

A CLASSIFIER MECHANISM FOR HOST-BASED INTRUSION DETECTION AND PREVENTION SYSTEM IN CLOUD COMPUTING ENVIRONMENT

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DEDICATION

Dedicated to my parents.

For their endless love, support and encouragement.

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Alhamdulillah with the will of Allah, I have successfully completed this research. Without the strength applied to me, I would not be able to finish this subject field on time devoted. This thesis is prepared to fulfil the requirements for Doctor of Philosophy from Faculty of Computer Systems & Software Engineering, Universiti Malaysia Pahang

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ABSTRAK

Serangan Distributed Denial-of-Service (DDoS) adalah insiden yang sering berlaku dalam persekitaran pengkomputeran awam yang menyebabkan gangguan utama prestasi. Sistem pengesanan dan pencegahan pencerobohan (IDP) adalah merupakan alat untuk melindungi daripada sebarang insiden tersebut, dan penempatan sistem ID/IP yang tepat pada rangkaian adalah sangat penting untuk pemantauan yang optimum dan mencapai keberkesanan yang maksimum dalam melindungi sistem. Walaupun dengan adanya sistem tersebut, tahap keselamatan pengkomputeran awam mesti dipertingkatkan. Semakin banyak serangan yang lebih kuat cuba untuk mengawal persekitaran pengkomputeran awam tersebut; serangan tersebut adalah termasuk hyperjacking mesin-maya (VM) dan juga ancaman keselamatan rangkaian tradisional seperti pengintipan trafik (memintas trafik rangkaian), pengintipan alamat dan pemalsuan VM atau alamat IP. Menguruskan IDPS berasaskan hos (H-IDPS) adalah sangat sukar kerana maklumat perlu dikongfigurasikan dan diuruskan oleh setiap hos, ianya penting untuk memastikan penganalisis keselamatan dapat memahami struktur rangkaian sepenuhnya bagi membezakan antara positif palsu dan masalah sebenar. Untuk tujuan tersebut, adalah sangat penting untuk memahami pengelas paling utama dalam pembelajaran mesin, kerana ianya menawarkan perlindungan terhadap penggera positif palsu dalam serangan DDoS. Bagi merancang lebih banyak pengelasan yang berkesan, sistem bagi menilai pengelas perlu dibangunkan. Dalam thesis ini, mekanisma reka bentuk untuk pengelas H-IDPS dalam persekitaran pengkomputeran awam telah dibangunkan. Reka bentuk mekanisme ini berdasarkan Optimasi Antlion hibrid Algoritma (ALO) dengan Multilayer Perceptron (MLP) untuk berlindung dari serangan DDoS. Untuk melaksanakan mekanisme yang dicadangkan, kami menunjukkan kekuatan pengelas menggunakan satu dataset yang dikurangkan dimensi menggunakan NSL-KDD. Selain itu, kami memberi tumpuan terperinci kepada kajian dataset NSL-KDD yang mengandungi hanya rekod terpilih. Dataset yang dipilih ini menyediakan analisis yang baik terhadap pelbagai teknik pembelajaran mesin untuk H-IDPS. Penilaian terhadap Sistem H-IDPS ini menunjukkan peningkatan ketepatan pengesanan pencerobohan dan mengurangkan penggera positif palsu berbanding hasil kajian lain yang berkaitan. Ini dapat digambarkan dengan menggunakan teknik matriks kekeliruan untuk mengatur pengelas, menggambarkan prestasi dan menilai tingkah laku secara keseluruhan.

ABSTRACT

Distributed denial-of-service (DDoS) attacks are incidents in a cloud computing environment that cause major performance disturbances. Intrusion-detection and prevention system (IDPS) are tools to protect against such incidents, and the correct placement of ID/IP systems on networks is of great importance for optimal monitoring and for achieving maximum effectiveness in protecting a system. Even with such systems in place, however, the security level of general cloud computing must be enhanced. More potent attacks attempt to take control of the cloud environment itself; such attacks include malicious virtual-machine (VM) hyperjacking as well as traditional network-security threats such as traffic snooping (which intercepts network traffic), address spoofing and the forging of VMs or IP addresses. It is difficult to manage a host-based IDPS (H-IDPS) because information must be configured and managed for every host, so it is vital to ensure that security analysts fully understand the network and its context in order to distinguish between false positives and real problems. For this, it is necessary to know the current most important classifiers in machine learning, as these offer feasible protection against false-positive alarms in DDoS attacks. In order to design a more efficient classifier, it is necessary to develop a system for evaluating the classifier. In this thesis, a new mechanism for an H-IDPS classifier in a cloud environment has been designed. The mechanism's design is based on the hybrid Antlion Optimization Algorithm (ALO) with Multilayer Perceptron (MLP) to protect against DDoS attacks. To implement the proposed mechanism, we demonstrate the strength of the classifier using a dimensionally reduced dataset using NSL-KDD. Furthermore, we focus on a detailed study of the NSL-KDD dataset that contains only selected records. This selected dataset provides a good analysis of various machine-learning techniques for H-IDPS. The evaluation process H-IDPS system shows the increases of intrusion detection accuracy and decreases the false positive alarms when compared to other related works. This is epitomized by the skilful use of the confusion matrix technique for organizing classifiers, visualizing their performance, and assessing their overall behaviour.

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LIST OF ABBREVIATIONS

ALAD	Application Layer Anomaly Detection
ALO	Antlion Optimization Algorithm
ANN	Artificial Neural Network
BPNN	Backpropagation Neural Network
CPU	Central Processing Unit
DARPPA	Defence Advanced Research Projects Agency
DDoS	Denial-Of-Service Attack
DNS	Domain Name System
EV	Evolutionary Computation
FDR	Fisher's Discriminant Ratio
FL	Fuzzy Logic
FN	False Negative
FP	False Positive
GA	Genetic Algorithm
GAR-forest	Greedy randomized adaptive search procedure with annealed randomness
GRASP	Greedy Randomized Adaptive Search Procedure
H-IDPS	Host-Based Intrusion Detection and Prevention System
HTTP	Hypertext Transfer Protocol
IASS	Infrastructure as A Service
ICMP	Internet Control Message Protocol
IDPS	Intrusion Detection System and Prevention System
IDS	Intrusion Detection System
IP	Internet Protocol Address
IPS	Intrusion Prevention Systems
IT	Information Technology
KNN	K-Nearest Neighbours
KVM	Kernel-Based Virtual Machine
LAN	Local Area Network
LDA	Linear Discriminant Analysis
LERAD	Learning Rules for Anomaly Detection

MLF	Multi-Level Fuzzy Min-Max Neural Network
MLP	Multilayer Perceptron
NN	Neural Network
NTP	Network Time Protocol
OTN	Option List
PASS	Platform as A Service
PCA	Principal Component Analysis
PCAP	Packet Capture
PHAD	Packet Header Anomaly Detection
QoS	Quality of Service
R2L	Remote to Local Attack
RQs	Research Questions
SAAS	Software as A Service
SU	Symmetrical Uncertainty
SVM	Support Vector Machine
SYN	Synchronize
TN	True Negatives
TP	True Positive
TTL	Time to Live
U2R	User to Root Attack
UDP	User Datagram Protocol
TCP	Transmission Control Protocol
VLAN	Virtual LAN
VMs	Virtual Machines
XML	Extensible Markup Language

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