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SPECIAL ISSUE PAPER

Modeling tools for detecting DoS attacks in WSNs

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ABSTRACT

Detecting denial-of-service (DoS) attacks and reducing the energy consumption are two important and frequent requirements in wireless sensor networks (WSNs). In this paper, we propose an energy-preserving solution to detect compromised nodes in hierarchically clustered WSNs. DoS detection is based on using dedicated inspector nodes (cNodes) whose role is to analyze the traffic inside a cluster and to send warnings to the cluster head whenever an abnormal behavior (i.e., high packets throughput) is detected. With previously introduced DoS detection schema, cNodes are statically displaced in strategic positions within the network topology. This guarantees good detection coverage but leads to quickly draining cNodes battery. In this paper, we propose a dynamic cNodes displacement schema according to which cNodes are periodically elected among ordinary nodes of each atomic cluster. Such a solution results in a better energy balance while maintaining good detection coverage. We analyze the tradeoffs between *static* and *dynamic* solutions by means of two complementary approaches: through simulation with the NS-2 simulation platform and by means of statistical model checking with the Hybrid Automata Stochastic Logic.

KEYWORDS

DoS attacks; detection method; statistical model checking; modeling tools

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1. INTRODUCTION

Detecting phenomena such as forest fires or seismic activities implies to keep watch over wide areas. Wireless sensor networks (WSNs) are often used to achieve this watch. The sensors that make up those WSNs are devices able to perform measurements on their surrounding environment and to send the collected data to a base station (BS). Because of their small size, the sensors have very limited resources: memory, computing capability, and available energy must be spent with care [1,15,32].

Other uses of WSNs include activities such as preventing chemical, biological, or nuclear threats in an area, or collecting data on a military field [2,3]. In such sensitive domains, the deployment of a WSN brings out strong requirements in terms of security. Various works deal with ways of preventing unauthorized access to data or with the necessary precautions to guarantee data authenticity and integrity inside the network [4,28,30,14]. But confidentiality and authentication are of poor use if the network is not even able to deliver its data correctly.

1.1. Denial of service in WSNs

Denial-of-service (DoS) attacks indeed aim at reducing or even annihilating the network ability to achieve its ordinary tasks, or try to prevent a legitimate agent from using a service [5,31,29]. Because of the limited resources of their nodes, WSNs tend to be rather vulnerable to DoS attacks. For instance, a compromised sensor node can be used in order to send corrupted data at a high rate, either to twist the results or to drain the node's energy faster.

The problem we deal with in this paper is the development and analysis of detection mechanisms that are efficient both in terms of detection (i.e., they guarantee a high rate of detection of flooding nodes) and in terms of energy (i.e., they guarantee a balanced energy consumption throughout the network).

1.2. Clustered WSNs

One way to save some battery power during communications may reside in the choice of the network architecture and of the protocol used to route the data from a sensor to the BS [6]. In a hierarchical WSN, the network is

divided into several clusters. The partitioning is carried out according to a clustering algorithm such as Low-energy Adaptive Clustering Hierarchy (LEACH) [7,8], Hybrid, Energy-Efficient Distributed clustering (HEED) [9], or one based on ultra-metric properties [10]. In each cluster, a single common node is elected to be a cluster head (CH), responsible for directly collecting data from the other nodes in the cluster. Once enough data has been gathered, the CHs proceed to data aggregation [11]. Then, they forward their results to the BS. CHs are the only nodes to communicate with the BS, either directly, through a long-range radio transmission or by multi-hopping through other CHs. To preserve the nodes' energy as long as possible, network reclustering is repeated periodically, with different nodes being elected as CHs. Note that clustering is not limited to a "single-level" partition. We can also subdivide a cluster into several "sub-clusters." The CHs from those "sub-clusters" would then send their aggregated data to the CHs of their parent clusters.

1.3. DoS detection: from static to dynamic guarding policies

In a hierarchically organized WSN, a *control node* (cNode in the remainder) is a node that is chosen to analyze the traffic directed to the CH of the cluster it belongs and to potentially detect any abnormal behavior. Therefore, cNodes provide us with an efficient way to detect DoS attacks occurring in the network.

Note that cNodes are only meant to detect DoS attacks; thus, they do not perform any sensing nor send any data (apart from attack detection alarms). cNodes-based detection was first presented in [12], but the authors do not mention any periodical (cNodes) re-election scheme.

One can suppose that the renewal of the election occurs each time the clustering algorithm is repeated. In [13], we proposed a dynamic approach: cNodes are re-elected periodically (any node in a cluster may be chosen, except the CH) with the election period selected to be shorter than that between two network clusterings. Intuitively, such dynamic approach (in comparison to that of [12]) leads to a more uniform energy consumption while preserving good detection ability.

1.4. Our contribution

In this paper, we address the problem of validating the aforementioned conjecture by means of modeling techniques. More specifically, our contribution regards the following aspects:

(1) We present a characterization of Markov chains models for representing DoS detection mechanisms and detail relevant steady-state measures analytically (i.e., we give the expression for the probability of detection of attacks in the Markov chain model).
(2) We present a number of numerical results obtained by simulation of DoS detection on WSN models by means of the network simulator NS-2 [26]. In particular, we simulate models of grid topology WSN including DoS (*static* and *dynamic*) detection policies.
(3) We present formal models of the DoS detection mechanisms expressed in terms of generalized stochastic Petri nets (GSPN). In combination to GSPN models, we also present a number of performance and dependability properties formally expressed in terms of the Hybrid Automata Stochastic Logic (HASL) [25].

The structure of the paper is as follows. In Section 2, we give an overview of DoS attack detection for cluster-based WSNs. In Section 3, we detail the networking solution that we want to model including LEACH clustering algorithm, which we refer to. In Section 4, we describe the structure of Markov chain models for modeling an attacked network. In Section 5, we present simulation experiments obtained with the NS-2 platform. In Section 6, we present the application of statistical model checking performance analysis to Petri Nets models of attacked WSNs. Finally, we give some final remarks in Section 7.

2. RELATED WORKS

To deal with DoS attacks in WSNs, many research studies have been conducted.

In [12], the authors propose a system detection based on static election of a set of special nodes called "guarding nodes," which analyze the network traffic. When detecting abnormal traffic from a given node, "guarding nodes" identify it as a compromised node and they inform the CH of it. In this study, the authors show the benefit of their method by presenting numerical analysis of detection rate, but they do not consider the energy of the elected node, which dies very quickly.

Back in 2001, most works focused on making WSNs feasible and useful. But some people already involved themselves into security. For instance, Perrig *et al.* proposed Security Protocols for Sensor Networks in [19] to provide networks with two symmetric key-based security building blocks. The first block, called Secure Network Encryption Protocol, provides data confidentiality, two-party data authentication, and data freshness. The second block, called μTESLA ("micro" version of the Timed, Efficient, Streaming, Loss-tolerant Authentication Protocol), assumes authenticated broadcast using one-way key chains constructed with secure hash functions. No mechanism was put forward to detect DoS attacks.

A sensor network may be recursively and periodically reclustered with an algorithm such as LEACH, as in our proposal. The resulting hierarchically clustered network often presents a good ability for distributing the energy consumption among the sensor nodes. But security concerns (other than DoS) also apply to those networks. In [20], Oliveira *et al.* propose to add security mechanisms via a revised version of LEACH protocol. SecLEACH uses random key

pre-distribution as well as μTESLA (authenticated broadcast) to protect communications. But the authors do not mention any mechanism to fight DoS attacks.

Elements from game theory have been used in several studies to detect DoS attacks in WSNs. In [16], Mohi *et al*. propose another way to secure the LEACH protocol against selfish behaviors. With S-LEACH, the BS uses a global intrusion detection system (IDS), whereas LEACH CHs implement local IDSs. The interactions between nodes are modeled as a Bayesian game, that is, a game in which at least one player (here, the BS) has incomplete information about the other player(s) (in this case, whether the sensors have been compromised or not). Each node has a "reputation" score. Selfish nodes can cooperate (to avoid detection) or drop packets. The authors show that this game has two Bayesian Nash equilibriums, which provide a way to detect selfish nodes or to force them to cooperate to avoid detection.

The best way to detect for sure a DoS attack in a WSN is simply to run a detection mechanism on each single sensor. Of course, this solution is not feasible in a network with constraints. Instead of fitting out each sensor with such mechanism, Islam *et al*. proposed in [21] to resort to heuristics in order to set a few nodes equipped with detection systems at critical spots in the network topology. This optimized placement enables distributed detection of DoS attacks as well as reducing costs and processing overheads, because the number of required detectors is minimized. But those few selected nodes are likely to run out of battery power much faster than normal nodes.

Sensors authentication and DoS detection in clustered networks may be assumed by a single architecture. In [23], Hsieh *et al*. present SecCBSN, an adaptive security design intended to Secure Cluster-Based Communication in Sensor Networks. Each node is equipped with a system that includes three modules. One is involved in the CH election and responsible for remembering the decision, which was made. Another module provides ciphered communication and secure authentication protocols between sensors. It uses the TESLA certificate to enable deployed sensors to authenticate new incoming nodes. It allows the creation of secure channels as well as broadcast authentication between neighboring sensors. The last security module is responsible for the detection of compromised nodes. When a node is suspected to harm the network, alarm protocols are used to warn the BS. The use of trust value evaluation then enables the setting and the propagation of black and white lists of sensors.

Some works examine the possibility to detect the compromising of nodes as soon as an opponent physically withdraws them from the network. In the method that Ho developed in [17], each node keeps watching on the presence of its neighbors. The Sequential Probability Radio Test is used to determinate a dynamic time threshold. When a node appears to be missing for a period longer than this threshold, it is considered to be dead or captured by an attacker. If this node is later redeployed in the network, it will immediately be considered as compromised without having a chance to be harmful. Nothing is done, however, if an attacker manages to compromise the node without extracting the sensor from its environment.

In [18], Misra *et al*. proposed a revised version of the Optimized Link State Routing protocol. This routing protocol called Distributed Denial of Service (DLSR) aims at detecting distributed DoS attacks and at dropping malicious requests before they can saturate a server's capacity to answer. To that end, the authors introduce two alert thresholds regarding this server's service capacity. They also introduce the use of learning automata, automatic systems whose choice of next action depends on the result of its previous action. There is no indication in their work about the overhead or the energy load resulting from the use of the DLSR protocol.

Son *et al*. proposed in [22] a novel broadcast authentication mechanism to cope with DoS attacks in sensor networks. This scheme uses an asymmetric distribution of keys between sensor nodes and the BS, and uses the Bloom filter as an authenticator, which efficiently compresses multiple authentication information. In this model, the BS or sink shares symmetric keys with each sensor node and proves its knowledge of the information through multiple Message Authentication Code (MAC) values in its flooding messages. When the sink floods the network with control messages, it constructs a Bloom filter as an authenticator for the message. When a sensor node receives a flooded control message, it generates their Bloom filter with its keys and, in the same way, the sink verifies message authentication.

Li and *Batten* exposed in [2] their method to detect and to recover from path-based DoS (PDoS) attacks in WSNs. They consider WSNs whose aim is to collect data and to store it into small databases. PDoS attacks may prevent legitimate communication, lead the sensors to battery exhaustion, and corrupt the gathered data. So the authors introduce the use of mobile agents (MAs), which use hash function values, node IDs, and traffic table to analyze the traffic and identify compromised sensors. Thus, the MAs are able to detect PDoS attacks with ease and efficiency, and to reply to the attack by proceeding to a recovery process. There are three distinct recovery processes available, depending on the percentage of compromised nodes in the network. Note that the authors use the assumption that MAs cannot be compromised.

3. DETECTION OF DoS ATTACKS

3.1. Wireless sensor networks

We focus on the problem of detecting DoS attacks in a WSN. We recall that a WSN consists of a finite set of sensors plus a fixed BS. Traffic in a WSN (mainly) flows from sensor nodes towards the BS. Furthermore, because WSN nodes have inherently little energy, memory, and computing capabilities, energy efficiency is paramount when it comes with mechanisms/protocols for WSN management.

Also, communications between sensors and the BS rely on wireless protocols. In the following, we assume that the nodes' mobility is limited or null.

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Our goal is to set an efficient method to detect compromised nodes that may try to corrupt data, or to saturate the network's capacity, by sending more data than it should. In this case, efficiency can be measured in two respects:

- the detection rate of the compromised node(s);
- the network's lifetime, as we want to spend as little energy as possible.

In order to achieve these goals, we focus on the following techniques: hierarchical network clustering and dynamical election of control nodes responsible for monitoring the traffic.

3.2. Hierarchical clustering

The class of WSNs we consider is that of hierarchically cluster-based networks. The set of sensors has been partitioned into several subsets called "clusters." Those clusters are themselves split into "sub-clusters." For better clarity, we will call *1-clusters* the sets resulting from the first clustering of the global set and *k-clusters* the subset issued from the splitting of any *(k − 1)-cluster*. The successive clusterings are carried out with the use of any existing clustering algorithm, such as LEACH [7,8], HEEDS [9], algorithms based on ultra-metric properties [11], and so on. Each cluster contains a single CH, designated among the normal nodes. The CH is responsible for collecting data from the other nodes of the subset. To follow up our naming conventions, we will call *k-CHs* the CHs belonging to the *k*-clusters. The *k*-CHs send the data they gathered to their $(k-1)$-CH, "0-CH" being the BS. In that way, the *k*-CHs are the only nodes to emit send packets towards the $(k-1)$-CHs. Normal nodes' transmissions do not have to reach the BS directly, which would often consume much more energy than communicating with a neighbor node.

3.2.1. LEACH functioning

Low-energy Adaptive Clustering Hierarchy is probably one of the easiest algorithm to apply to recluster the network. It is a dynamical clustering and routing algorithm. We use it for our simulations using NS-2. It splits a set of nodes into several subsets, each containing a CH. This CH is the only node to assume the cost-expensive transmissions to the BS.

Here is the LEACH detailed processing. Let P be the average percentage of clusters we want to obtain from our network at an instant t. LEACH is composed of cycles made of $1/P$ rounds. Each round r is organized as follows:

(1) Each node i computes the threshold $T(i)$:

$$T(i) = \begin{cases} \dfrac{P}{1 - P\cdot(r \mod \frac{1}{P})} & \text{if } i \text{ has not been CH yet} \\ 0 & \text{if } i \text{ has already been CH} \end{cases}$$

Each node chooses a pseudo-random number $0 \le x_i \le 1$. If $x_i \le T(i)$, then i designates itself as a CH for the current round. $T(i)$ is computed in such a way that every node becomes CH once in every cycle of $1/P$ rounds: we have $T(i) = 1$ when $r = (1/P) - 1$.

(2) The self-designed CH inform the other nodes by broadcasting a message with the same transmitting power, using carrier sense multiple access (CSMA) Media Access Control (MAC).
(3) The other nodes choose to join the cluster associated to the CH whose signal they receive with most power. They message back the CH to inform it (with the CSMA MAC protocol again).
(4) CHs compile a "transmission order" (time division multiple access) for the nodes that joined their clusters. They inform each node at what time it is expected to send data to its CH.
(5) CHs keep listening for the results. Normal sensors acquire measures from their environment and send their data. When it is not their turn to send, they stay in sleep mode to save energy. Collisions between the transmissions of the nodes from different clusters are limited thanks to the use of code division multiple access protocol.
(6) CHs aggregate and possibly compress the gathered data, and send it to the BS in a single transmission. This transmission may be direct, or multi-hopped if relayed by other CHs.
(7) Steps 5 and 6 are repeated until the round ends.

It is possible to extend LEACH by adding the remaining energy of the nodes as a supplementary parameter for the computation of the $T(i)$ threshold [24].

Note that each node decides whether to self-designate itself as a CH or not. Its decision does not take into account the behavior of surrounding nodes. For this reason, we can possibly have, for a given round, a number of CHs very different from the selected percentage P. Also, all the elected CHs may be located in the same region of the network, leaving "uncovered" areas. In that case, one can only hope that the spatial repartition will be better during the next round.

3.2.2. *k*-LEACH

Once the LEACH algorithm has been applied to determine a first set of clusters, nothing prevents us to apply it again on each cluster. This is how we obtained our *k*-clusters: we applied k times the LEACH algorithm recursively. We call those recursive iterations the *k-LEACH* algorithm. In practice, we had k equal to 2, for the following reasons:

- to save more energy than what we would do with 1-LEACH;
- to have a finer clustering of the network, in order to elect control nodes in each of the 2-clusters, to maximized the cover area and the probability to detect compromised nodes.

3.2.3. Other algorithms

Other possible clustering algorithms include HEED [9], which is designed to save more energy than standard

LEACH and could lead to a better spatial repartition of the CHs inside the network. But in our network, all the sensors have the same initial available energy, and every one of them is able to directly reach the BS if need be. Under those assumptions, LEACH may not consume more energy than HEED protocol and remains easier to use.

3.3. Attacks detection through cNodes

Along with normal nodes and CHs, a third type of node is present in the lower *k*-clusters of the hierarchy (Figure 1).

The *cNodes*—for *control nodes*—were introduced in [12] to analyze the network traffic and to detect any abnormal behavior from other nodes in the cluster. We refer the reader to [12] for a detailed description of the cNodes-based detection mechanism. In brief, cNodes analyze the input traffic for the 2-CH of their 2-cluster and watch out for abnormal traffic flows. Detection takes place whenever a cNode observes that at least one among the sensor nodes under its controlled perimeter sends data at a rate that is not within "regular behavior" thresholds. In that case, the cNode sends a warning message to the CH. Once the CH has received warnings from a sufficiently large number of distinct cNodes (note that in order to prevent a compromised cNode to declare legitimate nodes as compromised, the detection protocol requires that the CH receives warnings by a minimum number of distinct cNodes before actually recognizing the signaling as an actual anomaly), it starts ignoring the packets coming from the detected compromised sensor. cNodes may also monitor output traffic of the CHs and warn the BS if they come to detect a compromised CH.

cNodes are periodically elected among normal sensors. The guarding functionality of cNodes may lead to energy consumption higher than that of "normal" (i.e., sensing) nodes. In order to maximize the repartition of the energy load, we propose a scheme by which a new set of cNodes is periodically established with an election period shorter than the length of a LEACH round (i.e., the period between two consecutive CH elections). We propose three possible methods for the election process: self-election as for the CHs, election processed by the CHs, and election processed by the BS.

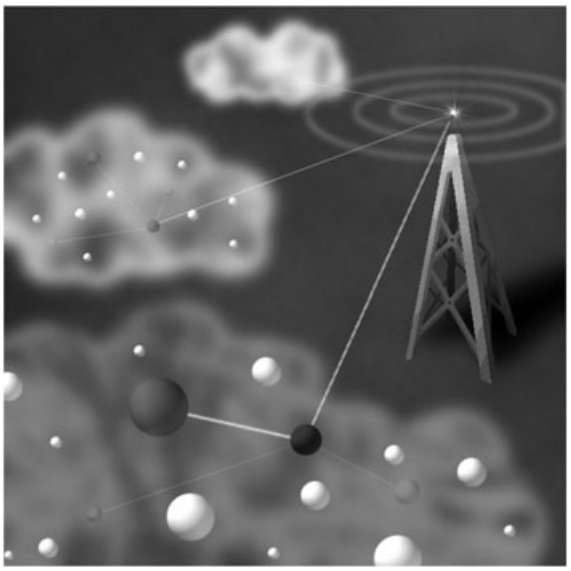

Figure 1. Cluster-based sensor network with cNodes.

3.3.1. Distributed self-election

The first possibility to elect the cNodes is to reuse the distributed self-designation algorithm defined for the election of the CHs. With this method, each non-CH node chooses a pseudo-random number comprised between 0 and 1. If this number is lower than the average percentage of cNodes in the network that was fixed by the user, then the node designates itself as a cNode. Otherwise, it remains a normal sensor.

This method has two drawbacks. Firstly, each node has to compute a pseudo-random number, which may not be necessary with other methods. Secondly, each node chooses to designate (or not) itself, without taking into account at any moment the behavior of its neighbors. As a result, the election proceeds with no consideration for the clustering that has been realized in the network. Indeed, it is unlikely that the set of elected cNodes will be uniformly distributed among the 2-clusters that were formed, and it is even possible to end up with some 2-clusters containing no cNodes (thus being completely unprotected against attacks).

A possible workaround for this second drawback could be a two-step election: in the first round, nodes self-designate (or not) themselves. Then, they signal their state to the 2-CHs they are associated to. In the second round, the 2-CHs may decide to designate some additional cNodes if the current number of elected nodes in the cluster is below a minimal percentage.

3.3.2. Cluster head-centralized election

The second possibility is to have the cNodes elected by the 2-CHs. In this way, each 2-CH elects the required number of cNodes (i.e., corresponding to user specifications). For example, if the 2-cluster contains 100 nodes and the desired percentage of cNodes in the network is 10%, the 2-CH will compute 10 pseudo-random numbers and associate them with node IDs corresponding with sensors of its 2-cluster. This solution is computationally less demanding as only the 2-CHs have to run a pseudo-random number generation algorithm. However it has yet another drawback: if a CH gets compromised, it will not be able to elect any cNode in its cluster thus leaving the cluster open to attacks. As, with the LEACH protocol, every sensor node becomes, sooner or later, a CH, the problem may occur for any compromised node hence propagating, potentially, throughout the network. Note that nothing prevents a compromised sensor from declaring

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itself as a CH node to the others at any round of the LEACH algorithm.

This method is the one that we have implement in our NS-2 simulation whose simulation outcomes will be discussed in Section 5.

3.3.3. Base station-centralized election

The third method consists in a centralized approach where the BS performs cNodes election. With this method, CHs send the list of nodes that compose their clusters to the BS, and the BS returns the list of elected cNodes. Observe that, opposite to sensor nodes, the BS has no limitation in memory, computing capacity, nor energy. Thus, the clear advantage of BS-centralized election is that all costly operations (i.e., pseudo-random numbers calculation) can be re-iterated in a (virtually) unconstrained environment (i.e., the BS). This technique is explained in detail in [13].

From a robustness point of view, the method is not completely safe either. In fact, if a compromised node was to declare itself as a CH, its escape method to avoid detection would consist in declaring its cluster as empty (i.e., by sending an empty list instead of the actual sensors in its cluster to the BS). In this case, the BS would not elect any cNode in its cluster; hence, the compromised CH would not be detected. To avoid such situation, the BS should react differently in case it receives an indication of empty cluster from some nodes. Specifically, in this case, the BS would have to consider that nodes not detected as or by CHs might not simply be dead, thus still consider them as eligible cNodes. The main drawback of this method is that the distributed nature of election (together with its advantages) is completely lost.

4. MODELING USING MARKOV CHAINS

Continuous Time Markov Chains (CTMC) are a class of discrete-state stochastic process suitable to model discrete-event systems that enjoy the so-called *memoryless* property (Markov property), that is, systems such that the future evolution depends exclusively on the current state (and not on the *history* that lead into it). It is well known that in order to fulfill the Markov property, delay of events must be exponentially distributed.

In this section, we describe how to structure CTMC models for modeling a WSN subject to DoS attacks and equipped with DoS detection functionalities. To illustrate the CTMC modeling approach, we focus on a specific (sub)class of WSN corresponding to the following points:

- The network consists of a single cluster containing one CH, N sensing nodes, and K cNodes.
- (Exactly) one amongst the N sensing nodes is a compromised node.
- Sensing node i ($1 \le i \le N$) generates traffic according to a Poisson process with rate λ_i.
- The compromised node c generates traffic according to a Poisson process with rate $\lambda_c \gg \lambda_1$.
- Each cNodes periodically performs a detection check with period distributed exponentially with rate μ. On detection of abnormal traffic a cNode reports the anomaly to the CH.
- The network topology corresponds to a connected graph: each node can reach any other node in the cluster.

The dynamics of WSN systems agreeing with the aforementioned characterization can straightforwardly be modeled in terms of a $K \cdot (N+1)$-dimensional CTMC.

States of such a CTMC consist of K-tuples $x = (x_1, x_2, \ldots, x_K)$ of macro-states $x_k = (x_{k_1}, x_{k_2}, \ldots, x_{k_N}, x_{k_d})$ encoding the number of overheard packets by cNode k. More precisely, component x_{k_j} ($1 \le j \le N$) of macro-state x_k is a counter storing the total number of packets sent by node j and overheard by cNode k, whereas component x_{k_d} is a boolean-valued variable, which is set to 1 on detection, by cNode k, of abnormal traffic. We also consider a *threshold function* $f: N^N \to \{0, 1\}$, which is used (by cNodes) to decide whether traffic rate have exceeded the "normal" threshold.

The arguments of f are an (N)-tuples $(n_1, \ldots, n_N)$, where $n_i \in N$ is the number of overheard packets originating from node i.

We illustrate the transition equations for such a CTMC. For simplicity, we illustrate only equations regarding transitions for a generic macro-state x_k: the equations for transitions of a generic (global) state $x = (x_1, x_2, \ldots, x_K)$ can be straightforwardly obtained by combination of those for the macro-states. In the following, x_{k_c} denotes the counter of received packets from the compromised node.

$$
\begin{aligned}
& x_k \to \text{Normal transmission} \\
& \to (x_{k_1}, \ldots, x_{k_i} + 1, \ldots, x_{k_c}, \ldots, x_{k_N}, 0) \text{with rate } \lambda_i \neq \lambda_c \\
& \to \text{Transmission by compromised node} \\
& \to (x_{k_1}, \ldots, x_{k_i}, \ldots, x_{k_c} + 1, \ldots, x_{k_N}, 0) \text{with rate } \lambda_c \\
& \to \text{Check and detection of abnormal traffic} \\
& \to (0, \ldots, 0, \ldots, 0, \ldots, 0, 1) \\
& \quad \text{with rate } \mu \times 1_{f(x_k) \ge threshold} \\
& \to \text{Check and no-detection of abnormal traffic} \\
& \to (0, \ldots, 0, \ldots, 0, \ldots, 0, 0) \\
& \quad \text{with rate } \mu \times 1_{f(x_k) < threshold}
\end{aligned}
$$

We assume that in the initial state, all counters x_{k_i} as well as the boolean flag x_{k_d} are set to zero. The aforementioned equations can be described as follows. When cNode k is in state x_k, a "normal transmission" from node i ($1 \le i \le N$, $i \neq c$) takes place at rate λ_i, leading to a state such that the corresponding counter x_{k_i} is incremented by one, leaving all remaining counters unchanged. Similarly, a "transmission by the compromised node" c happens with rate λ_c, leading to a state such that the corresponding counter x_{k_c} is incremented by one. Finally, checking for abnormal traffic conditions happens at rate μ, and

whenever the controlling function f detects that in (macro) state x_k the number of overheard packets from any node is above the considered threshold ($f(x_k) \geq threshold$), the detection flag x_{k_d} is raised (i.e., alarm is sent to the CH), and counters x_{k_j} are all reset (so that at the next check, they are updated with "fresh" traffic data). On the other hand, if traffic has not been abnormal over the last Exp(μ) duration ($f(x_k) < threshold$), counters x_{k_j} are reset while the detection flag is left equal to zero.

The detection probability for cNode k (DP_k) can be computed in terms of the steady-state distribution of the above described CTMC in the following manner:

$$DP_k = \sum_{x_{k_1},\ldots,x_{k_N}}^{\infty} \pi(x_{k_1},\ldots,x_{k_N},x_{k_d}=1)$$

where $\pi(x_{k_1},x_{k_2},\ldots,x_{k_N},x_{k_d})$ denotes the steady-state probability at (macro)state $x_k = (x_{k_1},x_{k_2},\ldots,x_{k_N},x_{k_d})$ of the CTMC.

4.1. Discussion

The above described CTMC modeling approach relies on the assumption that the period with which detection checking is performed is an exponentially distributed random variable. Indeed, such an assumption may introduce a rather significant approximation as in reality detection checking happens at interval of fixed length, or even "continuously." Therefore, stochastic modeling of DoS attacks detection requires to exit the Markovian sphere and to consider non-Markovian stochastic processes (more specifically, periodic detection checking can more accurately be modeled by means of deterministic distributions). We discuss non-Markovian modeling of DoS detection mechanisms in Section 6.

5. NUMERICAL RESULTS

A possible alternative to stochastic modeling is to develop executable implementations of the WSNs of interest by means of existing simulative framework, such as the NS-2 Network Simulator [26]. In this section, we present a selection of numerical results obtained by simulation of NS-2 models of WSN systems equipped with DoS detection mechanisms. The experiments we present are referred to one cluster consisting of a (10×10) regular grid topology with the following characteristics (Figure 2):

- Grid is a square of size a.
- CH is placed at the center of the grid (i.e., red node in Figure 2).
- The grid contains 100 (sensing) nodes displaced regularly.
- Each node can communicate directly with the CH (i.e., the transmission power is such that all nodes—e.g., the nodes in green in Figure 2—can reach a circle of radius $a\sqrt{2}/2$. In this way all nodes, included corner's, can reach the CH). No power adjustment is done by the nodes for transmission.

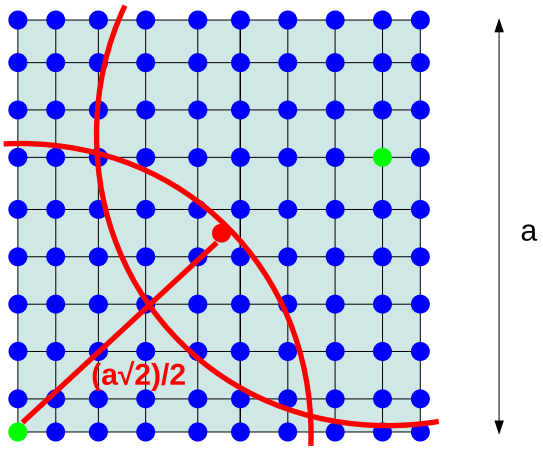

Figure 2. A 10×10 regular-grid cluster of size a.

In such network, cNodes (represented in green in Figure 2) are elected periodically either using the static approach or using the dynamic election mechanism described in previous sections. We have designed our experiments focusing on two performance measures: the rate of detection of attacks and the overall energy consumption. Table I reports about the (range of) parameters considered in our simulation experiments.

5.1. Detection rate

In order to evaluate the considered performance measure that is attack detection rate, we have considered the parameters given in Table I. We have assumed that the traffic generation follows a Poisson distribution with rate λ, which varies as the average transmission of an attacking node exceeds the average transmission of a normal node. In the experiments, we have considered a cluster with 100 nodes.

Figure 3 represents the detection rate for different numbers of cNode groups and for groups of different sizes. The same node is considered compromised in all the graphs. Notice that for 10 cNodes, group 2 did not detect any attack. With 15 cNodes, in average, three nodes detect

Table I. Simulation parameters.

Simulation time	100–3600 s
Rate	10–800 kbits/s
Packet size	500–800 bytes
Nodes number	100 (+ cluster head)
cNodes number	0–30
Compromised nodes number	1–10
Nodes queue size	50

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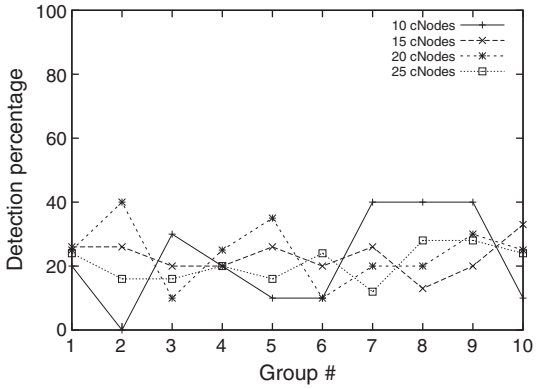

Figure 3. Detection versus group.

an attack in each group. We also note that when we increased the number of cNodes (20 and 25), the behavior remains similar, which suggests that we do not need to use more nodes than 15 nodes in each group.

Above $\lambda = 4$ packets/s, the dynamic method detects more attacks than the static one.

To enhance this difference, we give other results in Figure 4 below for an average of 10 compromised nodes.

In Figure 4, we notice that as the average transmission of attacking nodes increases, our dynamic solution detects more attacks than the static solution.

5.2. Consumed energy

All the simulations that were run to produce the results presented in this section used the parameters given in Table II.

Figure 5 shows the average energy consumption for all nodes (except for the CH and the flooding compromised node, which consume much more than usual nodes and act in the same way for both methods) at the end of the simulation, for various percentages of elected cNodes. The number of cNodes goes from 0 (no detection) to 30% (nearly one-third of the nodes).

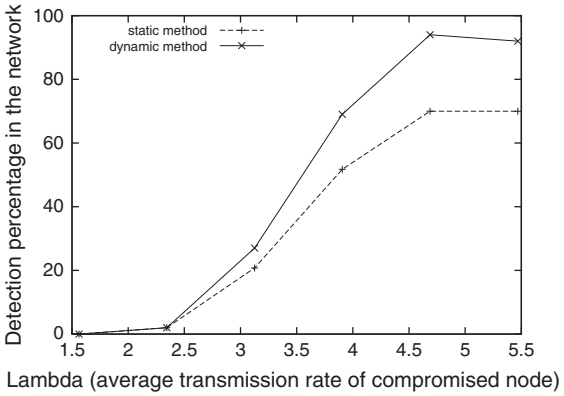

Figure 4. Detection versus lambda.

Table II. Simulation parameters.

Number of sensor nodes	100
Simulation time	500 s
Reception consumption	0.394 W
Emission consumption	0.660 W

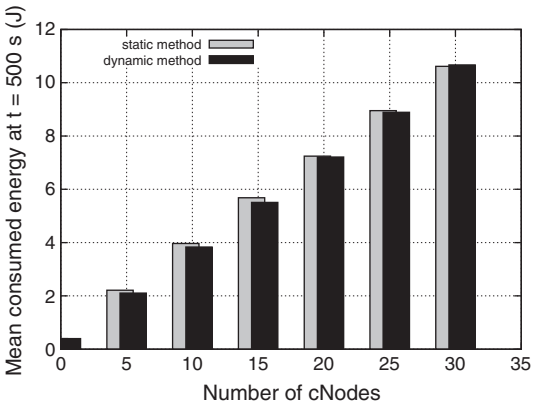

Figure 5. Average energy consumption.

Note that the "normal nodes" (non-cNodes sensors) do not receive messages from their neighbors, as they are "sleeping" between their sending time slots (see LEACH detailed functioning).

The average consumption is the same for static and dynamic methods: both methods use the same quantity of normal and cNode sensors.

Figure 6 depicts the standard deviation for the energy consumption at the end of the simulation. Once again, the CH and the compromised node are not taken into account.

One can observe that the standard deviation is much higher for the static solution: only the initial (and not re-elected) cNodes have a significant consumption over the simulation time, while the consumption is distributed among all the periodically elected nodes in the dynamic solution.

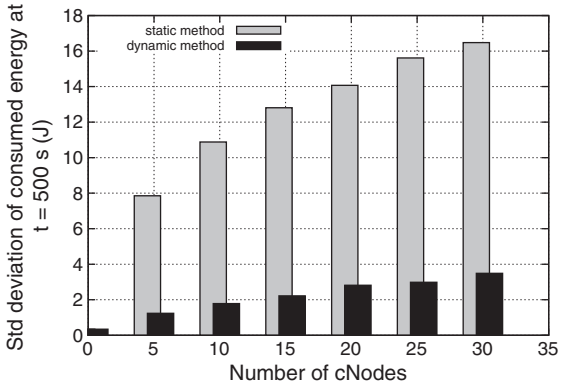

Figure 6. Energy consumption standard deviation.

For Figure 7, we have supposed that the nodes have an initial energy of 4 J. This is a small value, but 500 s is a small duration for a sensor lifetime. According to Wikipedia values and to what we have computed, a lithium battery (CR1225) can offer something such as 540 J, and a LR06 battery would provide something such as 15 390 J. Note that the compromised node was given an extra initial energy (we did not want it to stop flooding the network during the simulation). However, we set the initial energy to 4 J, and we notice for the first node's death for several percentages of cNodes.

As the cNodes are re-elected and the consumption is distributed for the dynamic method, the first node to run out of battery power logically dies later (up to five times later with few cNodes) than in the static method.

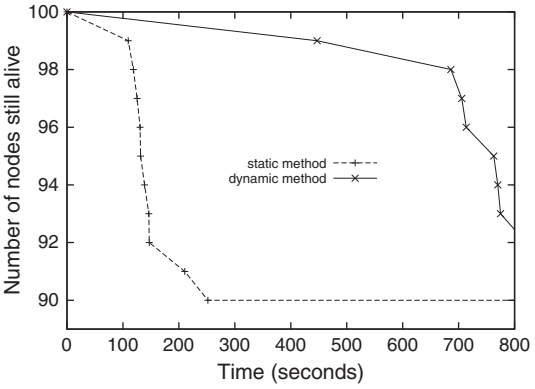

Figure 8. Nodes remained alive

5.3. Nodes' death and DoS detection

The duration of this new simulation was extended to 1 h (3600 s). Ten per cent of the sensors are elected as cNodes. The initial energy power was set to 10 J. So the considered parameters are given in Table III.

Figure 8 shows the evolution of the number of alive nodes in time.

As for the previous section, the non-cNodes sensors barely consume any energy regarding to cNodes' consumption (cNodes consume each time they analyze a message coming from one of their neighbor; other sensors do not). In the static method, elected cNodes consume their battery power and die (at about $t = 150$ s). That is why the 10 first sensors die quickly, whereas the other nodes last much longer (we expect them to live for 5 h). For the static method, the cNodes are re-elected, so the first node to die lives longer than for the previous method. It is a node that was elected several times, but not necessarily *each* time. Only two nodes have run out of energy at $t = 700$ s for the dynamic method. But at this point, the amount of alive nodes decreases quickly, and there is only one node left at the end of the first hour of simulation. Note that this was not reported on the aforementioned curve.

It is obvious that the nodes die much faster in the dynamic method, given that cNodes, the only nodes whose consumption is significant, are re-elected, whereas there are no more consuming cNodes in the network for the static method after the 10 first nodes are dead. Hence, it is interesting to consider how many nodes do effectively detect the attack as the time passes by. This is what is shown on Figure 9. The average number of cNodes that detected the attack (out of 10 cNodes) is presented for each 60 s-long period.

After the fourth minute, every cNode is dead for the static method, and the compromised node is no more detected. With the dynamic method, a raw average of 6.5 out of 10 cNodes detect the compromised nodes during each 10 s-long period corresponding to the dynamic

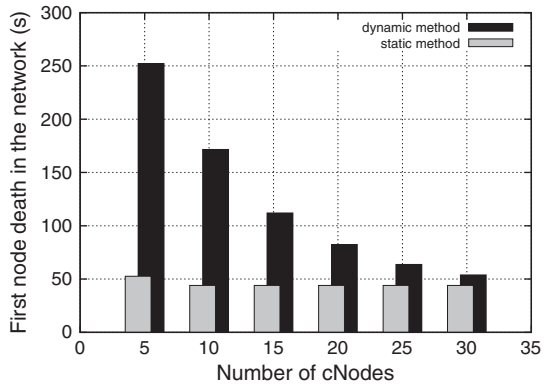

Figure 7. First death in the network.

Table III. Simulation parameters.

Number of sensor nodes	100
cNodes percentage	10%
Simulation time	3600 s
Reception consumption	0.394 W
Emission consumption	0.660 W
Initial energy amount	10 J

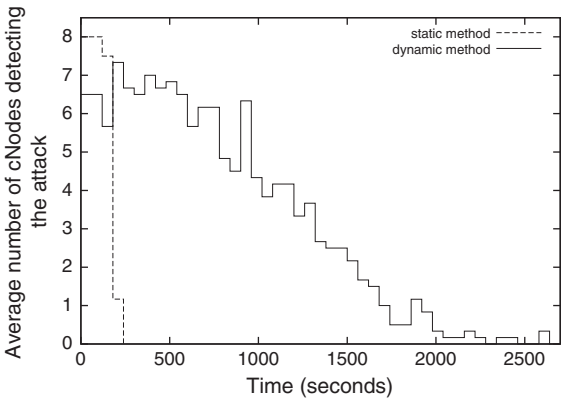

Figure 9. Denial-of-service detection.

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election. The flooding sensor is still detected by more than one node after half an hour.

In the following, we present a modeling approach of DoS detection using of GSPN, and we give some numerical results.

6. NON-MARKOVIAN MODELING AND VERIFICATION OF DoS

In previous sections we have pointed out that using Markov chains to model DoS detection mechanisms may inherently imply a significant approximation.

To obtain more accurate models of DoS detection, it is necessary to resort to a more general class of stochastic processes, namely the so-called Discrete-Event Stochastic Processes (DESP, also often referred to as Generalized Semi-Markov Processes). The main characteristics of DESP is that they allow for representing generally distributed durations, rather than, as with CTMC, being limited to exponentially distributed events.

In this section, we present a modeling approach of DoS detection in terms of GSPN [27], a class of Petri Nets suitable for modeling stochastic processes. By definition, the GSPN formalism is a high-level language for representing CTMCs. However, herein, we refer to its straightforward extension where *timed transitions* can model generally distributed durations. Such extended GSPN (eGSPN in the following) becomes a high-level language for representing DESPs. Furthermore, eGSPN is also the formal modeling language supported by the COSMOS [25] statistical model checker, a tool which allows for verification of (sophisticated) performance measures in terms of the HASL [25].

In the following, we provide a succinct description of both the GSPN modeling formalism and the HASL verification approach, before describing their application to the DoS attack detection case.

6.1. Generalized stochastic Petri nets

A GSPN model is a bi-partite graph consisting of two classes of nodes, *places* and *transitions* (Figure 10). Places (represented by circles) may contain *tokens* (representing the state of the modeled system), whereas transitions (represented by bars) indicate the events the occurrence of which determine how tokens "flow" within the net (thus encoding the model dynamics). The state of a GSPN consists of a *marking* indicating the distribution of tokens throughout the places (i.e., how many tokens each place contains). Roughly speaking, a transition is enabled whenever all of its *input places* contains a number of tokens greater than or equal to the multiplicity of the corresponding input arc (e.g., transition T1 in the left-hand part of Figure 10 is enabled, whereas T2 is not). An enabled transition may *fire* consuming tokens (in a number indicated by the multiplicity of the corresponding input arcs) from all of its input places and producing tokens (in a number indicated by the multiplicity of the corresponding output arcs) in all of its output places. Such informally described rule is known as the Petri net *firing rule*. GSPN transitions can be either *timed* (denoted by empty bars) or *immediate* (denoted by filled-in bars, e.g., transition T2 in left-hand side of Figure 10). Generally speaking, transitions are characterized by the following: (1) a distribution that randomly determines the delay before firing it; (2) a priority that *deterministically* selects among the transitions scheduled the soonest, the one to be fired; and (3) a weight that is used in the random choice between transitions scheduled the soonest with the same highest priority. With the GSPN formalism, the delay of timed transitions is assumed *exponentially* distributed, whereas with eGSPN, it can be given by any distribution with non-negative support. Thus, whether a GSPN timed-transition is characterized simply by its weight $t \equiv w$ ($w \in R^+$ indicating an Exp(w)-distributed delay), an eGSPN timed-transition is characterized by a triple: $t \equiv (\text{Dist-t}, \text{Dist-p}, w)$, where Dist-t indicates the type of distribution (e.g., Unif, Deterministic, LogNormal), Dist-p indicates the parameters of the distribution (e.g, $[\alpha, \beta]$), and $w \in R^+$ is used to probabilistically choose between transitions occurring with equal delay.[†]

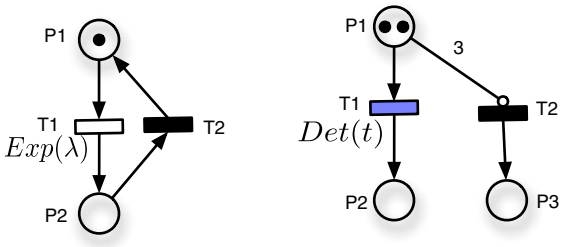


Figure 10. Simple examples of extended generalized stochastic Petri nets: timed transitions, immediate transition, and inhibitors arcs.

In the following, we describe how eGSPN models can be derived for modeling WSN scenario with DoS mechanisms. More specifically, in our eGSPN models, we will use only two types of timed transitions, namely exponentially distributed timed-transitions (denoted by empty bars, e.g., T1 in left-hand side of Figure 10) and Deterministically distributed timed-transitions (denoted by blue-filled-in bars, e.g., T1 in right-hand side of Figure 10). In our Petri nets models, we will also extensively exploit *inhibitor arcs*, an additional element of the GSPN formalism. An inhibitor arc is denoted by an edge with an empty circle in place of an arrow at its outgoing end (e.g., the arc connecting place P1 to transition T2 in the right-hand side of Figure 10). In the presence of inhibitor arcs, the semantics of GSPN *firing rule* is slightly modified; thus, a transition is enabled whenever all of its *input places* contains a number of tokens greater than or equal to the multiplicity of the corresponding

[†] A possible condition in case of non-continuous delay distribution.

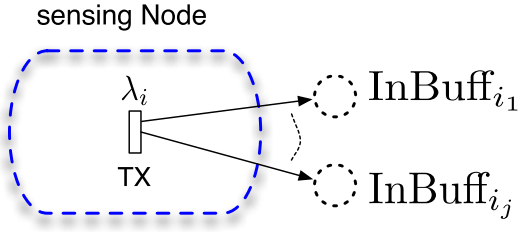


Figure 11. Generalized stochastic Petri nets model of a sensing node.

input arc and strictly smaller than the multiplicity of the corresponding inhibitor arcs (e.g., transition T2 in right-hand part of Figure 10 is also enabled, because P1 contains less than three tokens). Having summarized the basics of the syntax and semantics of the eGSPN formalism, we now describe how it can be applied to formally represent WSN systems featuring DoS mechanisms.

6.2. Modeling DoS attacks with eGSPN

We describe the eGSPN models we have developed for modeling DoS attacks in a grid-like network. For simplicity, we illustrate an example referred to a 9×9 grid topology. The proposed modeling approach can easily be extended to larger networks.

In a WSN with DoS detection mechanisms, the functionality of sensing nodes is different from that of cNodes. Here, we describe GSPN models for representing the following: (i) sensing nodes; (ii) statically elected cNodes; and (iii) dynamically eligible cNodes.

6.2.1. GSPN model of sensing nodes

Sensing nodes functionality is trivially simple: they simply keep sending sensed data packets at a pace that (following Section 4) we assume to be exponentially distributed with rate λ_i.

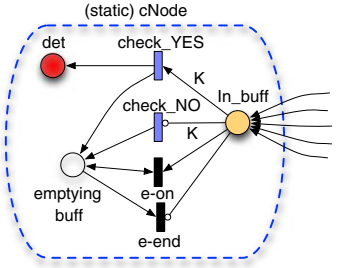
This can be modeled by a simple GSPN that consists of a single exponentially distributed timed-transition (labeled TX) with no input places (i.e., always enabled) and with as many outgoing arcs leading to the input buffer of the neighboring nodes (represented by dashed places labeled InBuff_{i_j} in Figure 11). Note that transition TX in Figure 11 has no input places, which means (according to the Petri Net firing rule) that it is always (i.e., perpetually) enabled. Note also that TX is an exponentially distributed timed-transition with rate λ_i, which complies with the assumption that each sensor node performs a sensing operation every δ_s time with $\delta_s \sim \text{Exp}(\lambda_i)$. To summarize, the *sensing* functionality of a specific node in a WSN is modeled by a single timed-transition provided with as many outgoing arcs as the number of neighbors of that node. The complete sensing functionality of a WSN can be modeled by combining several such GSPN modules.

6.2.2. GSPN model of cNodes

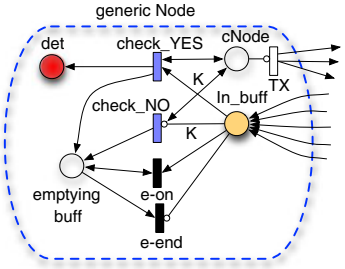
A cNode functionality, on the other hand, is entirely devoted to monitoring of traffic of the portion of WSN it is guarding on. From a modeling point of view, a distinction must be made between the case of statically elected cNodes (as in [12]) and that of dynamically eligible cNodes (as in [13]). In fact, with dynamic cNodes election, each node in the network can be elected as cNode; therefore, each node can switch between a sensing-only functionality and a controlling functionality. On the other hand, static cNodes will be control-only nodes.

Generalized stochastic Petri nets models for both *static* and *dynamic* cNodes are depicted in Figure 12(a) and (b), respectively. A cNode detects an attack whenever the overheard traffic throughput (i.e., number of overheard packets per observation period) exceeds a given threshold ρ_{attack}. Place "InBuff" (Figure 12(a)) represents the *input buffer* of a node, where packets received/overheard from neighbor nodes are placed. The "InBuff" place receives tokens (corresponding to overheard packets) through input arcs originating from neighbors sensing-node modules (i.e., the input arcs of place "InBuff" are the output arcs of the timed transition representing the corresponding sensing activity of each neighbor node).

To model the traffic monitoring functionality of cNodes, we employ two mutually exclusive, deterministically distributed timed-transitions labeled "checkYES" and "checkNO" in Figure 12(a) and (b). They correspond to the periodic verification performed by the cNode to



(a) GSPN model for a *statically elected* **cNode**



(b) GSPN model for a *dynamically eligible* **cNode**

Figure 12. Generalized stochastic Petri nets components representing cNodes behavior in a WSN with denial-of-service detection mechanisms.

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check whether the frequency of incoming traffic has been abnormal (over the last period). At the end of each (fixed) interval $[0, \Delta]$, either transition "checkYES" is enabled, if at least k packets have been received (i.e., place "InBuff" contains at least k tokens), or transition "checkNO" is enabled, if less than k packets have been received (i.e., place "InBuff" contains less than k tokens). In the first case (i.e., "checkYES" enabled), a token is added in the output place "det" representing the occurrence of a DoS detection; otherwise (i.e., "checkNO" enabled), no tokens is added to place "det."

After firing of either the "checkYES" or the "checkNO" transition, the emptying of the input buffer starts by adding a token in place "empty." This enables either immediate transition "e-on" (which iteratively fires until the input buffer is empty) or "e-end," which represents the end of the emptying cycle. Note that buffer emptying does not consume time, and it is needed in order to correctly measure the frequency of traffic at each successive sampling interval $[0, \Delta]$.

The GSPN model for the dynamic cNodes (Figure 12 (b)) is a simple extension of that for static cNodes obtained by adding an auxiliary place "cNodes" and an auxiliary exponentially distributed timed-transition "TX." This is needed because with dynamically elected cNodes, each node in the network may periodically switch from sensing-only to controlling-only functionality; hence, the corresponding GSPN model must represent both aspects. If the auxiliary place "cNode" contains a token, then the "controlling" functionality (i.e., the left part of the GSPN) is switched-on, and in that case, the GSPN of Figure 12(b) behaves exactly as that of Figure 12(a). Conversely, if place cNode is empty, then the "sensing" functionality is switched-on (i.e., transition "TX" is enabled because of the inhibitor arc between place "cNode" and transition "TX") while the "controlling" part of the net is disabled (i.e., in this case, the net of Figure 12(b) behaves exactly as that of Figure 11).

The earlier described GSPN models for sensing nodes, static cNodes, and dynamic cNodes can be used as basic building blocks to compose models of specific WSN topologies. In the following, we provide examples of GSPN for 9×9 WSN grid topology equipped with DoS detection functionalities.

6.2.3. GSPN model of DoS detection with static cNodes

Figure 13 illustrates a complete GSPN model for a 9×9 grid topology representing an example of DoS detection with static election of cNodes (as in [12]). In particular

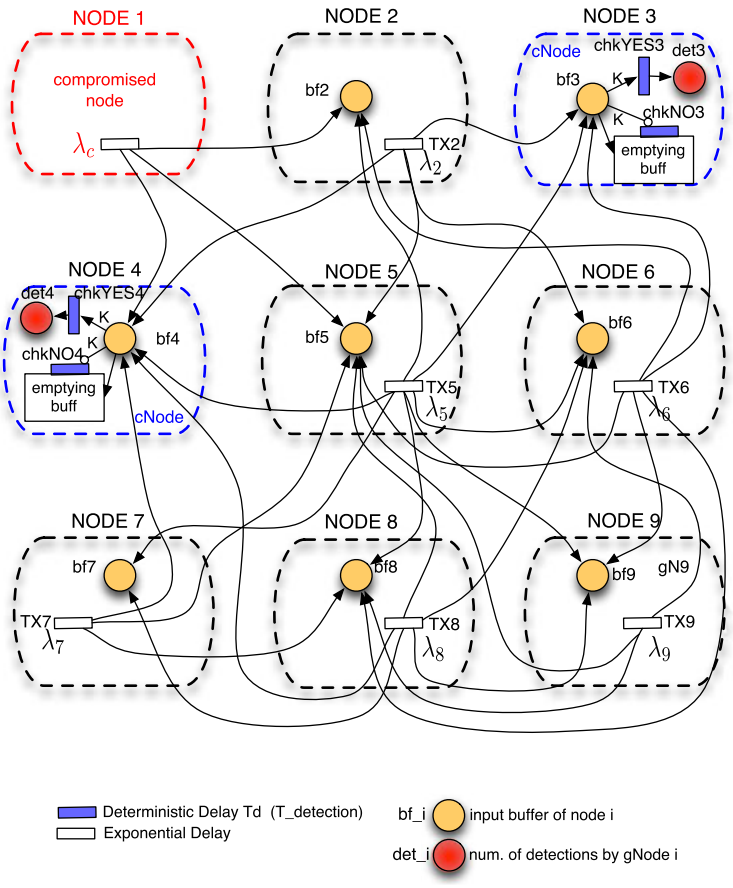


Figure 13. Generalized stochastic Petri nets model of a 9×9 grid topology with one (fixed) compromised node and two static cNodes.

in this example, we consider the presence of two cNodes (i.e., nodes 3 and 4) and one compromised node (i.e., node 1). Note that for simplicity, the "emptying buffer" part in the GSPN modules of the cNodes (i.e., nodes 3 and 4) is depicted as a box (i.e., the content of that box corresponds to the subnet responsible for emptying the "inBuff" place as depicted in Figure 12(a) and (b)).

This model can be used to study the performances of DoS detection with static cNodes in much respect, such as measuring the expected number of detected attacks within a certain time bound or also assessing the average energy consumption of cNodes. In the next section, we describe how to build GSPN models of WSNs with DoS detection and dynamic election of cNodes. The resulting GSPN is more complex than that for statically elected cNodes, as it must include an extra module, namely a GSPN module for periodically electing the cNodes.

6.2.4. GSPN model of DoS detection with dynamic cNodes

Figure 14 illustrates the GSPN model of a 9×9 grid topology for the case of DoS detection with dynamic election of cNodes (as in [13]). For simplicity, Figure 14 consists of two parts: the actual network topology part (Figure 14(a)) and the cNodes random election mechanism (Figure 14(b)).

The network model (Figure 14(a)) is obtained by composition of node's GSPN component in the same fashion as for the model of the WSN for DoS detection with static cNodes, only that now, all nodes must be reconfigurable as either sensors or controllers (thus, the basic GSPN components used to build the network topology are those of Figure 12(b)).

The cNodes election component (Figure 14(b)), on the other hand, consists of a single place, n mutually exclusive deterministically distributed timed-transitions (blue-filled) and n mutually exclusive immediate transitions (black-filled) (with $n = \binom{8}{2} = 28$, as we assume that, at each round, two cNodes are elected out of eight possible candidates; thus, for simplicity, we rule out the compromised node from the eligible ones). The deterministically distributed timed-transitions (blue-filled) of Figure 14(b) correspond to all possible different pairs of "cNode" places. At the end of each selection period, only (exactly) one such timed transition will be enabled and will fire retrieving, in this way, the tokens from the current pairs of active cNodes and inserting one token in the only (central) place of the net in Figure 14(b). At this point, all 28 immediate transitions will become enabled and a random choice will take place resulting in the selection of only (exactly) one of them. The selected transition will fire and by doing so will insert one token into each "cNode" place of the corresponding pair of cNodes to which it is connected, activating, in this way, the controlling functionality of the newly elected cNodes.

6.3. HASL verification of DoS detection models

One of the main motivations for developing GSPN models of discrete-event systems is that a fairly large and well-established family of formal methods can be applied to analyze them. Recently, a new formalism called HASL has been introduced, which provides a unified framework both for model checking and for performance and dependability evaluation of DESP models expressed in GSPN terms. In essence, given a GSPN model, we can express sophisticated performance measures in terms of an HASL formula and apply a statistical model checking functionalities to (automatically) assess them. In the following, we informally summarize the basics about the HASL verification approach, referring the reader to [25] for formal details.

6.3.1. HASL model checking

Model checking [34] is a formal verification procedure by which given a (discrete-state) model M and a property formally expressed in terms of a temporal logic formula φ, an algorithm automatically decides whether φ holds in M (denoted $M \vDash \varphi$). In the case of stochastic models (i.e., stochastic model checking [33]), formulae are associated with a measure of probability and verifying $M \vDash \varphi$ corresponds to assess the probability of φ with respect to the stochastic model M. HASL model checking extends this very simple concept in the sense that an HASL formula can evaluate to any real number (thus, it can represents a measure of probability as well as other performance measures).

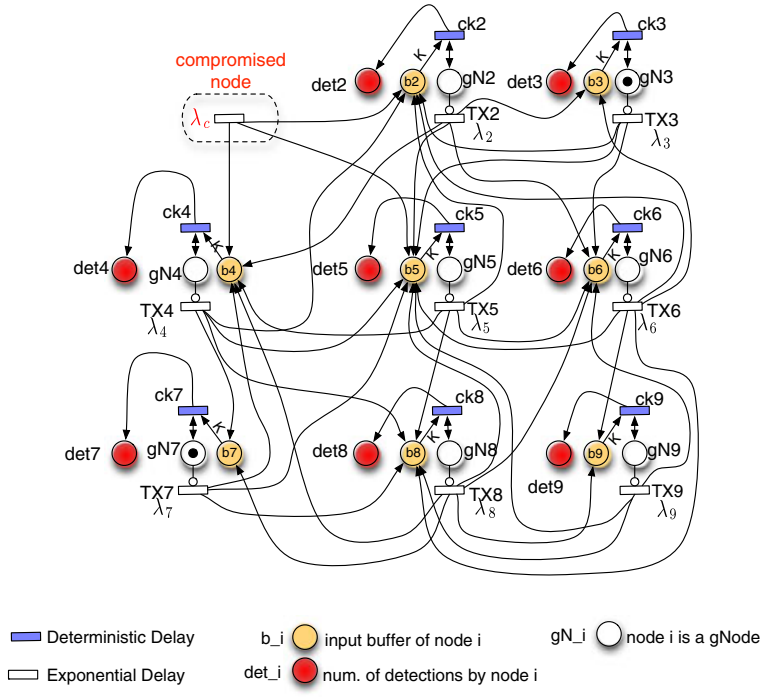
To do so, HASL uses Linear Hybrid Automata (LHA) as machineries to encode the dynamics (i.e., the execution paths or trajectories) of interest of the considered GSPN model. An LHA, simply speaking, is a generalization of timed automaton where clock variables are replaced by real-valued data variables.

In practice, a formula of HASL consists of two parts:

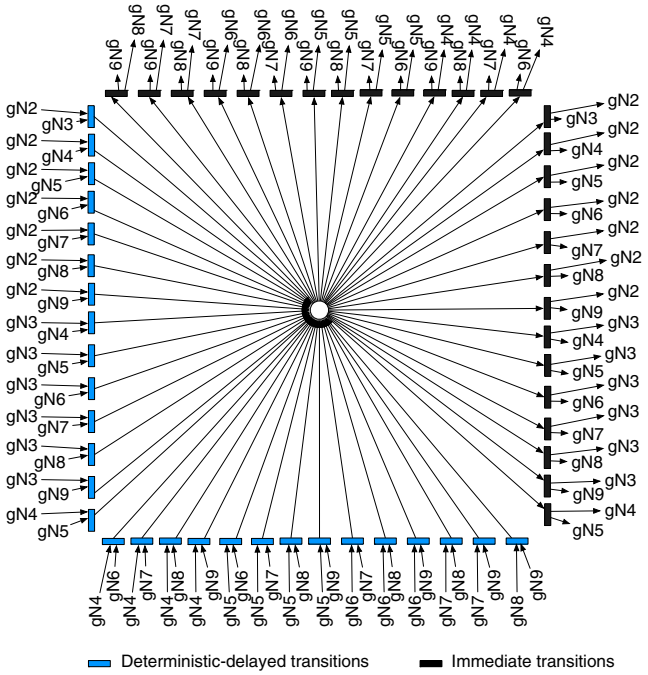
- An LHA used as a selector of relevant of timed execution of the considered DESP (path selection is achieved by synchronization of a generated DESP trajectory with the LHA).
- An expression Z built on top of data variables of the LHA according to the syntax given in Equation (1) and which represent the measure to be assessed.

$$\begin{aligned} Z &::= E(Y) \,|Z + Z|Z \times Z \\ Y &::= c|Y + Y|Y \times Y|Y/Y|\,\mathrm{last}(y)|\,\min(y) \\ &\quad\; |\,\max(y)|\,\mathrm{int}(y)|\,\mathrm{avg}(y) \\ y &::= c|x|y + y|y \times y|y/y \end{aligned} \tag{1}$$

The informal meaning of an HASL expressions Z (1) is as follows: x is a data variable of the LHA automaton associated to the expression. y is an (arithmetic) expression of data variables. Y is a path random variable, i.e., a variable that is evaluated against a synchronization path, a path resulting by the synchronization of a trajectory of



(a) the traffic part in a 9x9 topology



(b) the random election policy part: 2 cNodes are elected out of 8

Figure 14. Generalized stochastic Petri nets model of a 9×9 grid topology with one (fixed) compromised node and two randomly elected cNodes.

the DESP with the LHA associated to the formula. The basic operators (i.e., last(y), min(y), max(y), int(y), avg(y)) on top of which a path variable Y is built have intuitive meanings. In particular, last(y) indicates the last value of expression y along an accepted synchronized path, min (y) and max(y) indicate the minimum and the maximum

of y along a path, int(y) the integral of y along a path, and avg(y) the average of y along a path.

The HASL statistical model checking procedure works as follow:

- It takes a GSPN model and an HASL formula.
- It iteratively generate trajectories of GSPN model state-space and synchronize them with the LHA.
- The trajectories that have been "accepted" by the LHA are considered in the estimation of the measure of interest; the others are dropped.

6.4. HASL formulae for DoS models

Having seen the nature of HASL verification, we provide here few examples of HASL formulae (i.e., LHA + expression) that can be used to assess performance measures of the DoS (GSPN) models presented in the previous section. Such formulae may be readily assessed through the COSMOS model checker, and the results can be used to compare different DoS detection mechanisms.

The LHA we present are based on the following data variables:

- x_t: global time.
- x_{d_i}: number of attacks detected by cNode i ($1 \le i \le N$).
- x_{TX_i}: number of data transmitted by node i ($1 \le i \le N$).
- x_{bf_i}: flow of packets in buffer of node i ($1 \le i \le N$).

The LHA in Figure 15 is a template automaton that can be used for calculating different measures of a node (either a sensing or a cNode) of a WSN model. It refers to GSPN models (Figures 1 and 2). It consists of two locations and refers to the four data variables described earlier. In the initial location (l_1), the rate of change (i.e., the first derivative) of data variables is indicated (inside the circle). The global time variable x_t is incremented with rate $\dot{x}_t = 1$ following the linear flow of time. Counter variables x_{d_i} and x_{TX_i} (used to count occurrences of events) are unchanged in location l_1 (i.e., their rates are zero). Finally, variable x_{bf_i} is incremented with rate proportional to the number of tokens in the input buffer of cNode i (i.e., $\dot{x}_{bf_i} = M(bf_i)$); this data variable can

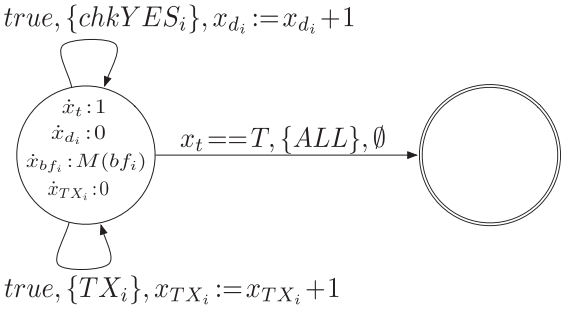


Figure 15. A Linear Hybrid Automata for assessing relevant measures of denial-of-service generalized stochastic Petri nets models.

be used to measure the average length of overheard packets by cNode i and thus to measure the average energy consumption of a cNode. The two self-loops transitions on location l_1 are used to increment the counter variables x_{d_i} and x_{TX_i} on occurrence of the associated events in the GSPN model. For example, transition $l_1 true, \{chkYES_i\}, x_{d_i} := x_{d_i} + 1 l_1$ indicate on occurrence of the GSPN transition labeled $chkYES_i$ (i.e., detection of an attack by cNode i) the variable x_{d_i} is incremented by 1. Transition $l_1 x_t == T, \{ALL\}, \emptyset\, l_2$ from l_1 to the accepting location l_2 indicates when the synchronization stops and the processed path is accepted. Precisely, this happens as soon as $x_t == T$, where $T \in R$ denotes a time bound, that is, as soon as the observed trajectories is such that the simulation time is T. In this case, no matter which GSPN transition is occurring (i.e., synchronization set is $\{ALL\}$), the transition from l_1 to l_2 will fire and the path generation will stop by accepting the path. In other words, the LHA in Figure 15 trivially accepts all paths of duration T. The value of the four data variables collected during synchronization of the LHA with the GSPN model will be then used for estimating relevant Z expressions.

In the following, we describe few examples of Z expressions that can be used in association to the LHA in Figure 15 to evaluate relevant measures of the DoS GSPN models.

- $Z_1 \equiv E(\text{last}(x_{d_i}))$: the expected number of detected attacks by cNode i after T time units.
- $Z_2 \equiv E(\text{last}(x_{d_i} + x(d_i)))$: the sum of attacks detected by cNode i and i'' after T time units.
- $Z_3 \equiv E(\text{last}(x_{TX_i}))$: the expected value of packets transmitted by node i after T time units.
- $Z_4 \equiv E(\text{avg}(x_{bf_i}))$: the expected cumulative flow of packets received by node i within T time units.

7. CONCLUSION

Detection of DoS attacks is a fundamental aspect of WSN management. In this paper, we have considered a class of DoS detection mechanisms designed to operate on clustered WSNs. The detection methods we have considered are based on deployment of special control nodes in the sensing field: that is, specific nodes that are responsible for monitoring the throughput of traffic of specific parts of the sensing field and signaling the presence of suspected attacked nodes in case anomalies are detected. Control nodes election is a crucial aspect of DoS mechanisms. In the literature, two basic election approaches have been proposed: a static election and a dynamic (random) election.

In this paper, we presented different modeling approaches for obtaining models of WSNs with DoS functionalities. First, we have described how Markov chains model should be structured for modeling DoS attack and detection, pointing out that because of the nature of DoS detection, Markovian models may inherently come with some significant approximation. We have then presented

numerical results obtained with virtual WSN implementation by means of the NS-2 network simulator. The outcome of such simulative experiments confirm the intuition that cNodes dynamic allocation guarantees a more uniform energy consumption (throughout the network) while preserving a good detection capability. Finally, we have presented formal non-Markovian models of DoS detection in terms of GSPN, a high-level formalism for generic DESP. We have illustrated how model of WSNs with DoS can be built "incrementally" by combination of small GSPN modules of single (sensing/controlling) nodes up to obtaining a model of the desired network. We have also stressed how the GSPN formalism is naturally well suited for modeling of the dynamic random cNodes election policy. Finally, we have briefly presented how expressive performance measures of the DoS GSPN models can be formally expressed and assessed by means of the recently introduced HASL. Future developments of this work include the execution of actual verification experiments on the presented GSPN models by means of the COSMOS statistical model checker, as well as the extension of the proposed modeling approaches to consider more complex network (different topologies and scales).

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