFS or DFS. Yan et al. present a sensor popularization method called *popularity boosting* [27]. Popularity boosting leverages a mechanism that botnets commonly use to allow new bots to get into other peers NLs. For instance, in the Sality botnet, a bot can send a *server-announcement-message* upon joining the botnet. If the bot fulfills a set of conditions, such as being publicly routable, it will be added at the end of the receiving bot's NL. This mechanism allows sensors to be quickly injected into the NL of active bots in a botnet. In [13], the authors present an algorithm that efficiently extracts all entries from a bot's NL in the GameOver Zeus botnet. Contrary to a random spoofing of IDs, their strategic approach guarantees to extract all entries from a bot's NL. Lastly, botnet detection mechanisms such as [8,17] also provide monitoring information about botnets. While the main goal this research is to detect botnets within a monitored network, this information can also be used for enumeration or derivation of connectivity between individual bots.

3.2 Monitoring Countermeasures

In this section, we introduce the landscape of monitoring countermeasures. We differentiate between countermeasures that have been implemented by botmasters and novel countermeasures that have been proposed by researchers.

Existing Anti-monitoring Mechanisms: As monitoring poses a threat to botmasters, some botnets implement features specifically aimed at preventing monitoring attempts. Many botnets such as *GameOver Zeus* [3], *Sality* [6], and *ZeroAccess* [18] implement restricted Neighborlist Reply Sizes (NLRSs). This means, that when being requested, they only share a subset of their NL to the requesting bot. This significantly increases the enumeration effort for crawlers.

Furthermore, *GameOver Zeus* implements an automated blacklisting mechanism that blacklists a node if it sends more than *five* requests within a sliding window of *one* minute. The Sality botnet also implements a simple trust mechanism called *Goodcount*. For each NL-entry, such a *Goodcount* value is maintained. A bot sends periodic messages to all its neighbors and increases a nodes *Goodcount* upon receipt of a valid reply and decreases the *Goodcount* otherwise. This locally maintained reputation mechanism prevents that a bot replaces well known active NL-entries with newer entries, e.g., sensors.

Proposed Advanced Anti-monitoring Mechanisms: Andriesse et al. analyzed whether sensors and crawlers can be detected, from the botmasters' perspective, based on protocol and behavioral anomalies [2]. Their findings suggest that crawlers can indeed be detected based on anomalous behavior. The anomalies that were used for identifying the crawlers, vary from implementation-specific ones to logical and protocol level misconducts. The authors were also able to detect sensor nodes based on deviating (protocol) features.

Karuppayah et al. present another mechanism, that uses a bot's local view to identify crawlers within a P2P botnet [14]. For that, they focus on protocol violations that are common for crawlers in all P2P botnets. Upon detection, a bot can blacklist the crawler and prevent any further communication with it.

In [5,11], the authors use graph connectivity metrics to identify sensor nodes within P2P overlays. Both approaches are based on the assumption that researchers and law enforcement agencies cannot aid the botnet in any way, including the returning of valid neighbors when being asked. Böck et al. [5] use the *Local Clustering Coefficient (LCC)* mechanism to detect sensors that do not have any neighbors or groups of sensors that are fully meshed. Moreover [11], improves upon this and introduces two other mechanisms based on *PageRank* [19] and *Strongly Connected Components (SCCs)*. Their proposed mechanisms cannot be easily avoided by defenders as they require either large numbers of colluding sensors or active sharing of valid neighbors when being requested. Lastly, Vasilomanolakis et al. propose the use of computational trust for calculating trust scores for all neighbors of a bot [25]. This allows them to automatically blacklist bots that refuse to cooperate in the sharing of commands.

4 Botnet Monitoring Under Adverse Conditions

The adoption of advanced countermeasures will change the landscape of botnet monitoring. Here, we define the term adverse conditions and discuss approaches for monitoring in the presence of countermeasures. Furthermore, we introduce the idea of leveraging the Membership Management (MM) to obstruct monitoring operations. Moreover, we discuss the limitations of the MM design with regard to the trade-off between monitoring resistance and the resilience of botnets.

4.1 Identifying the Worst-Case Monitoring Scenario

We contend, that existing botnet monitoring mechanisms may no longer be feasible under adverse conditions (see Sect. 3). Therefore, new approaches to monitor botnets are urgently needed. Based on our analysis of the related work, we propose *five* approaches to conduct monitoring in adverse conditions. Namely these are: *short-term monitoring*, *network traffic analysis*, *network scanning*, *taking control of active bots*, and *running botnet malware in controlled environments*.

Depending on the specifics of the implemented anti-monitoring mechanisms, *short-term monitoring* may be possible for monitoring using crawlers and sensors. To avoid preemptive blacklisting of legitimate bots, anti-monitoring mechanisms may require multiple anomalous interactions before a blacklisting occurs [25]. This can allow short-time monitoring, in which the anti-monitoring mechanisms are not triggered. Furthermore, if sufficient resources are available, blacklisted IPs can be replaced to perform continuous monitoring. The major drawback of this approach is the scarcity of IP addresses which leads to higher costs and eventually IPs run out due to blacklisting.

Network traffic analysis based monitoring approaches are not affected by the anti-monitoring mechanisms described in Sect. 3. Traffic based monitoring passively analyzes the network traffic and is therefore outside the scope of advanced countermeasures. Approaches such as [8,17] can detect botnet traffic on top of Internet Service Provider (ISP) level network traces. The benefit of this approach is that it provides a centralized view on all bot infections within the network and their neighbors. Nevertheless, this approach is unlikely to provide a holistic view of the botnet unless all ISPs cooperate and share their information.

Alternatively, another approach is to scan the Internet for botnet activity on specific ports. Such a *network scanning* approach has already been done to obtain bootstrap nodes for crawling the ZeroAccess botnet [15]. This requires the botnet to use a fixed port for its communication which is the case for botnets such as the ZeroAccess family [18]. In fact, tools such as ZMAP are capable of rapidly scanning the entire IPv4 address space [1]. However, many recent botnets implement dynamic ports to avoid being scanned easily.

Another approach to obtain intelligence about a botnet can be to *take control of active bots*. This could theoretically be realized by anti-virus companies or operating system manufacturers. Once the malware is identified, the related network traffic can be analyzed to identify other infected hosts. Furthermore, if detailed knowledge about the malware is available, malicious traffic could be blocked. This would allow the controlling parties to use the infected machines themselves as monitors by analyzing the MM traffic.

In addition, it is also possible to *run and observe botnet malware in a controlled environment*, such as a bare metal machine or a controlled virtual environment. Contrary to taking control of an infected device, a clean machine is deliberately infected with the botnet malware. This allows to set up machines specifically for botnet monitoring, e.g. not storing sensitive data, rate limiting network connections, or installing software to analyze the network traffic. Even with such safeguards, legal and ethical limitations need to be considered with this approach.

Defining exactly how much information can be gathered under adverse conditions is not possible, as combinations of monitoring and sophisticated countermeasures will only lead to a never-ending arms race. However, all of the discussed monitoring approaches can gather at least as much information as a regular bot without being detected. In fact, network-based monitoring approaches on the ISP level will likely observe traffic of multiple infections at once. To avoid the aforementioned arms race, we focus on the worst-case scenario and establish a lower boundary for monitoring under adverse conditions.

Based on the findings of this section, we want to define the term Monitoring Device (MD) *as any monitoring approach, that obtains intelligence based on the view of a bot*. Similarly, we define the term *adverse conditions* as a botnet environment in which any behavior deviating form that of a normal bot can be automatically detected by botmasters. Therefore, we argue that the lower boundary for monitoring operations in adverse conditions is *limited to the knowledge/view that can be obtained by any regular bot itself.*

4.2 Limiting Monitoring Information Through the MM Design

The amount of information a single bot can obtain influences the results of monitoring in adverse conditions. Hence, it is likely that botmasters will design their botnets such that a single bot learns as less as possible about the botnet without jeopardizing the resilience of the botnet itself. This can be achieved by tweaking the MM protocol of the botnet. At its core, the MM protocol must provide three features: maintain an NL, provide a means to update the NL and frequently check the availability of neighbors. To identify how these requirements are met by existing botnets, we identified and compared the related parameters of five existing P2P botnets in Table 1.

The need of maintaining an NL is commonly addressed with two parameters, the NL-size and the Neighborlist Minimum Threshold (NLMT). The NL-size is an integer indicating the maximum size of the NL. The NLMT is another integer indicating the minimum number of bots that should always be maintained. A bot will not remove any more bots once this threshold is reached, and it will start sending *NL*-requests to obtain fresh entries. Oftentimes, botnets do not explicitly state an NLMT and instead have NL-size = NLMT. To update a bot's NL, both push or pull based NL-updates can be used. Push based updates allow a bot to insert itself into another bot's NL and are commonly only used for bots joining a botnet. Pull based updates are usually realized through *NL-request* messages, which allow a bot to ask actively for additional bots. *NL-request* messages are often affected by an Neighborlist Reply Size (NLRS) which limits the number of bots shared upon a single request, and the Neighborlist Reply Preference (NLRP) which defines how the shared bots are selected. Lastly, to check the availability of their neighbors, bots commonly probe all NL-entries during the MMI.

To illustrate how MM can be used to limit monitoring information, we consider the following scenario. The NLMT indicates the minimal number of neighbors with whom a bot communicates regularly. Thus, limiting the NLMT is an effective measure to limit the knowledge that can be obtained by a bot. However, the NLMT is not the only parameter that can limit this type of knowledge. Other parameters such as the MMI, the number of nodes returned upon an NL-request, the churn behavior of the botnet or which neighbors are returned when being requested, can influence the amount of knowledge each bot can obtain about the botnet. In Sect. 6, we examine in detail, how each parameter influences the knowledge obtainable by a single bot, i.e., the lower boundary knowledge for monitoring operations under adverse conditions.

4.3 Botnet Design Constraints

Optimizing a botnet's MM to impede monitoring operations, comes at a cost. The usage of P2P overlays for inter-bot communication was initially intended

Table 1. Analysis of common MM parameters and their values.

	GameOver Zeus [3]	Sality [6]	ZeroAccess [26]	Kelihos F. [20]	Nugache [20]
Pull based updates	Yes	Yes	Yes	Yes	Yes
Push based updates	Always	Join	Join	Join	Join
MMI	30 min	40 min	1 s	10 min	Random
NL-size	50	1000	256	3000	100
NLRS	<= 10	1	16	250 (v3), 500 (v5,v6)	100
NLMT	25	980	Unknown	Unknown	Unknown
NLRP	Custom	Random	Latest	Latest	Latest

to improve the resilience against takedown attempts. However, we expect that the resilience of a botnet's overlay is inversely proportional to the monitoring resistance of a botnet. That is, by limiting the knowledge obtainable by a bot, the robustness of the resulting overlay suffers.

This can be visualized by observing two extreme cases. On the one hand, the most resilient network architecture is a complete mesh in which each node knows all other nodes in the system. Such a network is very resilient as the failure of some nodes does not influence the connectivity of the remaining nodes. However, in a complete mesh, every bot also has complete knowledge about the botnet population. On the other hand, a minimally connected network such as a ring provides minimal knowledge to nodes at the cost of poor resilience to node failures or targeted attacks. Therefore, a botmaster has to consider both resilience and resistance against monitoring operations when designing the MM.

4.4 Connecting the Dots

Within this section, we discussed possible approaches to conduct monitoring in adverse conditions, how MM can be used to obstruct monitoring operations, and the trade-off between monitoring resistance and resilience in MM design.

We argue, that we can use this information to identify a lower boundary for the success of monitoring operations in any P2P botnet. In fact, we have discussed several approaches to monitor P2P botnets, that can at least obtain as much knowledge as any regular bot. While the information of bots can be limited through MM design, this is limited by the trade-off with resilience. Therefore, we can establish a lower bound by determining the boundaries of optimal MM designs. That is, identifying the MM parameters that provide the greatest monitoring resistance while maintaining adequate resilience. In Sect. 6, we identify and discuss, what constitutes such an optimal MM design and to what extent monitoring is possible under such adverse conditions.

5 Modeling and Simulating Botnet Churn

As one of the core contributions of this paper, we propose and verify a novel churn model and generator, focused on the simulation of botnet churn based on real world measurements. Section 5.1 discusses the shortcomings of existing churn generators with regard to simulation of real world botnet churn. Furthermore, Sect. 5.2 introduces our churn generator.

5.1 Simulation of Real World Churn Models

The availability of a bot's neighbors directly influences whether old connections are retained or if newer connections need to be established. Therefore, churn significantly impacts the overall structure of the botnet overlay. This is why we consider churn generators as a crucial feature for a P2P botnet simulator.

A recent survey by Surati et al. [24] examined the existing P2P simulators. We analyzed each of these simulators with regard to their churn generator functionalities. Out of all simulators, *Peerfactsim.kom* [22] and *OverSim* [4] provide the most advanced churn functionalities. *Peerfactsim.kom* implements a churn generator that is based on the exponential distribution, whereas *OverSim* provides the choice between random, life-time and Pareto churn models. However, according to Stutzbach et al. [23] exponential and Pareto distributions do not fit churn characteristics observed in real world P2P networks. Moreover, a random churn model is also not suitable as it only provides rudimentary presentation of churn and does not characterize the network accurately. This leaves only the option of life-time based churn models. Such a churn, which is implemented in *OverSim*, allows the usage of different probability distributions, e.g., the Weibull distribution. According to both [11,23], Weibull distributions fit well with the churn observed in regular P2P networks and P2P botnets.

However, the implementation in *OverSim* has two major drawbacks. First, the life-time and down-time of nodes is drawn from the same probability distribution. We speculate that this is done to allow for an easily adjustable active population. However, this is a critical issue, as it is highly unrealistic that life- and down-time distributions are equal, at least in the case of P2P botnets. Second, the implementation in *OverSim* requires the overall population of the simulated network to be exactly double of the desired active population. This allows to have an equal number of active and inactive nodes. In combination to nodes joining and leaving based on the same distribution the active population is approximated throughout the simulation period. Given these drawbacks of *life-time* churn, all existing churn generators present severe drawbacks with regard to a realistic simulation of churn in P2P botnets.

5.2 The BotChurn (BC) Generator

Based on the aforesaid shortcomings of existing churn simulation models, we develop BC, a novel approach to simulate P2P botnet churn based on real world measurements. To overcome the drawbacks of existing churn generators, BC focuses on addressing the following three features: (*i*) individual distributions for life- and down-times of nodes, (*ii*) support for existing P2P churn measurements, and (*iii*) independently adjustable *active* and *overall* population parameters.

Support for distinct Weibull distributions for life- and down-times: One approach to overcome the issue of having a single distribution for life- and down-times would be to use two different distributions as it is done for the Pareto churn model [28]. However, obtaining accurate measurements of down-times is often not possible as many P2P botnets do not provide unique identifiers [6,18]. Therefore, it is difficult to accurately measure when a node rejoins a system.

As an alternative, BC is based on a life-time and an inter-arrival distribution. Theoretically, any probability distribution function can be used. However, we currently support only the Weibull distribution for life-time and inter-arrival measurements as it is found best suited for churn in P2P systems [11,23]. In contrast to *life-time* churn, BC starts with all nodes being inactive. Based on the times drawn from the inter-arrival distribution, a random inactive node is activated. Upon activation, a *life-time* value is assigned based on the life-time distribution. Once a bot's life-time comes to an end, it becomes inactive. This is a continuous process, where inactive bots will eventually rejoin the system based on the inter-arrival cycle.

Calculation of the average active population: One issue that needs to be addressed by our approach, is that whenever a node needs to be activated, an inactive node must be available to join the network. Therefore, the overall bot population needs to be larger than the average active population of the simulated botnet. This requires that we first calculate the average active number of bots based on the two input distributions.

According to the law of large numbers, with sufficiently long simulation time τ, with $\tau \to \infty$, the average inter-arrival time of nodes joining the system will converge towards the mean of the inter-arrival distribution. Therefore, the arrival-rate R_a will eventually converge towards the mean. However, the number of nodes leaving the system is dependent on the life-time distribution and the number of nodes active in the system. If we consider the average life-time λ and an active number of nodes N_a, on average nodes will go off-line at a rate of $\frac{\lambda}{N_a}$.

We can therefore calculate the average active population by identifying the active population N_a, at which the average departure-rate R_d is equal to the average arrival-rate R_a. This is achieved by solving Eq. 1.

$$R_a = R_d = \frac{\lambda}{N_a} \Rightarrow N_a = \frac{\lambda}{R_a} \tag{1}$$

Independent active- and overall-populations: Lastly, we want to address the need for an independently adjustable overall- and active-population. In BC, the overall-population can be set to any desired value. However, as discussed earlier, it should be bigger than the desired active-population.

Adjusting the active population requires additional effort. In more details, it is necessary to modify at least one of the two distributions, as the active population is directly related to both inter-arrival and life-time distributions. While this means that we modify the values obtained from real world measurements, this is often necessary to experiment with different sizes of botnets.

To adjust the active population, we can modify either the *inter-arrival* or the *life-time* Weibull distribution. As the reported measurements of Karuppayah [11] showed high similarity in the fitting of Weibull life-time distributions for botnets of different sizes, we maintain the input life-time distribution without any modification. Furthermore, it is not very likely that the size of a botnet has a direct influence on the life-time behavior of its individual nodes.

Therefore, we have to adjust the *inter-arrival* distribution to accommodate an adjustable active population. To adjust a Weibull distribution, one can either choose its *shape* β or *scale* α parameter. To change the real world measurements as little as possible, we want to change the parameter that is less similar across all botnets measured in [11]. The shape parameter of the reported *inter-arrival* distributions ranges from 0.61 to 1.04, whereas the scale parameter varies between 0.6801 and 160.2564. As the difference between the scale parameters is bigger across the measured botnets, we choose to modify the scale parameter α, while keeping the shape parameter β unaltered. With this modification, we can choose any desired active population value as an input to Eq. 1 and obtain the required arrival rate R_a.

6 Evaluation

Within this section, we present the evaluation of BotChurn (BC) and the influence of MM on monitoring resistance and resilience of botnets. Furthermore, an analysis on the effectiveness of monitoring in adverse conditions is also provided.

6.1 Datasets and Evaluation Metrics

In our evaluation, we utilize three datasets: (i) real world churn measurements of Sality and ZeroAccess botnets, (ii) real world graphs of the Sality botnet and (iii) a simulated dataset consisting of $1,458$ combinations of different parameters.

The real-world churn measurements, that we obtained from [11], consist of *inter-arrival* and *life-time* distributions. In this paper, we focus on three particular measurements. These are the ZeroAccess 16465 (ZA65) including non-superpeers, i.e., bots behind NAT or firewalls, ZeroAccess 16471 (ZA71) and Sality version three (SalityV3). The details for these datasets are given in Table 2.

The real-world snapshots of the Sality botnet were taken from [9]. The authors, present an analysis on the graph characteristics and resilience of the Sality and ZeroAccess botnets. The metrics used in their analysis are the *number of nodes*, *number of edges*, *degree*, *in-degree*, *out-degree*, *density*, *global clustering coefficient*, *average path length* and the *diameter* of the botnet. We utilize their publicly available snapshot of the Sality botnet to compare it against our simulated botnet topologies. More specifically, we utilize the dataset to compare

Table 2. Churn measurements by [11]; weibull parameters as tuples (shape, scale).

	ZeroAccess 71 (ZA71)	ZeroAccess 65 including non-super peers (ZA65)	Sality v3 (SalityV3)
Inter-Arrival: $R_a(\beta, \alpha)$	(0.95, 3.0769)	(1.04, 3.8023)	(0.66, 5.814)
Life-Time: $\lambda(\beta, \alpha)$	(0.21, 76.9231)	(0.18, 12.21)	(0.28, 1139.3174)
Active Population (N_a)	165	1037	1963

the graph characteristics and resilience reported by Haas et al. [9] against those from the generated topologies.

Our last dataset is generated using our simulation framework[1]. We simulated 1,458 different parameter combinations with 20 repetitions for a duration of 75 days each. Table 3, presents all parameter types and their values. The parameters used in our simulations consist of the churn model, the MM parameters as discussed in Sect. 4, the number of MDs and the active and overall population.

It is important to note, that the maximum NL-size is not independently varied but instead dependent on the Neighborlist Minimum Threshold (NLMT). In an analysis on the influence of each individual parameter, we found that the NL-size itself only has a minor influence on the resilience or monitoring resistance. The reason for this is, that bots only search for additional neighbors if the NLMT is reached. Therefore, we set the NL-size to be twice as large as the NLMT. Furthermore, we adjusted the overall population in relation to the active population. We chose to use a factor of *three*, *four* or *five*, as our simulations of the churn model have shown, that the simulated graphs are most similar to the real world graphs at an overall population about four times larger than the active population.

Table 3. Parameter combinations used for the evaluation.

Parameter	Value
Churn Model	SalityV3, ZA65, ZA71
Membership Management Interval (MMI)	30 m, 1 h, 2 h
Max NL-size	2x NLMT
Neighborlist Minimum Threshold (NLMT)	10, 25, 50
Neighborlist Reply Size (NLRS)	1, 5, 10
Neighborlist Reply Preference (NLRP)	Latest, Random
Number of MDs	1, (10, 50, 200, 500)
Active Population (N_a)	1963, 1037, 165
Overall Population (N_t)	x3, x4, x5 Active Population

[1] https://git.tk.informatik.tu-darmstadt.de/SPIN/BSF.

To evaluate our work, we utilize the network *resilience* and monitoring *resistance* metrics. We measure the *resilience* of a botnet similarly to [9]. Iteratively the bot with the highest in-degree is removed from the botnet, until the ratio of nodes disconnected from the largest *weakly connected component* exceeds a threshold $t \in [0, 1]$. Therefore, the $GraphResilience(t)$ denotes the fraction of bots that need to be removed, to have more than $t\%$ of the remaining bots disconnected from the botnet. Within our evaluation, we consider a threshold of $t = 0.5$, as it was least affected by outliers. The monitoring *resistance* indicates the difficulty of monitoring a botnet, i.e., the fraction of the overall population that could not be enumerated. We define monitoring resistance ρ in Eq. 2, based on the overall-population N_t, and μ the information obtained by an MD.

$$\rho = 1 - \frac{|\mu|}{|N_t|} \tag{2}$$

6.2 Simulation Setup

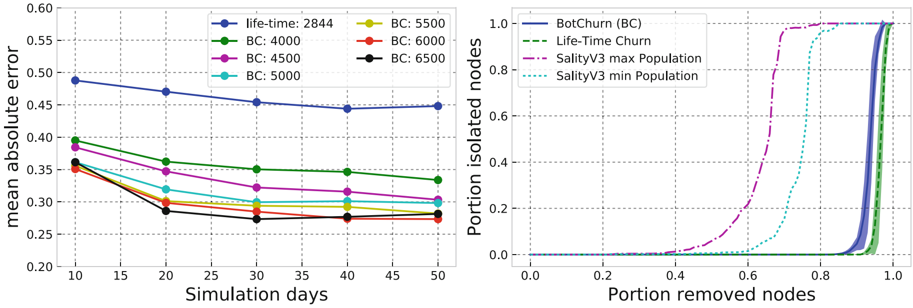
Within this subsection, we introduce our simulation setup. Overall we introduce three separate experiments: (*i*) an evaluation of BC, (*ii*) an analysis of the MM on monitoring resistance and network resilience, and (*iii*) an evaluation on how utilizing multiple MDs increases the intelligence gathered through monitoring.

For the evaluation of BC, we intend to investigate two research topics. First, the warm-up time required to reach the desired active population, and second, whether the generated topologies are more similar to the real-world characteristics reported in [9] than those created with OverSim's *life-time* churn generator.

To compare the two churn generators with the real world dataset, we run 24 simulations of the Sality botnet with each of them. To match the active population of the real world Sality graph provided by Haas et al. [9], we set the target active population to $1,422$. In addition, to compare the difference between the graph characteristics of the real world Sality botnet and the simulated topologies, we use the mean absolute error. The Mean Absolute Error (MAE) allows us to calculate the average difference between the graph characteristics of the simulated and real world dataset. To ensure, that the parameters are in comparable value ranges when calculating the error, we normalized all values through feature scaling. Furthermore, we compare the graphs with regard to their resilience.

To analyze the effects of each MM parameter with regard to monitoring resistance and botnet resilience we use our simulated dataset (see Table 3). Furthermore, to highlight the influence of each parameter, we analyze and discuss each of them individually. Every simulation is run for a period of 75 days, with the MD joining after 40 days. After the entire simulation time, we took a snapshot of the graph and then analyzed its monitoring resistance and graph resilience.

We expect, that a single MD will not yield enough intelligence to conduct successful monitoring in adverse conditions. This raises the question about how we can improve the knowledge obtained by monitoring operations. One approach is to broaden the information obtained via monitoring by increasing the number of MDs. To analyze the effects of aggregating the information of multiple MDs,



(a) MAE at different populations. **(b)** Graph resilience comparison.

Fig. 1. Comparison of *life-time* churn, BC and the real world Sality botnet graph.

we repeated the simulations with the most monitoring resistant and resilient MM parameter combinations, i.e., under the most adverse conditions. To keep the number of MDs within a realistic range, we ran the simulations with 10, 50, 200 and 500 deployed MDs. Note that, 500 is close to the highest number of sensors ever reported (512) to be used to monitor a botnet [2].

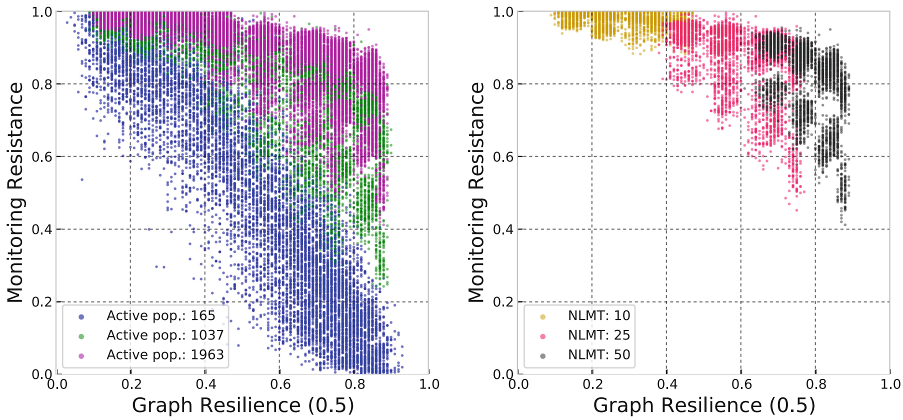
6.3 Results

In this subsection, we present the results of our evaluation.

BotChurn (BC) evaluation. Before the comparison between simulated and real world graphs, we evaluated the warm-up period required by BC to reach the desired active population. The results for all three investigated churn models indicate, that the active population is reached within less than 40 days.

Figure 1a, depicts the mean absolute error between simulated graphs and a real world Sality snapshot obtained from [9]. The results clearly indicate, that the graphs generated with BC are closer to the real world botnet. Furthermore, our churn generator performs best at an overall population between 5, 500 to 6, 500. This is about twice as much as the overall population in *life-time* churn, which does not allow to adapt the overall population. While the error for BC generated botnets may still seem high, we want to point out that the error is dominated by only two out of 13 graph properties. In fact, the average path length and diameter are so similar throughout all graphs, that due to the normalization even slight changes cause large errors. For BC at a population of 6000, the average path length is 1.7045 compared to 1.5149 in Sality and the diameters are 2 and 3 respectively. If we remove these two outliers from the calculation, the error drops from 27% to only 15%.

Figure 1b, compares the average resilience of the simulated graphs against the resilience of the real world graph at its maximum and minimum population. Interestingly, the simulated networks are significantly more resilient than the real world Sality graphs. The reasoning behind this finding is that the connections



(a) Active Population **(b)** NLMT

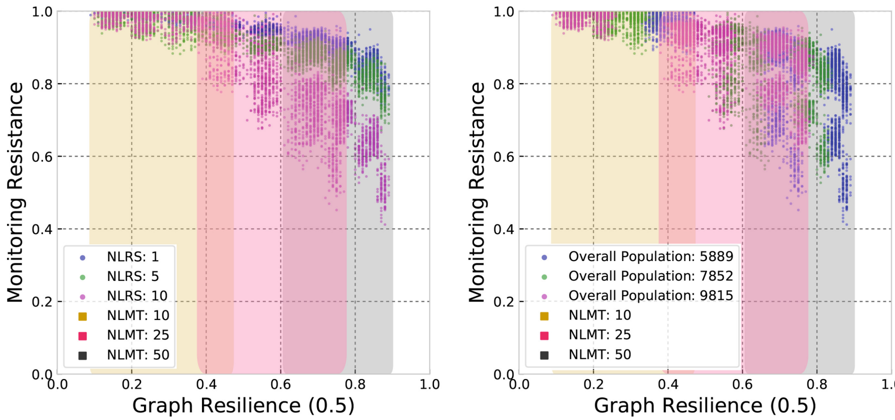
Fig. 2. Influence of individual parameters on monitoring resistance and resilience.

in all graphs are made prominently through a strongly connected core. However, the simulated graphs also have more connections among bots at the edges of the graph, which leads to the higher resilience. We speculate, that this is largely caused by the Goodcount mechanism of Sality and the botnet being active for several years. Even though, the resilience of the simulated graphs are significantly higher than the real world Sality, similar resilience has been observed for the ZeroAccess botnet [9]. In summary, the graphs generated with BC are more similar to the real-world graphs than those create with *life-time* churn.

MM Design Evaluation. We now investigate, the influence each parameter has on monitoring resistance and botnet resilience. As the first parameter, we look at the influence of the *active population*. The results depicted in Fig. 2a indicate, that the active population[2] of the botnet has a significant impact on its monitoring resistance. We argue that there is a two-fold reasoning behind this behavior. First, if more highly stable nodes are available in the botnet, they must share the in-degree of the less stable nodes and therefore, it is less likely for an MD to be within a bot's NL. Second, parameters such as the NL-size do not scale with the active population. Therefore, the information contained in a MD's NL amounts to a significantly larger fraction of the population in small botnets when compared to larger botnets.

Out of all MM parameters, the *Neighborlist Minimum Threshold (NLMT)* has the greatest influence on the resilience of a botnet. Figure 2b, highlights this influence in a scatter plot of all simulation runs with an active population of 1963. As the botnets with such a population size are most resistant to monitoring, we omit other active populations in the subsequent analysis due to clarity/space reasons. While the highest resilience obtained by botnets with an NLMT of 10

[2] The scatter plots depict all parameter variations, with one of them being highlighted.



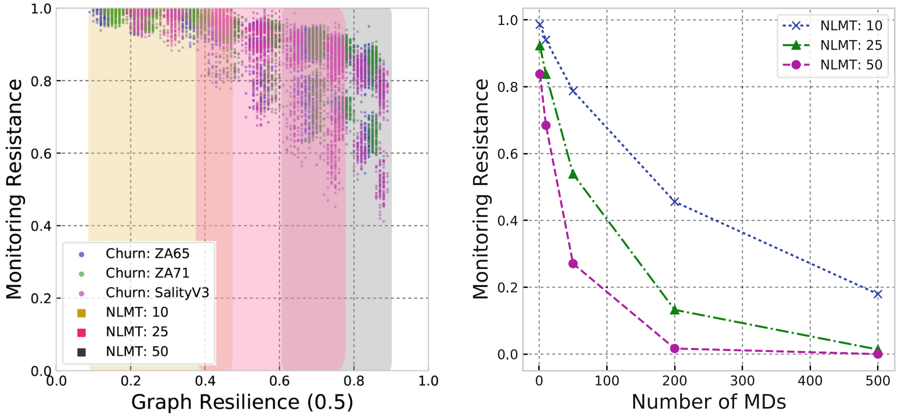
(a) NL Reply Size **(b)** Overall Population

Fig. 3. Influence of individual parameters on monitoring resistance and resilience.

is approximately 40%, botnets with an NLMT of 50 approached a resilience of almost 90%. However, the increase of resilience comes at the cost of decreasing monitoring resistance (see also Sect. 4). As the resilience of the botnet is evaluated based on global knowledge of the botnet, we cannot state the best value for a botnet's NLMT. While a low NLMT hampers the gathering of information required to conduct an attack, a high NLMT is more likely to withstand an attack even if a lot of information is obtained by botnet defenders.

The effects of the *Neighborlist Reply Size (NLRS)* on the monitoring resistance of a botnet increases with higher NLMTs. Figure 3a illustrates, that with increased resilience the difference between an NLRS of 1 and 10 changes significantly. This growth of resilience is caused by the increasing NLMT, which is highlighted by the colored overlays. While the difference between an NLRS of 1, 5, or 10 does not seem to have a significant influence at an NLMT of 10, it is clear that an NLRS of 1 is superior at NLMTs of 5 and 10. We speculate, that the reason for this is, that an NL-reply is likely to contain more entries than the requesting bot needs. As an example, if a bot with 47 out of 50 neighbors receives an NL-reply with 10 entries, that is seven more bots than it required to have a full NL. Therefore, an NLRS of 1 is preferable with regard to monitoring resistance, as no unnecessary information is shared.

Similar to the active population, the *overall population* greatly influences the resilience of the botnet. Figure 3b, depicts the analysis of overall populations of 5889, 7852, and 9815 for an active population of 1963. The figure shows, that the resilience increases with a lower overall population. This pattern is repeated based on different NLMTs which are highlighted by the colored overlays. We argue, that this is caused by the increased likelihood of any node being online. As the overall population is lesser, a node will rejoin the botnet more frequently.



(a) Churn Model **(b)** Multiple MDs

Fig. 4. Influence of parameters on monitoring resistance (and resilience).

The difference among the three observed churn models seems to be most pronounced in the resilience of the botnet. Our analysis results in Fig. 4a, indicate that the botnets differ slightly with regard to resilience and monitoring resistance. The churn models $SalityV3$ followed by $ZA71$ create more resilient botnets, whereas $ZA65$ has the highest monitoring resistance. Nevertheless, the scaling of churn models appears to work well with only small differences between the churn models with regard to resilience and monitoring resistance.

The *NLRP*, minimally influences the monitoring resistance of a botnet. Interestingly, the preferable parameter value changes with growing NLMT. Our results indicate that a random selection is preferable for an NLMT of one, whereas returning the last seen neighbors is better for NLMTs of higher values.

The range of values we analyzed for the *MMI*, did not show any influence on monitoring resistance or resilience. Nevertheless, a lower MMI may reduce the probability of a bot getting disconnected from the botnet. At the same time, the shorter the MMI, the more communication overhead will be incurred by the botnet. We expect that with increased message overhead, it will be easier to detect the botnet. Therefore, any of the values is good with regard to monitoring resistance and resilience, but may cause the botnet to be more susceptible to detection.

In summary, we identified that among the MM parameters, NLMT and NLRS have the greatest effect on monitoring resistance and botnet resilience. Contrary, the MMI and NLRP exhibit only minor effects. We argue, based on our results, that a parameter combination of NLMT $= 10$, NLRS $= 1$, NLRP $=$ *random* and MMI $= 1h$, exhibits the most adverse conditions for monitoring. Furthermore, our analysis of active and overall population indicates that with growing population the monitoring resistance increases significantly. Lastly, the three evaluated churn models showed similar behavior for the observed active populations.

Successful Monitoring in Adverse Conditions. For our last experiment, we analyzed how increasing the number of MDs influences the monitoring resistance of a botnet. Figure 4b, presents the results of deploying multiple MDs for the botnets with the most adverse conditions. In addition to the optimal parameter combination identified in the previous section, we varied the NLMT to cover the more resilient botnets as well. One can observe how an increase in MDs results in a decreased monitoring resistance of the botnet. However, the increase in knowledge does not increase linearly with the increase in MDs. This is the case due to two reasons: (*i*) knowledge gained by adding additional MDs may overlap with existing knowledge and therefore not add to the overall knowledge, and (*ii*) the potential increase in knowledge is limited by the total population of the botnet. Due to these factors, we can only enumerate the entire botnet for an NLMT of 50. Moreover, this is only possible with 500 deployed MDs. However, a fraction of the nodes remains unknown in the NLMT = 25 scenario, and almost 20% of the overall population remain undiscovered using 500 MDs in a botnet with an NLMT of 10.

We argue, that this clearly indicates that *short term monitoring*, *deploying bots in controlled environments*, or *controlling active bots* requires a large pool of diverse IP addresses to effectively monitor botnets in adverse conditions. As suggested by [2,11], this could be realized through collaboration of multiple parties. Furthermore, network based monitoring is a promising approach, as large amounts of bots can be observed at once without requiring a pool of IP addresses. However, a drawback of this approach is that it requires the collaboration of multiple ISPs which may prove to be difficult, as they are usually reluctant about sharing private data.

7 Conclusion and Future Work

In this paper, we argue that once botnets adapt more advanced countermeasures, monitoring as we know it today will no longer be feasible. We defined the term *adverse conditions* as a botnet environment in which any deviation from the behavior of a regular bot can easily be detected by the botmaster. Furthermore, we investigated the idea of designing a botnet's MM to further limit the knowledge obtainable by monitoring.

To thoroughly analyze botnets, we discussed different churn models and propose BotChurn (BC), a novel churn generator for botnets. In our experiments, we identified a lower boundary for intelligence gathering in adverse conditions. In particular, our results indicate that the MM design significantly affects both the monitoring resistance and resilience of the botnet. Finally, we conducted additional simulations in which we aggregated the intelligence obtained by multiple MDs, to observe how this increases the intelligence obtained via monitoring. The results indicate, that such a distributed approach provides a way to improve the gathered intelligence. However, this requires a significant amount of available IP addresses. To overcome this, we suggest that future research considers the concept of collaborative monitoring. If the defenders combine their resources, this would increase the quality of the gathered intelligence and also reduce the cumulative cost to conduct monitoring.

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