

Big Data Security Analysis Approach Using Computational Intelligence Techniques in R for Desktop Users

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Abstract—Big Data security analysis is commonly used for the analysis of large volume security data from an organisational perspective, requiring powerful IT infrastructure and expensive data analysis tools. Therefore, it can be considered to be inaccessible to the vast majority of desktop users and is difficult to apply to their rapidly growing data sets for security analysis. A number of commercial companies offer a desktop-oriented big data security analysis solution; however, most of them are prohibitive to ordinary desktop users with respect to cost and IT processing power. This paper presents an intuitive and inexpensive big data security analysis approach using Computational Intelligence (CI) techniques for Windows desktop users, where the combination of Windows batch programming, EmEditor and R are used for the security analysis. The simulation is performed on a real dataset with more than 10 million observations, which are collected from Windows Firewall logs to demonstrate how a desktop user can gain insight into their abundant and untouched data and extract useful information to prevent their system from current and future security threats. This CI-based big data security analysis approach can also be extended to other types of security logs such as event logs, application logs and web logs.

Keywords—Big Data, Security Analysis, Computational Intelligence Techniques, CI, R, Desktop User, Windows Firewall Logs

I. INTRODUCTION

Security analysis is becoming an increasingly complex task for desktop users due to the high volume of data generated from different security tools in the form of firewall logs, event logs, application logs, web logs and many other security logs. The efficient handling and processing of this collected data requires high system resources and powerful analysis tools. However, traditional systems and tools are not capable of handling and analysing these large unstructured datasets. In the absence of appropriate processing mechanism for these large datasets, these valuable datasets may become useless and a resource overhead for the other important applications. Therefore, desktop users require an easy to implement and inexpensive big data security analysis approach that meets their data processing requirements within their limitations. However, most of the security analysis solutions are not affordable to the ordinary desktop user due to their costs and the requirement for powerful systems. Another issue is the sophisticated use of these complex tools, whereas, many ordinary users are

untrained IT users or reluctant to receive long and complex IT applications training. Therefore, desktop users require a relatively simple, economical and resource efficient data analysis approach. R is an open-source data analysis tool consisting of various CI packages for advanced data analysis. However, it requires a basic understanding of statistics which is desirable for any data analysis. R may not be suitable for the data collection or cleaning functions but it could be used for various analyses with some additional supporting tools.

This paper presents an intuitive and inexpensive security analysis approach using CI techniques in R for Windows desktop users. The choice of Windows desktop was as result of its popularity, where the Microsoft Windows operating system, has approximately 70% of the computer operating system market [1]. Therefore, there are large populations of Windows desktop users. If Windows desktop users can find or design an easy to implement and inexpensive big data security analysis solution supported by their system, then they can analyse very large security logs to extract meaningful security information to improve their systems security, making it more robust [2], [3]. In this proposed security analysis approach, the combination of Windows batch programming, EmEditor (which can be replaced with any powerful editor) and R are used for analysis purposes. R hosts several CI packages related to artificial neural networks, evolutionary algorithms, fuzzy systems and hybrid intelligent systems for designing intelligent systems. This security analysis approach involves several stages, where data collection and merging are performed by using a Windows batch script; data cleaning and editing are carried out by using EmEditor; and finally, R is used for structuring the data, performing analysis using CI techniques, visualising and interpreting the results. The experimental simulation is based on a real dataset of 1,006,889,160 bytes (1.01 GB) with more than 10 million observations, which are collected from the Windows Firewall logs during the log recording process for a 30 day period. Subsequently, security analysis is carried out on the collected Windows Firewall logs to demonstrate how a desktop user can gain insight into their abundant and untouched data and extract useful information to prevent their system from current and future security threats [2]. This CI-based big data security analysis approach can also be extended to other types of security logs such as event logs, application logs and web logs.

The remainder of this paper is organised as follows: Section II explains the theoretical background of data analysis tool **R**, Windows Firewall and fuzzy reasoning; Section III illustrates the design and implementation process of the proposed security analysis approach including its various stages: collecting and merging logs, cleaning and editing logs, converting text logs into an **R** table structure, analysing **R** datasets using CI techniques, and visualising and interpreting the results; Section IV explains the big data scalability of this approach for desktop users. Finally, Section V concludes the paper and suggests some future areas of extension.

II. THEORETICAL BACKGROUND

This section presents the background information about the data analysis tool **R**, Windows Firewall and fuzzy reasoning.

A. **R**

R is an open-source statistical computation and data visualisation software tool. It is the result of collaboration of a large team of developers, researchers, statisticians and data scientists from around the world. **R** is available for all the main operating systems such as UNIX, Windows and MacOS platforms. **R** comprises data handling facilities, a superior mechanism for matrix computations, a plethora of data analysis and graphical packages, and a simple programming language [4]. The most powerful feature of **R** is subsumption i.e. its support to external packages. Currently, **R** has incorporated around 5000 packages through the CRAN family of Internet sites [5]. **R** also hosts several CI packages related to artificial neural networks, evolutionary algorithms, fuzzy systems and hybrid intelligent systems for designing intelligent systems. Therefore, combining **R** with some data collecting and cleaning tools could facilitate a potential data analysis solution for desktop users. **R** is used as a computational tool for routine statistics production by many official statistics agencies. Besides official statistics, it is used in many other sectors such as finance, retail, manufacturing, science, and academic research, which is making it a popular tool among statisticians and researchers [4].

B. Windows Firewall

Microsoft embedded the firewall utility in Windows operating systems since Windows XP SP2 and is now available with all versions of Windows. Windows Firewall with “advanced security” features is a stateful firewall that examines and filters all packets for IPv4 and IPv6 traffic. The packet filtering process is based on the user or administrator-defined rules and on that basis it allows or blocks the network traffic. The firewall automatically blocks all incoming traffic unless it is a response to a request by the host or it is specifically allowed by writing a firewall rule. Windows Firewall can also be configured with “advanced security” for a specific port number, application name, service name, or other criteria based traffic; then this traffic can be allowed explicitly [6]. These features are designed for advanced users who need to manage network security in an enterprise environment. It is not often intended for the use in home networks.

C. Fuzzy Reasoning

Fuzzy reasoning is the process of deriving logical conclusions from an existing fuzzy rule base [7]. It mimics the ability of the human mind to summarize data and focus on decision-relevant information [8]. Fuzzy reasoning is more effective and useful for those systems where a system cannot be defined in precise mathematical terms or models due to uncertainties, unpredicted dynamics and other unknown phenomena [9]. In network security, much of the information and traffic data is incomplete and imprecise in nature. Therefore, fuzzy reasoning is comparatively more suitable than other types of reasoning approaches [10], [11], [12], [13]. Fuzzy reasoning is based on a fuzzy rule base, and it can be derived by subject matter experts or extracted from data through a rule induction process. If the fuzzy rule base is a dense rule base then, any rule inference method such as Mamdani inference [14] or Takagi-Sugeno inference [15] can be used.

III. SECURITY ANALYSIS OF WINDOWS FIREWALL LOGS USING COMPUTATIONAL INTELLIGENCE TECHNIQUES IN **R**

The security analysis for desktop users is a challenging task due to the limitation of system resources and technical IT skills. Therefore, this section presents the design and implementation of the proposed CI-based big data security analysis approach for desktop users for performing security analysis within their limitations. This security analysis only focuses on Windows desktop users. The experiment is carried out on a Windows 7 operating system and desktop with configuration (Processor=Intel Core i7 3.0 GHz (4 cores), RAM=16 GB, L2 Cache=8 MB, Ethernet=100 Mbps). This security analysis requires two software tools: any powerful text editor (such as EmEditor in this implementation) and **R** (with RStudio IDE). Unlike the other security analysis, where prior technical training is necessary, here any user with basic knowledge of statistics and elementary IT skills can conduct the security analysis without any prior technical training. This desktop-oriented security analysis approach has several stages as shown in Fig. 1. The description of the various stages are as follows:

A. Collecting and Merging Windows Firewall Logs using Windows Batch Script

The Windows Firewall logs are recorded in the “pfirewall.log” by default. The maximum size of the “pfirewall.log” file is 4096 KB. After exceeding this limit, it saves the logs in a backup file called “pfirewall.log.old” of 4096 KB. Both log files do not grow beyond this size, and when the “pfirewall.log” file exceeds the maximum limit again, the old log entries are deleted to make room for the newly created ones. In this security analysis of Windows Firewall logs, a reasonable sized file was required to perform extensive analysis and that was created in the simplest way by writing a Windows batch script as shown in Fig. 2. This batch script worked in the background during the period of the complete experiment. Initially, the “mergedLog” file was created with one line of a header containing all the 17 default variables of the “pfirewall.log” file. Finally, the “mergedLog” file of 1,006,889,160 bytes (1.01 GB) with more than 10 million observations was obtained during the gradual log recording process for 30 day period.

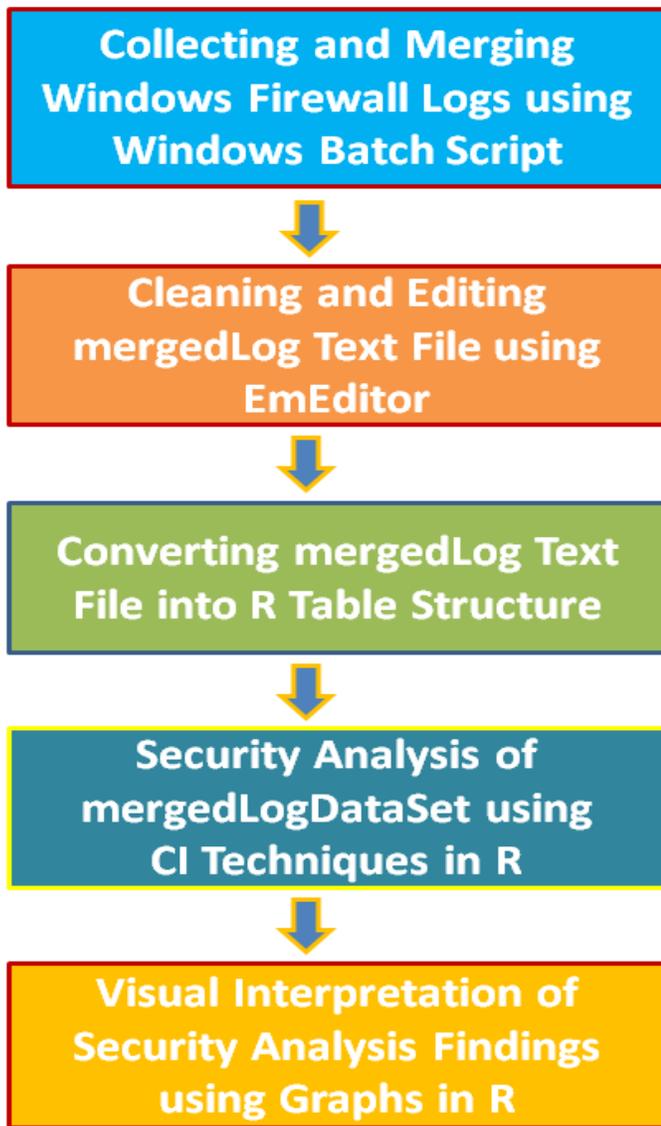


Fig. 1. Stages of big data security analysis approach for analysing Windows Firewall logs

```

C:\Windows\System32\LogFiles\Firewall\mergedLogCreation.bat - Notepad++
File Edit Search View Encoding Language Settings Macro Run Plugins Window ?
mergedLogCreation.bat
1 :loop
2 if exist pfirewall.log.old |
3 rename pfirewall.log.old pfirewall.log_&date:~10,2&date:~7,2&date:~4,4&_ttime:~0,2&ttime:~3,2&ttime:~6,2&
4 move +5 pfirewall.log_&date:~10,2&date:~7,2&date:~4,4&_ttime:~0,2&ttime:~3,2&ttime:~6,2& > templog
5 type templog >> mergedLog
6 |
7 goto loop
Batch file length: 304 lines: 7 Ln:7 Col:10 Sel:0|0 Dos:Windows UTF-8 w/o BOM BNS
  
```

Fig. 2. Windows batch script for creating a mergedLog file of Windows Firewall logs

B. Cleaning and Editing mergedLog Text File using EmEditor

Normally, the collected data may be incorrect, incomplete, improperly formatted, or duplicated and require cleaning and editing for removing these impurities [16], [17]. While the log file was a simple text file with no major cleaning issues, only a powerful data editor (EmEditor) was used rather than a proper cleaning tool. Notepad++ and other desktop editors were not capable of handling a very large text file, whereas

EmEditor could easily handle a file size up to 248 GB [18]. For this analysis, the “mergedLog” file (above 1 GB) was cleaned and edited using EmEditor as shown in Fig. 3. The “mergedLog” file was created in a way that the first five lines of the “pfirewall.log.old” were removed every time, before copying it to the “mergedLog” file. However, the “mergedLog” file still needed to be checked manually for various purposes and aligned with the format defined in the **R** table structure. If the “mergedLog” file did not fit in the **R** format, then **R** could generate an error message, and data could not be imported. Therefore, the major cleaning and editing task in “mergedLog” file was to check spaces between the two fields and align all lines including the header and last line if required.

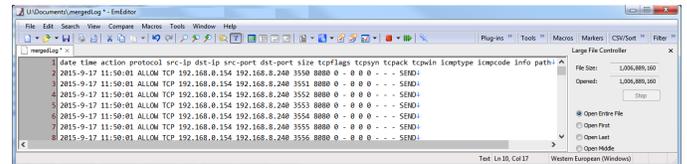


Fig. 3. Cleaning and editing mergedLog text file in EmEditor

C. Converting mergedLog Text File into R Table Structure

R supports a table-kind of data structure based on the **R** data frame. Therefore, the data frames are the fundamental data structure in **R**. The read.table() reads a file in table format and creates a data frame from it. The syntax of this function is shown in Equation 1.

$$data_frame_name = read.table(file_name, header = F/T, sep = “”) \quad (1)$$

where the “header” is a logical value indicating whether the file contains variable names as its first line and “sep” is the field separator character. In this implementation, the merged log file “mergedLog” was converted into a table-kind of data structure using the read.table() function as shown in Fig. 4.

```

> mergedLogDataSet =
  read.table("C:/Documents/mergedLog", header=T, sep="")
  
```

Fig. 4. Creation of mergedLogDataSet in R

If the structure, header and content of the merged log file were accurate, then it created a dataset called “mergedLog-DataSet” in **R** as shown in Fig. 5. This dataset was displayed in the “Environment and History Pane” of **RStudio IDE** and contained 10866240 observations and 17 variables similar to the firewall header variables. The actual table structure of the “mergedLogDataSet” (see Fig. 6) could be seen in the “Script Editor Pane”, usually at the opposite side of the “Environment and History Pane” in **RStudio IDE**.



Fig. 5. Created mergedLogDataSet with number of observations and variables

Fig. 6. Table structure of mergedLogDataSet in R

The structure-related information of this mergedLogDataSet could be seen by the “str” command as shown in Fig. 7. This “mergedLogDataSet” was directly created from the Windows Firewall merged log text file; therefore, the data types of all the 17 variables were a “factor”. This data type information was crucial for the statistical analysis because the “factor” was categorical data in R and for many computing models, it needed to be converted into numerical data.

```
> str(mergedLogDataSet)
'data.frame': 10866240 obs. of 17 variables:
 $ date : Factor w/ 1 level "2015-10-17": 1 1 1 1 1 1 1 1 1 1 ...
 $ time : Factor w/ 5915 levels "11:50:21","11:50:22",...: 1 1 1 1 1 1 1 1 1 1 ...
 $ action : Factor w/ 3 levels "ALLOW","DROP",...: 1 1 1 1 1 1 1 1 1 1 ...
 $ protocol : Factor w/ 5 levels "","2","ICMP",...: 4 4 4 4 4 4 4 4 4 4 ...
 $ src.ip : Factor w/ 26 levels "","127.0.0.1",...: 4 4 4 4 4 4 4 4 4 4 ...
 $ dst.ip : Factor w/ 39 levels "","127.0.0.1",...: 16 16 16 16 16 16 16 16 16 ...
 $ src.port : Factor w/ 22563 levels "","10","100",...: 245 246 247 248 249 250 251 254 255 256 ...
 $ dst.port : Factor w/ 512 levels "","1025","1026",...: 508 508 508 508 508 508 508 508 ...
 $ size : Factor w/ 8 levels "","0","148",...: 2 2 2 2 2 2 2 2 2 2 ...
 $ tcpflags : Factor w/ 2 levels "","S",...: 1 1 1 1 1 1 1 1 1 1 ...
 $ tcpsyn : Factor w/ 369 levels "","0","100070860",...: 2 2 2 2 2 2 2 2 2 2 ...
 $ tcpack : Factor w/ 2 levels "","0",...: 2 2 2 2 2 2 2 2 2 2 ...
 $ tcpwin : Factor w/ 4 levels "","0","1024",...: 2 2 2 2 2 2 2 2 2 2 ...
 $ icmpcode : Factor w/ 6 levels "","134","135",...: 1 1 1 1 1 1 1 1 1 1 ...
 $ icmpcode : Factor w/ 3 levels "","0","9",...: 1 1 1 1 1 1 1 1 1 1 ...
 $ info : Factor w/ 2 levels "","1",...: 1 1 1 1 1 1 1 1 1 1 ...
 $ path : Factor w/ 3 levels "","RECEIVE",...: 3 3 3 3 3 3 3 3 3 3 ...
```

Fig. 7. Created mergedLogDataSet with number of observations and variables

D. Security Analysis of mergedLogDataSet using CI Techniques in R

The main aim of the security analysis could be different for different users depending on their requirements. This particular analysis focuses on summarising the “mergedLogDataSet” for extracting vital information, deciding the security status of the desktop using the null hypothesis and binomial analysis, investigating the abnormalities in detail based on targeted protocols and IP addresses, designing an intelligent system to predict the risk of attack and, finally, a graphical illustration of the security analysis findings. The sequence and details of the various analyses are as follows:

- 1) *Windows Firewall Rules for Security Analysis:* In this simulation, a small number of firewall rules were created for security analysis purpose. Subsequently, this rules-based traffic data was collected in the “pfirewall.log” file. Two inbound rules were created to block two particular computers for specific traffic as shown in Fig. 8. The first rule was created to block the computer with IP address 192.168.0.50 for only ICMP packets, and the second rule for the computer with IP address 192.168.0.51 for only TCP packets. Therefore, enough dropped activities could be recorded during the log generation period. Similarly, stopping some activities at the host end (192.168.0.154), an outbound rule was also created to block the outgoing ICMP packets to other computers as shown in Fig. 9. These blocking rules generated enough “drop” traffic in the firewall log for security analysis.

Fig. 8. Incoming ICMP and TCP Drop Rules for IP addresses 192.168.0.50 and 192.168.0.51 respectively

Fig. 9. Outgoing ICMP Drop Rule for the host IP address 192.168.0.154

2) *Preliminary Statistical Analysis of Windows Firewall Log:* The simplest data analysis command in R is the “summary” command which gives reasonable statistics about the given dataset. However, it may be insufficient for detailed investigations or to predict future trends. Thus, some advanced analysis packages may be needed depending on the nature of the study. In Fig. 10, the summary command shows statistics about the “mergedLog” file, which could be very useful for further investigations. This summary includes information related to the date, time, action, protocol, source address, destination address, source port, and destination port, which are quite clear and understandable.

```
> summary(mergedLogDataSet)
      date      time      action      protocol      src.ip
2015-10-17: 362218 12:48:17: 54960  ALLOW      :7952160 240 192.168.0.50 :4222880
2015-10-7 : 424208 12:48:24: 47520  DROP      :2913840 2 1200 192.168.0.51 :2703840
2015-10-1 : 310001 12:47:52: 46560  INFO-EVENTS-LOST: 240 ICMP:1829520 192.168.0.154 :2633280
2015-10-16: 414415 12:47:48: 43680  TCP       :6775680 127.0.0.1 : 970080
2015-10-15: 250070 12:47:18: 42240  UDP       :2259600 Fc00:1::1:1:udb8:21dc:7530:96d5: 208560
2015-10-3 : 294652 12:47:47: 42240  (Other) :8810676 (Other):10589040 (Other) : 38880
      dst.ip      src.port      dst.port      size      tcpFlags      tcpsyn      tcpack
192.168.0.154 :6922800 - :1830960 0 :9007680 0 :5268000 - :4090560
127.0.0.1 : 970080 53 : 28560 8000 : 993120 44 :1469760 5:1507680 - :4090560 0:6775680
255-255-255-255: 872880 137 : 17520 3582 : 866800 60 :189360 184868396 : 5760
192.168.8.240 : 537840 138 : 12000 3956 : 866640 148 : 80040 104933933 : 5760
192.168.0.50 : 533280 59416 : 12000 50000 : 631440 178 : 80640 106313781 : 5760
192.168.0.51 : 524160 61539 : 11760 5357 : 556080 52 : 26400 1063202916 : 5760
(Other) : 8810676 (Other):8953440 (Other):5101200 (Other): 11760 (Other) :1484640
      tcpwin      icmpcode      info      path
- :4090560 - :9036720 - :9036720 - :10866000 - : 240
0 :5268000 134 : 7920 0:1676400 1: 240 RECEIVE:7463280
1024:1469760 135: 57360 9:153120 SEND :3402720
8192: 37920 136: 50400
5 : 720
8 :1713120
```

Fig. 10. Summary analysis of mergedLogDataSet

3) *Null Hypothesis and Binomial Exact Analysis:* The summary analysis presented is only superficial data, however the firewall log file was very large. Therefore, for ordinary users, it is very difficult to extract meaningful security information from this firewall log. The first step for a user would be to decide whether the collected traffic data is close to the normal/ideal traffic level or not. Thus, a different statistical analysis is required to assess the current security status of the desktop. The null hypothesis in R is the simplest analysis to compare the statistical significance of the data without complicating the analysis with further details. The central action of any firewall is to allow or drop packets based on their rules. For this, the “table()” function displays a table of the counts at each combination of the factor levels. In Fig. 11, table() function displays and simplifies the firewall actions against all 10866240 packets, where 7952160 packets are “allowed” and 2913840 packets are “dropped”. Therefore, based on the number of packets allowed (successes), the null hypothesis is constructed to determine the collected traffic status/level.

In the null hypothesis, the number of allowed packets

```
> table(mergedLogDataSet$action)

      ALLOW      DROP  INFO-EVENTS-LOST
7952160    2913840                240
```

Fig. 11. Summary of allow, drop and lost packets

(7952160) was compared with the ideal traffic condition when all the packets (10866240) could have been allowed for checking the statistical similarity between the two samples, so the desktop security level could be assessed with its ideal traffic condition. With the significance level = 0.05 and the level of confidence = 95%, the p-value given by the prop.test() function was $2.2e - 16$ (i.e., p-value < .Machine\$double.eps in R) as shown in Fig. 12. This value $2.2 * 10^{-16}$ (0.000000000000000022) was effectively close to zero (actually numerically indistinguishable from 0) and much smaller than the value (0.05) of the significance level. Additionally, the value 0 did not lie within the confidence interval (-0.2684409 and -0.2679139) as shown in Fig. 12. Therefore, the correlation was statistically significant, and the null hypothesis was rejected with the high degree of significance. This result stated that the desktop's current traffic condition was not normal and, thus, there was a need for further detailed investigation about the types of attacks/threats.

```
> prop.test(c(7952160, 10866240), c(10866240, 10866240))

2-sample test for equality of proportions with continuity correction

data:  c(7952160, 10866240) out of c(10866240, 10866240)
X-squared = 3365300, df = 1, p-value < 2.2e-16
alternative hypothesis: two.sided
95 percent confidence interval:
 -0.2684409 -0.2679139
sample estimates:
 prop 1      prop 2 
0.7318226 1.0000000
```

Fig. 12. Null hypothesis analysis to determine the desktop security status based on the allowed traffic

The results of the null hypothesis test were also verified precisely by the Binomial exact test in R. In Fig. 12, the probability of successes (in this case allowed packets) is $0.7318226 \approx 0.73$. Therefore, the Binomial exact value was calculated using the binom.test() function as shown in Fig.13. However, the p-value was the same as the previous p-value calculated by prop.test() function. Thus, both tests rejected the null hypothesis with the significance level = 0.05 and the level of confidence = 95%. Consequently, a further detailed analysis was required to obtain the nature of the risks and attacks to the desktop.

```
> binom.test(7952160, 10866240, 0.73)

Exact binomial test

data:  7952160 and 10866240
number of successes = 7952200, number of trials = 10866000, p-value < 2.2e-16
alternative hypothesis: true probability of success is not equal to 0.73
95 percent confidence interval:
 0.7315591 0.7320860
sample estimates:
probability of success
0.7318226
```

Fig. 13. Binomial exact analysis to determine the desktop security status based on the allowed traffic

4) ICMP/TCP/UDP Packets and IP Address Analysis:

The null hypothesis and binomial analysis led to the further investigation of the firewall log to identify the causes of security breaches. In the summary analysis results shown in Fig. 10, the protocols and IP address related information could be easily observed and useful to analyse the causes. Fig. 14 shows the summary table of the total ICMP, TCP, and UDP packets recorded in firewall logs over the simulation period. In Windows Firewall, the protocol options available are TCP, UDP, ICMP, and a protocol number for packets that are not TCP, UDP, or ICMP. Therefore, "2" is a protocol number and "-" is used for the lost packets (see Info-Events-Lost in Fig. 11).

```
> table(mergedLogDataSet$protocol)

-      2  ICMP  TCP  UDP
240  1200 1829520 6775680 2259600
```

Fig. 14. Summary of total ICMP, TCP, and UDP packets

Here, Figs. 15 and 16 show the detailed analysis of the two protocols ICMP and TCP, and two computer systems with IP addresses: 192.168.0.50 and 192.168.0.51. The system with IP address 192.168.0.50 was blocked for only ICMP packets during the experiment for the maximum period of time but not for the entire duration. Therefore, Fig. 15 shows almost all ICMP packets (350640) as the dropped packets where the source IP address was 192.168.0.50. Another rule was written for the host (192.168.0.154) to stop any outgoing ICMP packets; consequently, all 532800 packets were dropped, which were tried to send to the destination IP address 192.168.0.50. However, other TCP and UDP packets were allowed through the firewall. The system with IP address 192.168.0.51 was blocked

```
> table(mergedLogDataSet$protocol[mergedLogDataSet$src.ip=="192.168.0.50"])

-      2  ICMP  TCP  UDP
0      0 354240 3705120 162720

> table(mergedLogDataSet$protocol[mergedLogDataSet$src.ip=="192.168.0.50" & mergedLogDataSet$action=="DROP"])

-      2  ICMP  TCP  UDP
0      0 350640      0      0

> table(mergedLogDataSet$protocol[mergedLogDataSet$dst.ip=="192.168.0.50"])

-      2  ICMP  TCP  UDP
0      0 532800      0  480

> table(mergedLogDataSet$protocol[mergedLogDataSet$dst.ip=="192.168.0.50" & mergedLogDataSet$action=="DROP"])

-      2  ICMP  TCP  UDP
0      0 532800      0      0
```

Fig. 15. Summary of protocols for IP address 192.168.0.50

for only TCP packets during the experiment for the maximum period of time but not for the entire duration. Therefore, Fig. 16 shows almost all TCP packets (1507680) as the dropped packets where the source IP address was 192.168.0.51. The previously written rule for the host (192.168.0.154) to stop any outgoing ICMP packets also enforced here; consequently, all 522720 packets were dropped, which were tried to send to the destination IP address 192.168.0.51. However, other TCP and UDP packets were allowed through the firewall.

5) *Designing the Fuzzy Inference System for Predicting Risk of Attack:* An analysis often requires the modelling and development of an intelligent system for future incident response and prevention purposes [19]. R is a powerful analysis tool which hosts several CI packages related to artificial neural networks, evolutionary algorithms, fuzzy systems and hybrid intelligent systems for designing intelligent systems.

```

> table(mergedLogDataSet$protocol[mergedLogDataSet$src.ip=="192.168.0.51"])
  -      2  ICMP  TCP  UDP
  0 480 303360 1519200 880800
> table(mergedLogDataSet$protocol[mergedLogDataSet$src.ip=="192.168.0.51" & mergedLogDataSet$action=="DROP"])
  -      2  ICMP  TCP  UDP
  0      0      0 1507680  0
> table(mergedLogDataSet$protocol[mergedLogDataSet$dst.ip=="192.168.0.51"])
  -      2  ICMP  TCP  UDP
  0 522720  0 1440
> table(mergedLogDataSet$protocol[mergedLogDataSet$dst.ip=="192.168.0.51" & mergedLogDataSet$action=="DROP"])
  -      2  ICMP  TCP  UDP
  0 522720  0      0

```

Fig. 16. Summary of protocols for IP address 192.168.0.51

Additionally, the use of all these CI techniques in **R** is relatively easy as compared to several other analysis packages. Here, a fuzzy inference system is designed using a *sets* package (see Fig. 17) to predict the risk of attack based on the previous analysis. This is a quite simple design accomplished in only two stages as shown in Figs. 18 and 19.

Previous analyses revealed useful information about the traffic data and security issues. However, it does not offer any model to cope with future attacks, and the only way to protect systems from future attacks is still the Firewall rules. Nonetheless, this information can be used to build an intelligent model to monitor future attacks [10], [11], [12], [13]. The detailed analysis of the “mergedLog” file and its dataset revealed that the rate of ICMP and TCP packets may help system to predict the future risk of the attack in addition to the Firewall rules. Subsequently, for the baselining of this host, the range of ICMP packets (0-2000 packets/second) and TCP packets (0-8000 packets/second) were determined to decide the normal and abnormal traffic conditions. The baseline information is used to design two fuzzy input variables *icmprate* and *tcpate*; further details can be found in [10], [11], [12], [13]. Based on these two fuzzy input variables, the fuzzy output variable *attackrisk* is determined which predicts the risk of an attack in percentage (0-100). All the fuzzy input and output variables are divided into three fuzzy range *low*, *medium* and *high* as shown in Fig. 18. Afterwards, a sample fuzzy rule base (see Fig. 19) is designed for the fuzzy inference system (see Fig. 20) to predict the risk of attack. This system can be employed alongside Firewall rules to predict the possibility and level of an attack which is not possible in Windows Firewall; further details can be found in [10], [11], [12], [13].

```

> install.packages("sets")
% Total % Received % Xferd Average Speed Time Time Time Current
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
:00:01 --:--:-- 382k

```

The downloaded binary packages are in
/var/folders/g3/94x8nbd77jc16s4xmkp0j_000000gn/T//RtmpUd7gTu/downloaded_packages

```

> library(sets)

```

Fig. 17. Installation of Sets package for designing a fuzzy inference system in **R**

This simple and easy design of the fuzzy intelligent system in **R** to monitor and predict the risk of an attack is only one example of the strength of **R** and its support for CI techniques. The other CI techniques such as artificial neural networks, evolutionary algorithms and hybrid intelligent systems can also be used in the same way to design various intelligent systems. Additionally, the baseline analysis and range of parameters can be adjusted and manipulated depending on the requirement of a particular host/network.

```

> variables <-
  set(icmprate =
    fuzzy_variable(low =
      fuzzy_triangular(corners = c(0, 300, 600)),
      medium =
        fuzzy_triangular(corners = c(500, 850, 1200)),
      high =
        fuzzy_triangular(corners = c(1000, 1500, 2000))),
    tcpate =
      fuzzy_variable(low =
        fuzzy_triangular(corners = c(0, 1500, 3000)),
        medium =
          fuzzy_triangular(corners = c(2000, 3500, 5000)),
        high =
          fuzzy_triangular(corners = c(4000, 6000, 8000))),
    attackrisk =
      fuzzy_variable(low =
        fuzzy_triangular(corners = c(0, 20, 40)),
        medium =
          fuzzy_triangular(corners = c(30, 50, 70)),
        high =
          fuzzy_triangular(corners = c(60, 80, 100)))
  )

```

Fig. 18. Defining linguistic fuzzy variables in **R**

```

> rules <-
  set(
    fuzzy_rule(icmprate %is% low && tcpate %is% low,
      attackrisk %is% low),
    fuzzy_rule(icmprate %is% low && tcpate %is% medium,
      attackrisk %is% medium),
    fuzzy_rule(icmprate %is% low && tcpate %is% high,
      attackrisk %is% high),
    fuzzy_rule(icmprate %is% high && tcpate %is% medium,
      attackrisk %is% medium),
    fuzzy_rule(icmprate %is% medium && tcpate %is% high,
      attackrisk %is% high),
    fuzzy_rule(icmprate %is% high && tcpate %is% high,
      attackrisk %is% high)
  )

```

Fig. 19. Designing fuzzy rule base in **R**

E. Visual Interpretation of Security Analysis Findings using Graphs in **R**

The final step of this security analysis approach is to present the findings in simple readable and visualised format. **R** is a very powerful tool for data visualisation due to many external packages such as lattice, ggplot2, vcd or hexbin for the enhanced graphics presentation of information [20]. In this security analysis, some of the main findings are presented using the simple built-in graph function “plot”, however, the advanced package “ggplot2” can also be used to give a more informative and appealing presentation. Fig. 21 uses the plot command and Fig. 22 depicts its resultant information about all allowed, dropped and lost packets, showing that the desktop allowed 73% of packets as compared to the dropped and lost 27% of packets. Fig. 23 uses the plot command to draw source IP addresses and their corresponding actions. Fig. 24 shows the resultant graph of the plot command indicating how many packets were allowed or dropped from the particular source IP address. The red and green colours shows allowed and dropped packets respectively for that source IP address.

Similarly, Fig. 25 uses the plot command to draw destination IP addresses and their corresponding actions. Fig. 26 shows the resultant graph of the plot command indicating how many packets were allowed or dropped for the particular destination IP address. The red colour shows allowed packets and cyan colour shows dropped packets for that destination IP

```
> system <- fuzzy_system(variables, rules)
> print(system)
A fuzzy system consisting of 3 variables and 6 rules.
```

Variables:

```
attackrisk(low, medium, high)
icmprate(low, medium, high)
tcprate(low, medium, high)
```

Rules:

```
icmprate %is% low && tcprate %is% high => attackrisk %is% high
icmprate %is% low && tcprate %is% medium => attackrisk %is% medium
icmprate %is% low && tcprate %is% low => attackrisk %is% low
icmprate %is% high && tcprate %is% high => attackrisk %is% high
icmprate %is% medium && tcprate %is% high => attackrisk %is% high
icmprate %is% medium && tcprate %is% medium => attackrisk %is% medium
```

Fig. 20. Resultant fuzzy inference system in R

```
> plot(mergedLogDataSet$action, main="Allowed and Dropped Packets",
xlab="Action", ylab="Number of Packets", las=1, col=rainbow(3), col.lab="blue")
```

Fig. 21. Plot command to draw allowed and dropped packets

address. In all security analyses, the nature of the analysis and its interpretations are determined by the user/analyst.

IV. BIG DATA SCALABILITY OF APPROACH FOR DESKTOP USERS

Any big data analysis approach for desktop users should be able to cope with the *variety* of data, increasing *volume* of data, and *velocity* of data (real time processing) on their desktops. Today’s desktops consist of multi-core processors and increased memory. **R** is employed in the proposed approach and it can achieve this goal; however, it requires the support of additional packages to handle variety of data and make the optimised use of memory and processor [21], [22], [23], [24].

R can handle a variety of data such as spreadsheet-like data, relational databases, binary files: image files and XML documents [21]. It can also import data from other statistical systems such as EpiInfo, Minitab, S-PLUS, SAS, SPSS, Stata,

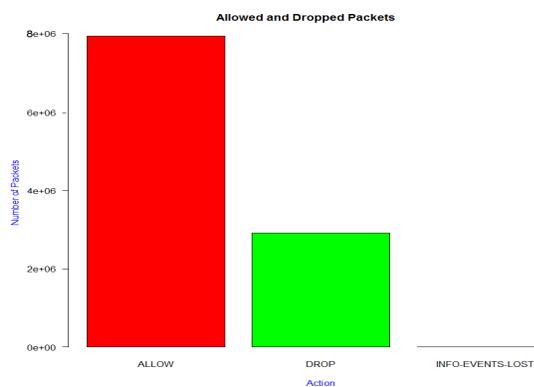


Fig. 22. Illustration of allowed and dropped packets

```
> plot(mergedLogDataSet$src.ip, mergedLogDataSet$action, main="Source IP Address vs. Action",
xlab="Source IP Address", ylab="Action", col=rainbow(5))
```

Fig. 23. Plot command to draw source IP address and corresponding actions

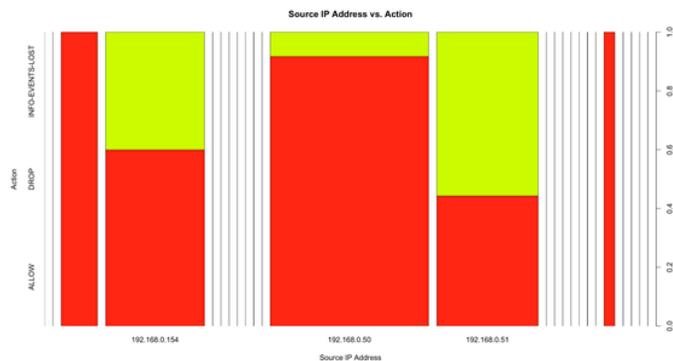


Fig. 24. Illustration of source IP address and corresponding actions

```
> plot(mergedLogDataSet$dst.ip, mergedLogDataSet$action, main="Destination IP Address vs. Action",
xlab="Destination IP Address", ylab="Action", col=rainbow(2))
```

Fig. 25. Plot command to draw destination IP address and corresponding actions

Systat [21]. However, it requires the support of some additional packages to handle variety of data. The easiest form of data to import into or export from **R** is a simple text file (log file).

R consists of several packages to deal with increasing volume of data with limited memory. If the file size is quite large as compared to the existing memory of the system, then the “ff” package can be used to perform effective and fast data processing. The “ff” package provides data structures that are stored on disk but behave as if they were in RAM by transparently mapping only a section (pages) in main memory, the effective virtual memory consumption per “ff” object [25]. Another solution to the handling of increasing volume of data is the “big” package family that consists of several packages for performing tasks on large datasets such as bigmemory [26], biganalytics, bigtabulate, synchronicity and bigalgebra [23].

Since its inception, **R** was designed to use only a single thread (processor) at a time. Today, **R** operates the same way unless linked with multi-core/multi-threaded libraries [22]. The multi-core machines of today offer parallel processing power, therefore, to make use of multiple cores, **R** requires the support of add-on packages related to High-Performance and Parallel Computing (HPPC) [27]. There are several packages available for parallel processing in **R** such as parallel, multicore, snow, snowfall, Rmpi, pbdMPI, Rborist, h2o, randomForestSRC,

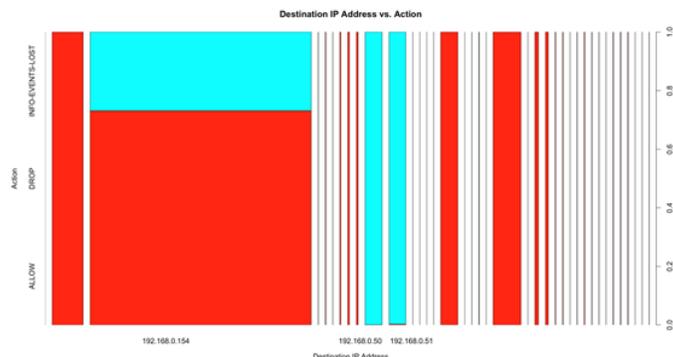


Fig. 26. Illustration of destination IP address and corresponding actions

Rdsm, Rhpc. Package “parallel” is built on packages “multicore” and “snow” and provides replacements for most of the functionality of these packages [28]. Package “parallel” handles running much larger chunks of computations in parallel. A typical example is to evaluate the same **R** function on many different sets of data. For Windows desktop users, Microsoft **R** Open includes multi-threaded math libraries to improve the performance of **R** and also works on all OS Windows/Unix/Mac [29]. These libraries make it possible for several common **R** operations, such as matrix multiply/inverse, matrix decomposition, and some higher-level matrix operations, to compute in parallel and use all of the processing power available to reduce computation times [30].

V. CONCLUSION

This paper has presented an intuitive and inexpensive big data security analysis approach using Computational Intelligence (CI) techniques for Windows desktop users. It is based on the combination of Windows batch script, EmEditor (which can be replaced with any powerful editor) and **R**. This security analysis approach was carried out on a real dataset of 1,006,889,160 bytes (1.01 GB) with more than 10 million observations, which were collected in the Windows Firewall log file “pfirewall.log” and integrated into the “mergedLog” file over the period of 30 days. This desktop-oriented security analysis deduced the security status of the desktop, and sources and causes of the security breaches successfully. Based on the analyses results, a fuzzy inference system was designed to predict the risk of attack and protect the desktop. This security analysis approach and its successful implementation on the modest desktop configuration demonstrates the potential of the proposed approach. However, this particular implementation was limited to the simulated data based on certain firewall rules, a small number of protocols and IP addresses; it would be important to extend rules and areas of investigation, and collect external traffic for making this approach a generalised security analysis approach.

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