
# DATA DRIVEN DEVICE FAILURE PREDICTION

THESIS

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# Abstract

As society becomes more dependent upon computer systems to perform increasingly critical tasks, ensuring those systems do not fail also becomes more important. The Air Force, much like many other organizations, depends heavily on desktop computers for day to day operations. Unfortunately, the software that runs on these desktop computers is still written by humans and as such, is still subject to human error and consequent failure. A natural solution is to use statistical machine learning to predict failure. However, since failure is still a relatively rare event, obtaining labelled training data to train these models is not trivial. This work explores predicting failure in the Microsoft enterprise authentication service using realistically generated failure data in an effort to increase up-time in desktop computers and improve mission effectiveness.

# Acknowledgments

Nothing worth doing, is possible alone. This work is no exception. Thanks to my advisors, course instructors, and committee members for working with me and guiding me through this exciting endevour. Thanks to my fellow classmates for commiserating with me through the unrelenting flood of coursework. Finally, but most importantly, thanks to my wife for always being there, supporting my often erratic work schedule, and making sure I never forgot to eat.

Paul L. Jordan

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# I. Introduction

As dependency upon computers grows, so too do the associated risks. Computer systems are all around us. Some of these computer systems play insignificant roles in our lives while others are responsible for sustaining our lives. Unfortunately, the software that controls these systems is written by humans and consequently subject to human error. As a result, these systems are prone to failure which in many cases is insignificant, but in others, could have severe consequences. Every day, critical infrastructure and Air Force missions systems depend on the reliability of computer systems. As a result, being able to predict pending failure in computer systems can offer tremendous, and potentially life-saving applications in today's technologically advanced world. While actually being able to accurately predict failure has unfortunately not been proven possible, there has been work over the past several decades attempting to make educated predictions about the failure of machines through the use of machine learning algorithms [23]. Unfortunately, much of this work has gone unused.

Failure has been defined as the result of a software fault or error. There a number of ways to reduce the number of errors produced by a piece of software, but the software development life-cycle is shrinking and less time and effort are being devoted to reducing errors before deployment. This leaves real-time error prevention or handling. In recent years, it seems the recommended solution to this problem is to make massively redundant systems that can withstand failure [2]. As hardware becomes more affordable, this is an effective approach in many ways, but ultimately is still

not cost efficient. In some cases, funds may not be available to achieve this sort of redundancy. Consequently, this research focuses on a small piece of the general field of reliable computing: Online Failure Prediction (OFP). OFP is the act of attempting to predict when failures are likely so that they can be avoided. Chapter II outlines the recent work done in this field, much of which has gone unimplemented due to the complex and manual task of training a prediction model. If the underlying system changes, the efficacy of a prediction model can be drastically reduced until it is re-trained. Furthermore, training requires access to labelled training data. Since failure is such a rare event, access to this type of training data may not be possible.

Irrera et al. [15] presented a framework in 2015 to automate the process of dynamically generating failure data and using it to train a predictor after an underlying system change. This framework is called the Adaptive Failure Prediction (AFP) Framework and this research explores an implementation of it. More specifically, this research presents results after implementing a modernized AFP using a Microsoft (MS) Windows Server Domain Controller (DC) that is capable of generating more diverse and specific failure data for training. Successive software updates are then applied until the model selected becomes useless, the framework is then allowed to re-train a new more effective predictor.

## 1.1 Problem Statement

According to the operators in the operational community, predicting and alerting on impending network service failures currently uses thresholds and rules on discrete items in enterprise system logs. For example, if the Central Processing Unit (CPU) and memory usage on a device exceeds 90%, then an alert may be issued. This approach works, but only for certain types of failures and in order to minimize the false positives, it only makes recommendations when the system is already in a

degraded performance mode. To maintain network resilience, the operational organizations responsible for communications support desperately need some means of gaining accuracy and lead-time before a service failure occurs.

To increase that lead time and make more accurate predictions, this research explores predicting failure by analyzing data reported by a target system. Preceding a service failure event, multiple indicators from disparate sources, perhaps over a long period of time, may appear in system logs. The log entries of interest are also quite rare compared with normal operations. Because of these constraints, identifying failure indicators can be nearly impossible for humans to perform. Further, in most cases, restoring service is more important than identifying the indicators that may or may not have existed.

Failure prediction can be approached in several ways. For example, the simplest approach is to use everyday statistical analysis to determine the mean time between failures of specific components. The analysis of all components making up a system can be aggregated to make predictions about that system using a set of statistics-based or business-relevant rules. Unfortunately, the complexity of modern architectures has outpaced such off-line statistical-based analysis. OFP differs from other means of failure prediction in that it focuses on classifying the current running state of a machine as either failure prone or not, or in such a way that it describes the confidence in how failure prone a system is at present [23].

In recent years much of the work in OFP has gone unused due to the dramatic decrease in cost and complexity involved in building hardware-based redundant systems [15]. Furthermore, in most cases OFP implements machine learning algorithms that require manual re-training after underlying system changes. More troubling is that system changes are becoming more frequent as the software development life cycle moves toward a more continuous integration model. To help solve these chal-

lenges, the framework presented in [15] uses simulated faults to automatically re-train a prediction algorithm to make implementing OFP approaches easier. This work extends that framework to capture developments since its writing and generalize it so it works for a broader class of devices by exploring and developing the fault-load. Specifically, this work explores additional kinds of faults and modernizes the fault injection tool by translating it from the IA32 architecture to the x86-64 architecture.

## 1.2 Hypothesis

The implementation of an AFP framework with a more representative fault load for the MS Windows enterprise infrastructure will lead to accurate failure prediction with better lead time than is available today without any prediction model. This hypothesis is tested by implementing the AFP in a scaled virtual environment and evaluating its performance after successive software updates. Prior to this research, the faults produced and consequently predicted by the AFP were the result of first-order software faults. This research evaluates the performance of the AFP when second and third order faults are introduced. Additionally, the implementation of the AFP was not possible on modern MS Windows infrastructure because the fault injection tool used, had not been written for the x86-64 architecture, and was incapable of injecting faults in protected system processes.

## 1.3 Research Goals

The goal of this research is to inform decision makers about the potential benefits of implementing a machine learning based failure prediction model to predict failures in computer systems. This research should demonstrate the efficacy of the AFP framework and proposed extensions when used on the MS Windows enterprise architecture. A long-term goal of this research is to drive the improvement of the

AFP framework and increase its adoption and resulting cost savings. In the near-term, the increased representativeness of the faults generated should lead to better predictions and increased availability in enterprise services. Finally, the translation of the IA32 General Software Fault Injection Technique (G-SWFIT) tool to the x86-64 architecture should enable the same advantages of software fault injection for 32-bit systems on 64-bit systems [8].

## 1.4 Impact of Research

Every day, many of the Air Force's critical missions depend on computer infrastructure. An essential piece of this infrastructure is the authentication mechanisms that protect sensitive information. Unfortunately, the software at the core of this infrastructure is written and maintained by humans and thus susceptible human error. This research will enable the Air Force and many others that use the MS Enterprise Infrastructure to accurately predict pending service outages thereby providing lead-time in order to avoid those outages. The result is cost savings in personnel and equipment. Further advantages are difficult to quantify such as a decreased risk of mission failure due to network service outage.

## 1.5 Assumptions and Limitations

This research assumes indicators of failure are present and available with enough lead-time to accurately make decisions and take mitigation action should failure be predicted based on these indicators. Furthermore, it has not been proven possible to accurately predict future events without a priori knowledge. This research presents a method of predicting failure, but this method is completely useless at predicting *act of God* events. Finally, this method is capable of predicting system failure based on underlying software faults and not indicators about malicious attacks against the

target system.

## 1.6 Results

Because a prediction method is not presently deployed on any Air Force network, any level of dependable prediction is better than what is currently available. This research shows that after an underlying system change, this method of predicting failure is capable of automatically training a more effective prediction algorithm so that this technique can be implemented on an Air Force network with little to no impact on manpower. Consequently, it is expected that this research will inform decision makers and allow them to implement this technique in a production environment.

Specifically, the technique presented in this research could most effectively be implemented and used by the Cyber Security and Control System (CSCS) weapon system employed at the 561st and 83d Network Operation Squadrons (NOS) and their associated detachments to reduce the number of network service outages, increasing uptime, leading to improved mission effectiveness in both the support and operational domains. Further, this technique is general enough to be employed outside of the Air Force to increase mission effectiveness across the Department of Defense (DOD). External to the DOD, this research further generalizes an approach that could be used to help increase availability of nearly any computer system.

# II. Overview of Online Failure Prediction (OFP)

This chapter reviews current research regarding OFP and its many approaches to build a foundation for this research. Further, the taxonomy of approaches developed by Salfner, et al. [23], is updated by classifying approaches since its publication and creating a new sub-category.

The rest of this chapter is organized as follows. In Section 2.1, a brief background on the topic of OFP is given including definitions, terminology, and measures of performance used by the community. In Section 2.2, the approaches relevant to this research are presented followed by a brief summary in Section 2.3.

## 2.1 Background

In 2010, Salfner, et al. [23] published a survey paper that provides a comprehensive summary of the state of the art on the topic of OFP. In addition to the review of the literature up to the point of publication, they provide a summary of definitions and measures of performance commonly used in the community for couching the OFP discussion.

### 2.1.1 Definitions.

#### 2.1.1.1 Proactive Fault Management (PFM).

Salfner, et al. [23] define PFM as the process by which faults are handled in a proactive way, analogous with *fault tolerance* and basically consisting of four steps: OFP, diagnosis, action scheduling, and action execution as shown in Figure 1. The final three stages of PFM define how much lead time is required to avoid a failure when predicted during OFP. *Lead time* is defined as the time between when failure

is predicted and when that failure will occur. Lead time is one of the most critical elements of a failure prediction approach.

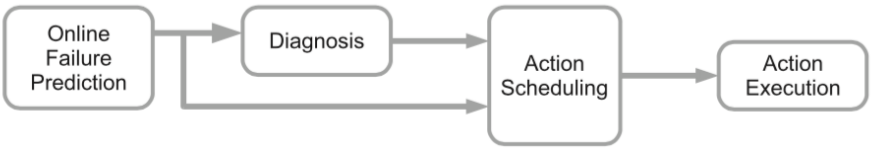



**Figure 1. The stages of proactive fault management [23].**

OFP is defined as the first step in PFM shown in Figure 1. OFP is the act of analyzing the running state of a system in order to predict failure in that system. Once failure has been predicted, a fault tolerant system must determine what will cause the failure. This stage is called the *diagnosis* stage or "root-cause analysis" stage. During the *diagnosis* stage, the analysis must be conducted so that a system knows which remediation actions are possible. After it is determined what will cause a failure, a fault tolerant system must schedule a remediation action that is either performed by an operator or done automatically. This stage is known as the *action scheduling* stage and normally takes as input the cost of performing an action, confidence in prediction, effectiveness/complexity of remedy action and makes a decision about what action to perform based on that input. In some cases a remedy action can be so simple that even if the confidence in the prediction is low, the action can still be performed with little impact on the overall system and its users. A thorough analysis of the trade-off between cost of avoidance and confidence in prediction and the associated benefits is described in [4]. Finally, in order to avoid failure, a system must execute the scheduled remediation action or let an operator know which actions can be taken in a stage called *action execution*.

#### 2.1.1.2 Faults, Errors, Symptoms, and Failures.

This research uses the definitions from [1] as interpreted and extended in [23] for the following terms: failure; error (detected versus undetected); fault; and symptom.

*Failure* is an event that occurs when the delivered service deviates from correct service. In other words, things can go wrong internally; as long as the output of a system is what is expected, failure has not occurred.

An *error* is the part of the total state of the system that may lead to its subsequent service failure. *Errors* are characterized as the point when things go wrong [23]. Fault tolerant systems can handle errors without necessarily evolving into failure. There are two kinds of errors. First, a *detected error* is an error that is reported to a logging service. In other words, if it can be seen in a log then it is a detected error. Second, *undetected errors* are errors that have not been identified by an error detector. Undetected errors are things like memory leaks. The error exists, but as long as there is usable memory, it is not likely to be reported to a logging service. Once the system runs out of usable memory, undetected errors will likely appear in logs and become a detected errors. A *fault* is the hypothesized root cause of an error. Faults can remain dormant for some time before manifesting themselves and causing an incorrect system state. In the memory leak example, the missing *free* statement in the source code would be the fault.

A *symptom* is an out-of-norm behavior of a system's parameters caused by errors, whether detected or undetected. In the memory leak example, a possible symptom of the error might be delayed response times due to sluggish performance of the overall system.

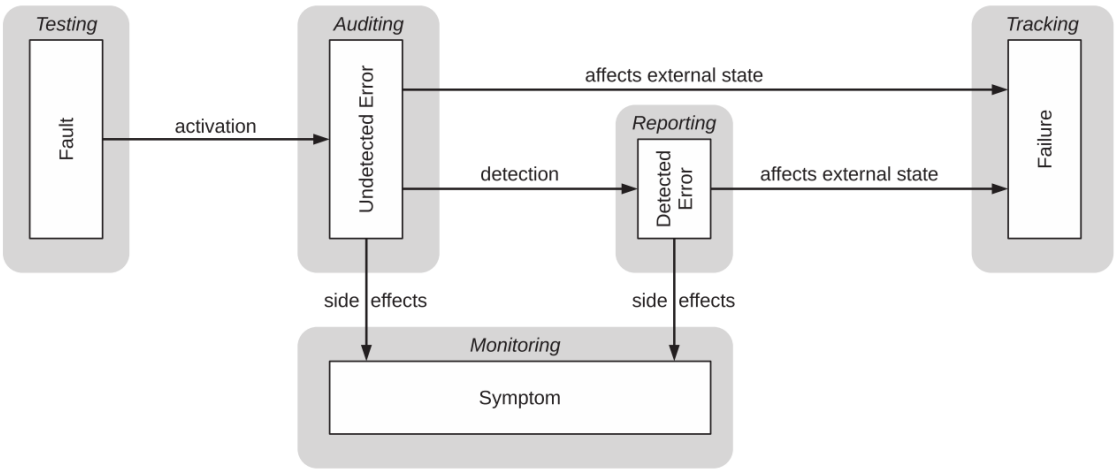



**Figure 2. How faults and errors evolve into failure with the associated methods for detection represented by enclosing gray boxes [23].**

Figure 2 illustrates how a software fault can evolve into a failure. Faults, errors, symptoms, and failures can be further categorized by how they are detected also shown in Figure 2. Salfner, et al. [23] introduces a taxonomy of OFP approaches and classifies failure prediction approaches by the stage at which a fault is detected as it evolves into a failure: auditing, reporting, monitoring, and tracking. Testing is left out because it does not help detect faults in an online sense.

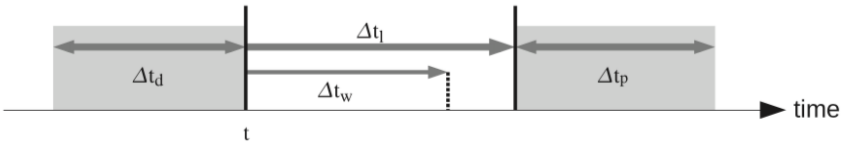



**Figure 3. The timeline for OFP [23].**

Figure 3 demonstrates the timeline associated with OFP. The parameters used by the community to define a predictor are as follows:

- Present Time: $t$

- Lead Time: $\Delta t_l$, is the total time at which a predictor makes an assessment about the current state.
- Data Window: $\Delta t_d$, represents the time from which data is used for a predictor uses to make its assessment.
- Minimal Warning Time: $\Delta t_w$, is the amount of time required to avoid a failure if one is predicted.
- Prediction Period: $\Delta t_p$, is the time for which a prediction is valid. As $\Delta t_p \rightarrow \infty$, the accuracy of the predictor approaches 100% because every system will eventually fail. As this happens, the usefulness of a predictor is diminished.

As the above parameters are adjusted, predictors can become more or less useful. For example, it is clear that as a predictor looks further into the future potentially increasing *lead time*, confidence in its prediction is likely to be reduced. On the other hand, if *lead time* is too small, there will likely not be enough time to effectively take remediation action. In general, OFP approaches seek to find a balance between the parameters, within an acceptable bound depending on application, to achieve the best possible performance.

## 2.2 Approaches to OFP

### 2.2.1 OFP Taxonomy.

The taxonomy by Salfner, et al. [23] classifies many of the OFP approaches in the literature into four major categories. These four major categories are defined by the four techniques used to detect faults in real-time: auditing, monitoring, reporting, and tracking as illustrated in Figure 2. The taxonomy is shown in Figure 4.

Since this research focusses on real-time *data-driven* device failure prediction approaches, our focus is on the *reporting* category of Salfner's taxonomy. The *reporting*

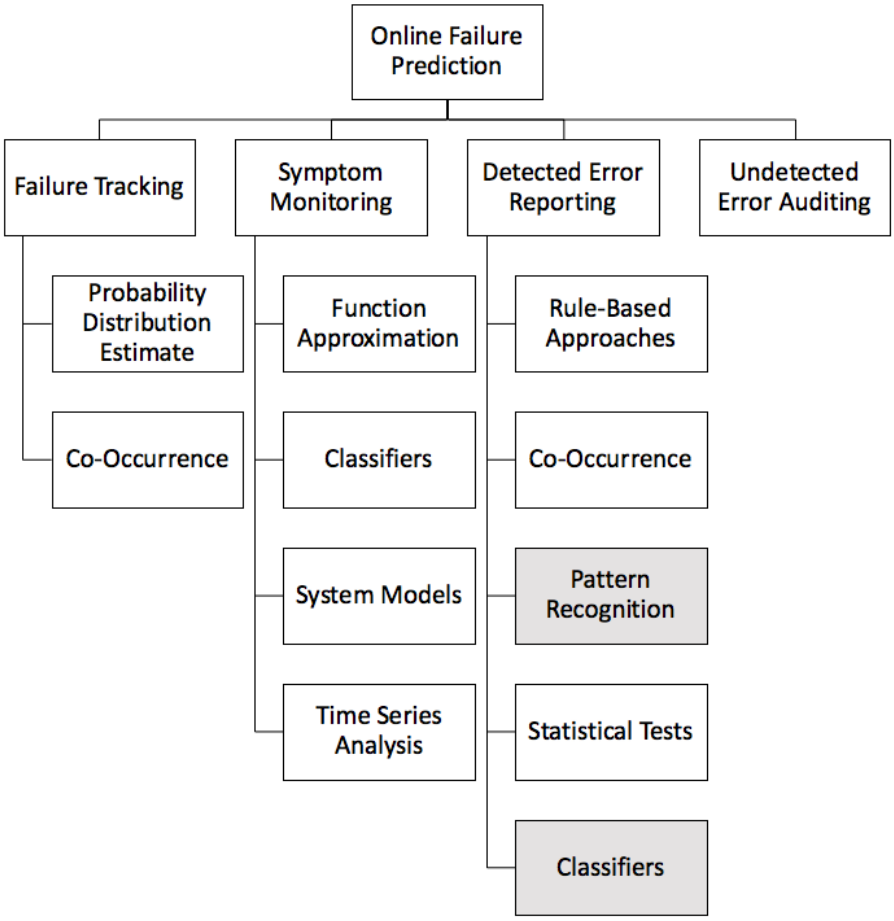



**Figure 4. Taxonomy of approaches to online failure prediction [23]. The two categories into which this research falls are highlighted.**

category organizes failure prediction techniques that attempt to classify a state as failure prone based on reported errors. Salfner, et al. [23] further organize the reporting category into five sub-categories: rule-based systems; co-occurrence; pattern recognition; statistical tests; and classifiers.

*Rule-Based Systems* attempt to classify a system as being failure-prone or not based a set of conditions met by reported errors. Since modern systems are far too complex to build a set of conditions manually, these approaches seek to find automated ways of identifying these conditions in training data. *Co-occurrence* predictors

generate failure predictions based on the reported errors that occur either spatially or temporally close together. *Pattern Recognition* predictors attempt to classify patterns of reported errors as failure prone. *Statistical Tests* attempt to classify a system as failure-prone based on statistical analysis of historical data. For example, if a system is generating a much larger volume of error reports than it typically does, it may be a sign of pending failure. *Classifiers* assign labels to given sets of error reports in training data and then make failure predictions based on observed labels in real-time data.

This research focusses on pattern recognition OFP approaches, which are shown in Figure 5. Strategies employed in the other sub-categories are closely related and thus are also explored in this research.

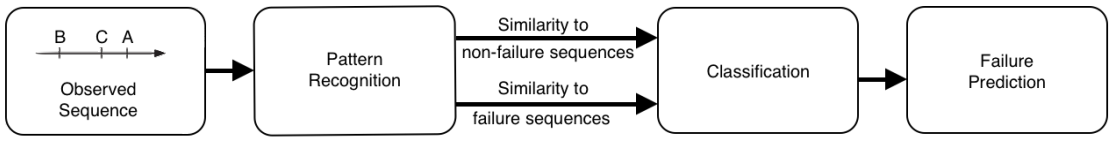



**Figure 5. How pattern recognition is accomplished in reported errors [23].**

### 2.2.2 Data-Driven OFP.

#### 2.2.2.1 Pattern Recognition.

Salfner, et al. [25] proposed an approach to predicting failures by learning patterns of similar events using a semi-Markov chain model. The model learned patterns of error reports that led to failure by mapping the reported errors to the states in the Markov chain and predicted the probability of the transition to a failure-prone state. They tested the model using performance failures of a telecommunication system and reported a precision of 0.8, recall of 0.923, and an F-measure of 0.8571, which drastically outperformed the models to which it was compared.

Given the results, the semi-Markov Chain model is compelling however, it depends on the sequence of reported errors to remain constant in order to be effective. Today, most software is multi-threaded or distributed so there is no guarantee that the sequence of reported errors will remain constant. Further, the authors reported that this approach did not scale well as the complexity of the reported errors grew.

In 2007, Salfner, et al. extended their previous work in [25] using semi-Markov models [24]. They generalized the Hidden Semi-Markov process for a continuous-time model and called it the Generalized Hidden Semi-Markov Model (GHSMM). By making this generalization, the model was able to effectively predict the sequence of similar events (or in this case, errors) in the continuous time domain. The authors then tested the model and training algorithm using telecommunication performance failure data and compared it to three other approaches. While this GHSMM model did not perform as well as their previous work, it did outperform the models to which it was compared and more importantly did not depend on the sequence of reported errors. In other words, this new GHSMM model predicted failure for permutations of a known failure-prone sequence making it more suited for a distributed or parallel system.

The GHSMM approach has been well received by the community, although appears to be limited in use to a single system. Unfortunately, this approach as well as its predecessor, does not scale well and does not adapt to changes to the underlying system without retraining.

#### 2.2.2.2 Classifiers.

Domeniconi, et al. [7] published a technique that used Support Vector Machine (SVM) to classify the present state as either failure prone or not based on a window of error reports as an input vector. As Salfner points out in [23], this SVM approach

would not be useful without some sort of transformation of the input vector since the exact same sequence of error messages, rotated by one message, would not be classified as similar. To solve this permutation challenge, the authors in [7] used singular value decomposition to isolate the sequence of error reports that led to a failure.

This SVM approach used training data from a production computer environment with 750 hosts over a period of 30 days. The types of failures the system was trying to detect was the inability to route to a web-page and an arbitrary node being down. Many approaches involving SVMs have been explored since and seem to be popular in the community [7, 9, 10, 15, 20].

#### 2.2.2.3 Hybrid Approaches.

*Fujitsu Labs* has published several papers on an approach for predicting failure in a cloud-computing environment [27, 31, 32]. Watanabe, et al. [31, 32] report on findings after applying a Bayesian learning approach to detect patterns in similar log messages. Their approach abstracts the log messages by breaking them down into single words and categorizing them based on the number of identical words between multiple messages. This hybrid approach removes the details from the messages, like node identifier, and Internet Protocol (IP) address while retaining meaning of the log message.

Watanabe et al.'s [31] hybrid approach attempts to solve the problem of underlying system changes by learning new patterns of messages in real-time. As new messages come in, the model actively updates the probability of failure by Bayesian inference based on the number of messages of a certain type that have occurred within a certain time window. The authors claim that their approach solves three problems: 1) The model is not dependent upon a certain lexicon used to report errors to handle different

messages from different vendors; 2) The model does not take into account the order of messages necessarily so in a cloud environment where messages may arrive in different orders, the model is still effective; and 3) The model actively retrains itself so manual re-training does not need to occur after system updates. The model was then tested in a cloud environment over a ninety day period. The authors reported a precision of 0.8 and a recall of 0.9, resulting in an F-measure of 0.847.

Fronza, et al. [9] introduced a pattern-recognition/classifier hybrid approach that used an SVM to detect patterns in log messages that would lead to failure. The authors used random indexing to solve the problem previously discussed of SVMs failing to classify two sequences as similar if they are offset by one error report. The authors report that their predictor was able to almost perfectly detect non-failure conditions but was poor at identifying failures. The authors then weighted the SVMs to account for this discrepancy by assigning a larger penalty for false negatives than false positives and had better results.

### 2.2.3 Industry Approaches to OFP.

Because hardware has become so easy to acquire, industry has sought to avoid the problem of software failure by implementing massive redundancy in their systems. The work in [15, 31] attributes the problem avoidance to the fact that until recently, implementing and maintaining a failure predictor was difficult. As we decrease the length of the software development life cycle, software updates are being published with increasing frequency leading to rapid changes in underlying systems. These changes can often render a predictor useless without re-training, which is often a manual and resource intensive process.

Redundancy is not without problems however. Implementing redundant systems to avoid the failure problem can be expensive and can add overhead and complexity

making a system more difficult to manage.

### 2.2.4 Adaptive Failure Prediction (AFP) Framework.

The AFP Framework by Irrera, et al. [15] shown in Figure 6, presents a new approach to maintaining the efficacy of failure predictors given underlying system changes. The authors conducted a case study implementing the framework using virtualization and fault injection on a web server.

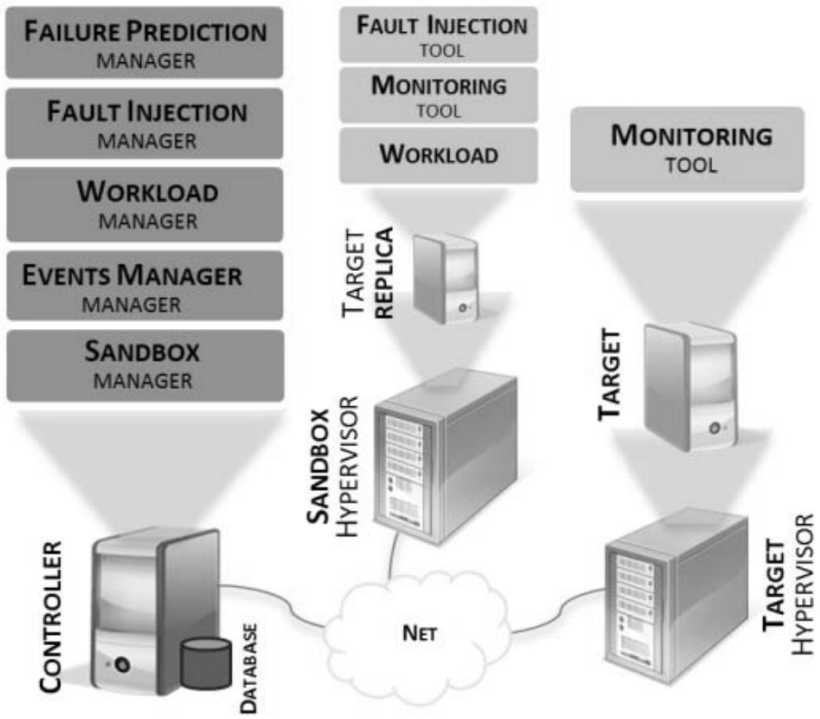



**Figure 6. How the AFP framework is implemented [15].**

The framework built upon past work by Irrera, et al. [11, 14] to generate failure data by injecting software faults using a tool based on General Software Fault Injection Technique (G-SWFIT) [8] in a virtual environment for comparing and automatically re-training predictors. With the introduction of the framework, Irrera, et al. [15]

report results of a case-study. After implementing the AFP using a web server and an SVM predictor, they report that their findings demonstrate their framework is able to adapt to changes to an underlying system which would normally render a predictor unusable.

In general, the use of simulated data is not well received by the community, however the authors in [12,14] report evidence supporting the claim that simulated failure data is representative of real failure data. Further, the authors suggest that since systems are so frequently updated and failures are in general rare events, real failure data is often not available. Moreover, the literature shows that even if there is a certain type of failure in training data and a predictor can detect and predict that type of error accurately, it will still miss failures not present in the training data. By injecting the types of faults that one can expect, each failure type is represented in the training data.

Irrera, et al. [15] reported good results and concluded that the AFP is an effective tool. Unfortunately, the AFP is not a universal solution and requires significant work to be implemented on a modern Microsoft (MS) Windows enterprise network. Furthermore, the fault load previously explored does not completely represent all possible failures [17].

## 2.3 Summary

This chapter covered the definitions, measures of performance, and approaches that are relevant to this research as organized under the subsection of *reporting* within the OFP field of study. There has been a tremendous amount of research surrounding the topic of OFP and many prediction approaches have been presented. Unfortunately, these approaches do not appear on modern operational systems and failures are still relatively prevalent. Recent approaches as covered here have sought

to make predictors more adaptive to the changes in underlying systems in an effort to make implementing existing failure predictors easier. In this work, we plan to extend the AFP framework and further generalize the approach.

# III. Methodology

The purpose of the Adaptive Failure Prediction (AFP) framework is to automate the generation of realistic labelled failure data for the purposes of automatically training a failure prediction algorithm. The framework breaks down into modules so that it can be more easily adapted for different applications. This chapter presents three topics. The first describes the process that the framework executes in order to generate the labelled training data and train a failure prediction algorithm. The second describes each module of the extended AFP framework. The final section outlines extensions to the AFP not covered in the other two sections.

This chapter outlines the implementation and extensions to the AFP Framework [15] as well as an experiment to validate those extensions and further generalize the framework. The AFP was originally tested on a single system running an operating system that has been deprecated. Consequently, the results from the case study conducted using the AFP are limited in utility and require generalization to be useful to the general community.

## 3.1 Failure Data Generation

This work extends the AFP framework [15] by conducting another case study with an Microsoft (MS) Windows Server acting as an Active Directory (AD) service with a more representative fault load as well as a new implementation of the General Software Fault Injection Technique (G-SWFIT) technique for the x86-64 architecture. The case study is done using three new types of faults: third-party memory leak, third-party Central Processing Unit (CPU) hog, and process memory corruption. For completeness, the standard G-SWFIT technique is also used. Finally, findings are reported after implementing this framework using two different statistical machine

learning techniques: boosted decision trees and Support Vector Machine (SVM). In both cases, feature reduction is performed as is done by Fulp et al. [10], on a sliding time window as is done by Irrera, et al. [13] and Vaarandi [29].

This section outlines the step-by-step procedure by which the extended AFP is evaluated to show how effective it is when used on Windows Server deployments. This is done by dividing the steps taken in an experiment into the three major phases as defined in [15]: preparation phase, execution phase, and training phase.

### 3.1.1 Preparation Phase.

In this phase the AFP is prepared to run for the first time as described in [15]. The Cross Industry Standard Process for Data Mining (CRISP-DM) [5] should be applied to this situation when evaluating how to best apply the AFP for a particular target. For the purposes of this research, our focus is on the MS Windows Directory Services and predicting failure in those services. To demonstrate the efficacy of the AFP, a predictor must be evaluated before and after a significant software update. As a result, the most critical preparation made in evaluating this framework is to hold back all software updates on the target system prior to the first run of the execution phase. The performance of various prediction techniques will be evaluated both before and after the Windows Update is allowed to run. A complete list of the updates installed is shown in Appendix C.

This phase is ultimately the manual act of implementing the framework. Each module of the implementation for this work is detailed in Section 3.2 and is therefore not discussed further here.

### 3.1.2 Execution Phase.

A general outline of this phase is shown in Figure 7. This phase is divided into three major steps: data collection and failure prediction, event checking, and training/update as described in this section.

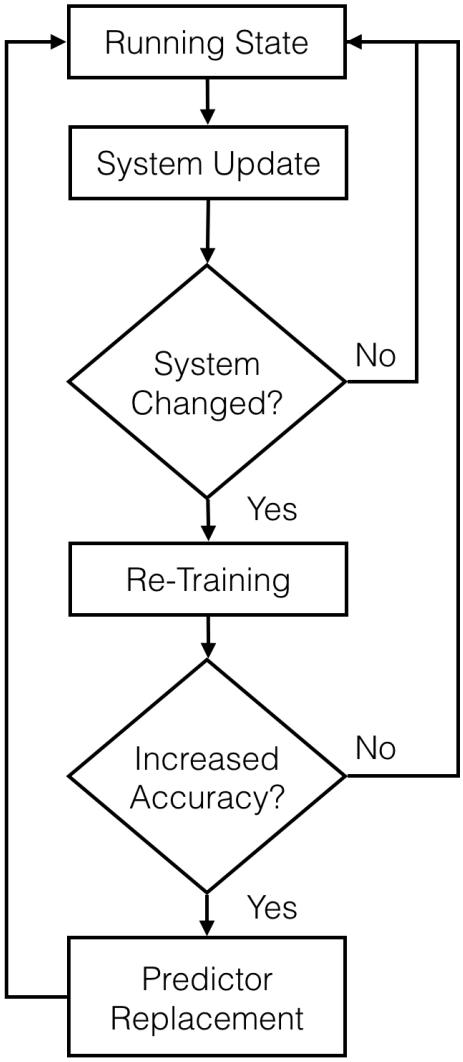



**Figure 7. The flow of the major steps involved in the AFP framework execution phase [15].**

#### 3.1.2.1 Data Collection and Failure Prediction.

In this phase, the system has a working predictor providing input to some sort of decision system. It should be noted here that this decision system does not have to be automated. The system in this phase is making failure predictions about the current state based on the last run of the training phase. This function is not implemented in this research as it is application specific. The output of this process in this experiment is a warning message which indicates failure.

#### 3.1.2.2 Event Checking.

Concurrent with the data collection and failure prediction sub-phase, the AFP continuously monitors events that may alter the underlying system. For this experiment, these events are software updates. The output of each episode of this phase is a binary decision to either begin the training phase, or not. In this experiment, the training phase is manually triggered upon completion of a major software update.

#### 3.1.2.3 Failure Predictor (Re-)Training and Update.

The purpose of this sub-phase is to initiate the training phase and compare its results (a new predictor) with the currently employed predictor. Should the new predictor perform better, the old predictor is replaced by the new.

### 3.1.3 Training Phase.

The training phase is broken down into five major steps: target replication, data generation & collection, dataset building, predictor training, and analysis. The general flow is shown in Figure 8. Each phase is outlined in the following sub-sections.

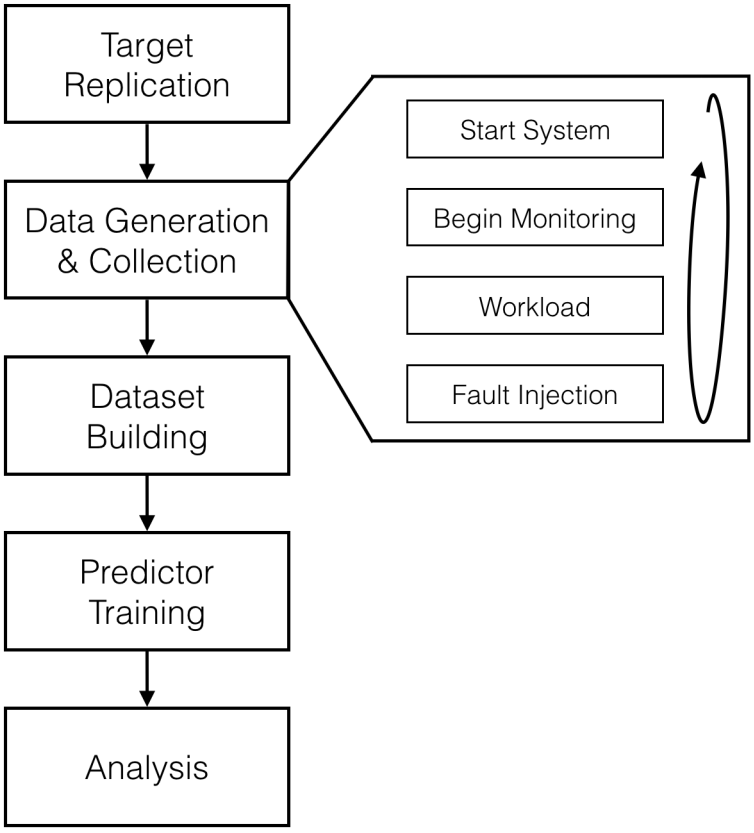



**Figure 8. The flow of the major steps involved in the AFP framework training phase [15].**

#### 3.1.3.1 Target Replication.

During this phase a virtual clone of the target is made. After the clone is made, the fault injection and monitoring software is installed. In this experiment, the monitoring tool is the same as on the production system but care must be taken to ensure the host-name is changed so the log messages generated during this phase are not confused with messages from the production system.

#### 3.1.3.2 Data Generation & Collection.

The purpose of this phase is to generate the data to train a new prediction algorithm. As a result, this sub-phase must be executed several times to generate

statistically meaningful datasets. In this phase, the controller triggers the cloned target startup. Once startup is complete and the system enters an idle state, the monitoring tool begins collecting data from the target. After monitoring has begun, the workload is started. Once the workload has entered a steady state, the fault load is started. Finally, when failure occurs, monitoring stops, the workload stops, and the system is rebooted for the next run. To generate golden data (or data with no failures present to aid training), the first run omits the fault injection step.

The most critical part of this process is labelling the data when failure occurs. For the purposes of this experiment, failure is defined by the log message ID 4625: An account failed to log on[1]. When this occurs in conjunction with known valid credentials on an account that is not disabled, the preceding data window defined for the experiment is labelled as failure prone. Additionally, the workload generator used in this research reports when authentication fails and transmits a syslog message to the controller.

#### 3.1.3.3 Dataset Building.

In this phase, the raw syslog messages are formatted and encoded to train the prediction model. The purpose of this phase is to prepare the raw messages to be used as numeric inputs for the training phase. Irrera, et al. [15] loaded all event messages into a database for processing. In this work, the events are initially stored in a flat file on the Ubuntu machine by the syslog daemon. The raw log messages appear in a flat text file as follows:

```
May  8 14:31:52 dc.afnet.com MSWinEventLog 5 Security 3 Sun May 08 14:31:50 2016 4672 Microsoft-
     Windows-Security-Auditing N/A Audit Success dc.afnet.com 12548 Special privileges assigned to new
      logon. Subject: Security ID: S-1-5-21-2379403389-181978965-2953995107-500 Account Name:
     Administrator Account Domain: AFNET Logon ID: 0x9beb4e7a Privileges: SeSecurityPrivilege
     SeBackupPrivilege SeRestorePrivilege SeTakeOwnershipPrivilege SeDebugPrivilege
```

[1] https://support.microsoft.com/en-us/kb/977519

SeSystemEnvironmentPrivilege SeLoadDriverPrivilege SeImpersonatePrivilege

SeEnableDelegationPrivilege

The messages are formatted using the *Snare*[2] MSWinEventLog format which can be divided into several categories. The first is the time-stamp and host name of the sender prepended by the syslog server daemon: *May 8 14:31:52 dc.afnet.com*. The remainder of the message contains tab delimited values where the keys (and consequent features) are shown in Table 1. Of these features, Criticality, EventLogSource, EventID, SourceName, and CategoryString are selected for further encoding.

**Table 1. Typical authentication message sent as keys that correspond to the values as designated in the *Snare* protocol for MSWinEventLog used by the SolarWinds syslog agent.**

| Key | Value |
|---|---|
| HostName | dc.afnet.com |
| Criticality | 5 |
| EventLogSource | Security |
| Counter | 3 |
| SubmitTime | Sun May 08 14:31:50 2016 |
| EventID | 4672 |
| SourceName | Microsoft-Windows-Security-Auditing |
| UserName | N/A |
| SIDType | Audit Success |
| EventLogType | dc.afnet.com |
| ComputerName | 12548 |
| CategoryString | Special privileges assigned to... |
| ExtendedDataString | Security ID: S-1-5-21-2379403... |

The raw messages are then encoded. First, the events are filtered by EventID as is done by Fulp et al. [10] to reduce the noise generated by successful login attempts. Log messages with IDs shown in Table 2 are filtered from the input.

Next, to encode the time dimension and reduced the sequential message ordering dependency, a sliding time window is created by counting each unique entry for each feature within the data window ($\delta t_d$) as is done by Vaarandi [29]. During this stage,

[2] http://wiki.rsyslog.com/index.php/Snare_and_rsyslog

the number of messages that were reported in the data window is also recorded and used as a feature.

Finally, each time window preceding the failure within $\delta t$ is labelled as failure prone as is done by Irrera, et al. [15]. This encoding enables the use of classification algorithms in the training phase. An example of the final encoding is shown in Table 3.

**Table 2. Microsoft Log Message IDs**[3]

| ID | Message |
|---|---|
| 4624 | An account was successfully logged on. |
| 4634 | An account was logged off. |
| 4672 | Special privileges assigned to new logon. |
| 4769 | A Kerberos service ticket was requested. |
| 4770 | A Kerberos service ticket was renewed. |
| 4776 | The computer attempted to validate the credentials for an account. |

**Table 3. Sample time window after message translation.**

| Predictor | Value |
|---|---|
| FailureWindow | 0 |
| NumObservations | 2 |
| Criticality: 6 | 2 |
| Criticality: 2 | 0 |
| Criticality: 4 | 0 |
| EventLogSource: Application | 1 |
| EventLogSource: System | 1 |

#### 3.1.3.4 Predictor Training.

The purpose of this phase is to use the data generated by the forced failure of the virtual clone to train a machine learning algorithm to classify a system as failure prone or not.

During this phase, each of the $k$ datasets produced by the $k$ runs of the execution phase, each containing a single failure, are used to train a statistical classification

[3] `https://support.microsoft.com/en-us/kb/977519`

model. Each dataset is an $n \times p$ matrix where $n$ is the number of sliding time windows and $p$ is the number of predictors present in the output of the dataset building phase. These $k$ datasets are used to conduct a $k-1$-fold cross validation training and evaluation process where the first $k-2$ datasets are used to train the statistical model. The remaining set is used to validate the trained model. The data is then rotated and repeated $k-1$ times. Parameters for the classification model are selected based on the output of this cross validation. Finally, statistics and performance are reported on the final model's performance on the held out data set.

#### 3.1.3.5 Analysis.

During this phase, the precision, recall, f-measure, and area under the Receiver Operating Characteristic (ROC) curve are computed using the figures measured in the previous phase so that the new predictor can be compared against the old. If a new predictor outperforms the old, the old is replaced with the new. Upon completion of this phase, control flow returns to the *Event Checking* phase.

## 3.2 Implementation of the AFP

### 3.2.1 AFP Framework Implementation.

This experiment replicates the experiment in [15] except in place of the web-server an MS Windows Server running AD Domain Services. In addition, several extensions to the original experiment are made and presented here. Multiple prediction techniques have been applied using this framework to further generalize and validate the framework. The original AFP architecture is shown in Figure 9 with the parts that are modified in this work highlighted.

### 3.2.2 AFP Modules.

Irrera, et al. [15] outline multiple modules into which they have broken the AFP Framework for organizational purposes. This research does not modify these modules, instead, it takes a more granular approach and presents a modified architecture and details each element of that architecture.

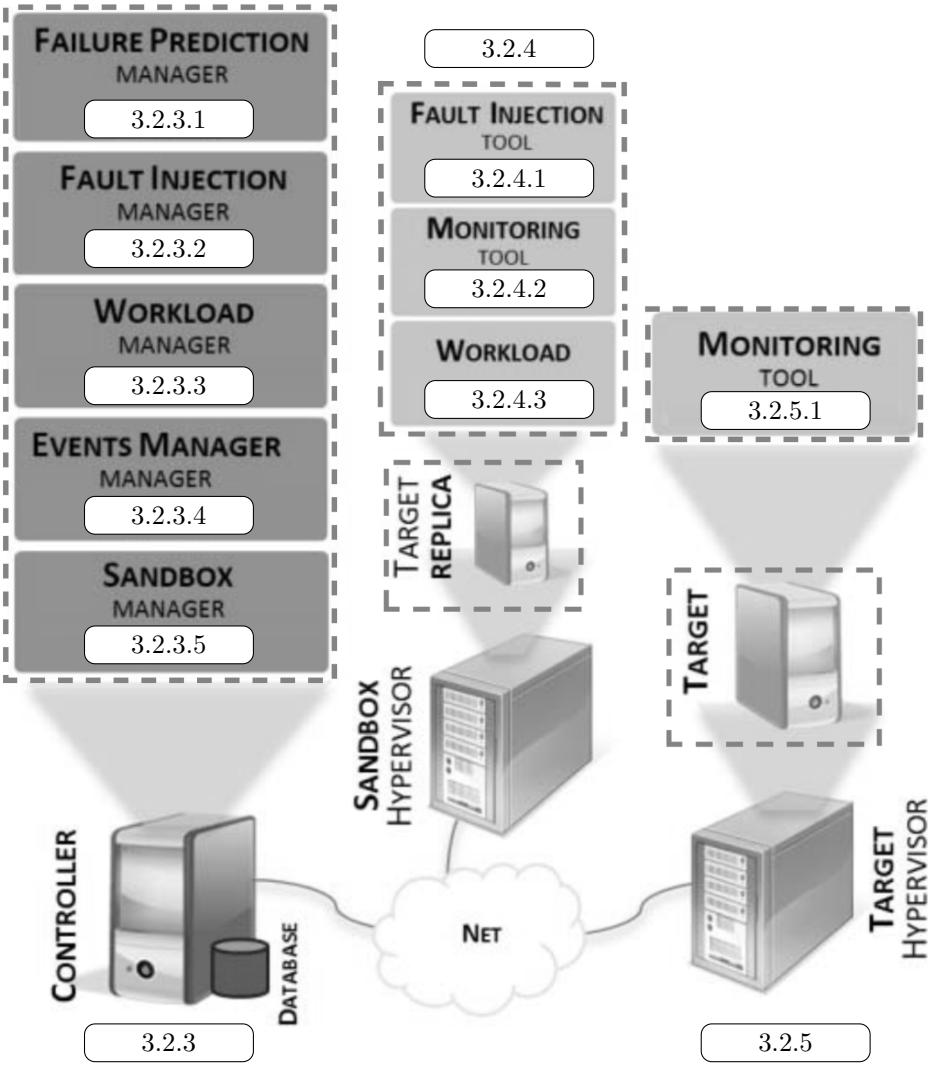



**Figure 9. The AFP framework implementation [15] with modified components highlighted.**

The following sections detail the virtual environment in which this architecture was constructed. For reference, this virtual environment was hosted on two VMWare

ESXi 5.5 hypervisors each with two 2.6 Gigahertz (GHz) AMD Opteron 4180 (6 cores each) CPUs and 64 Gigabyte (GB) memory. The individual Virtual Machine (VM)s are described in Tables 4, and 5.

**Table 4. Hypervisor 1 Configuration (Sandbox/Target).**

| Qty. | Role | Operating System | CPU / Mem. |
|---|---|---|---|
| 1 | DC | Win. Server 2008 R2 | 2 / 2 GB |
| 5 | Client | Win. 7 | 1 / 512 MB |

**Table 5. Hypervisor 2 Configuration (Controller).**

| Qty. | Role | Operating System | CPU / Mem. |
|---|---|---|---|
| 1 | RDP | Win. Server 2008 R2 | 1 / 4 GB |
| 1 | Log | Ubuntu 14.04 LTS | 1 / 1 GB |

### 3.2.3 Controller Hypervisor.

The controller functions in this experiment are split between two systems on a single hypervisor shown in Table 5. One system is an MS Windows Server responsible for workload management and fault injection management. The additional Windows server also hosts remote desktop services to allow the load generator to execute third party authentication with the Domain Controller (DC). The other system is an Ubuntu 14.04 server that performs the failure prediction management and event management. Each of these functions is detailed in the following sections.

#### 3.2.3.1 Failure Prediction.

The failure prediction module predicts failure using machine learning algorithms trained using the labelled training data generated by the rest of this framework. This module is constantly either training a new predictor because a software update occurred, or predicting failure based on log messages and possibly other features produced by the production system.

The AFP failure prediction function as outlined in [15], is performed by a SVM predictor using *libsvm*. Additionally, the original experiment made use of a database that stored the features and observations used for the failure prediction training algorithm. This experiment does not modify the failure prediction module drastically as it has already been shown in previous work that the Online Failure Prediction (OFP) area of study is well explored [23]. This research makes use of a different tool-set to execute the training and predicting phases. Due to its widespread use in the statistical community [16], the prediction and training algorithms make use of the *R* programming language.

#### 3.2.3.2 Fault Injection.

This module is responsible for managing the fault load used to create realistic failure data. Irrera, et al. [15] use a single tool implementing the G-SWFIT for this module and pointed out that this module is the most critical piece of the AFP implementation. G-SWFIT was developed by Duraes, et al. [8] to emulate software failures for the purposes of software testing. The method is widely implemented for use in software fault injection both commercially and academically [6, 14, 21, 28].

Recently, studies have questioned the representativeness of the failures generated by G-SWFIT [6,17]. In each case, the workload generated was critical in creating representative faults. This concern has been addressed in this research and is discussed in Section 3.2.3.3.

An additional concern regarding fault injection has been that some injected faults may not elude modern software testing and as a result never actually occur in production software [21]. The recommended remedy is to conduct source code analysis to determine which pieces of code get executed most frequently and avoid fault injection in those areas. Unfortunately, the target of this research is not an open source project

and as a result, some of the faults and resulting failures may never happen in a production environment. Fortunately, the fault injection tool that has been developed for this research automatically scans each library loaded by the target executable for fault injection points and then is capable of evenly distributing the faults it does inject.

Because of the concerns with fault injection, this research implements three additional types of fault load that more exhaustively represents realistic faults that may be encountered by a target process. This experiment trains a predictor using failures generated by third-party applications purposefully written to slowly consume all available resources on a target system. Specifically, the third-party application contains a memory leak that slowly allocates all free system memory until the target application crashes. Next, failures are recorded as the result of a third-party application consuming all CPU time. Source code for this application is included in Appendix B. Finally, failure is recorded after corrupting heap space in memory (versus program memory as done by the G-SWFIT). This type of fault could be caused by privileged third party applications writing to the target processes allocated memory. Finally, for completeness, this experiment uses a tool developed for this work that implements the G-SWFIT technique.

This work introduces an x86-64 implementation of the G-SWFIT technique called Windows Software Fault Injection Tool (W-SWFIT) for Windows Software Fault Injection Tool. The source code for W-SWFIT has been published as open source on Github[4] so that others may use it for any of the reasons cited in the original G-SWFIT paper [8]. For completeness, the source is also included in Appendix **??**.

For this research, the original plan was to use the same fault injection tool used in the original case study by Irrera, et al. [15]. Unfortunately, that tool, and all

[4] `https://github.com/paullj1/w-swfit/`

prior G-SWFIT implementations were incapable of injecting faults into x86-64 binary executables. Further, many of the commercial products that were evaluated for this research were incapable of dealing with modern Address Space Layout Randomization (ASLR). As a result, W-SWFIT was developed for this research and is capable of injecting faults into all user and kernel mode applications on modern MS Windows operating systems.

The key contributions of W-SWFIT are ASLR adaption, the x86-64 translations that have performed. Further, as pointed out by Irrera, et al. [13], prior implementations of the G-SWFIT were not capable of injecting faults into protected (kernel mode) processes. Since the focus of this research is on a protected system process, this capability was critical, and as a result, W-SWFIT was implemented in a way that made protected process injection possible.

G-SWFIT works by scanning binary libraries already in memory for patterns (or operators) that match compiled errors made during development. The faults were based on the Orthogonal Defect Classification [3] and are shown in 6. As pointed out by Salfner, et al. [23] Duraes, et al. [8], failures are ultimately the result of software developer errors. Unfortunately, G-SWFIT has only previously been implemented for Java applications [19, 26], and the IA32 instruction set [8]. The target application in this research is strictly an x86-64 (also known as x64 or amd64) application and the patterns identified previously are incompatible. Consequently, a fault injection tool capable of mutating x86-64 instructions in the same way was required. W-SWFIT implements two of the operators in [8] in the x86-64 language by translating the operators shown in Table 6 from IA32 to x86-64. The translation of these operators was not trivial given the complexity of the x86-64 architecture. However, a simple example is shown using the entry/exit points of a function in Tables 7, and 8. The

rest of the translations were done using the *Capstone* [5] library and can be seen in source code for W-SWFIT.

**Table 6. Table of Faults Injected [8].**

| Type | Description | ODC Classes |
|---|---|---|
| MIFS | Missing "If (cond) { statement(s) }" | Algorithm |
| MFC | Missing function call | Algorithm |
| MLAC | Missing "AND EXPR" in expression used as branch | Checking |
| MLPC | Missing small and localized part of the algorithm | Algorithm |
| WVAV | Wrong value assigned to a value | Assignment |
| MVI | Missing variable initialization | Assignment |
| MVAV | Missing variable assignment using a value | Assignment |
| WPFV | Wrong variable used in parameter of function call | Interface |

**Table 7. Funtion Entry/Exit Patterns (IA32) [8].**

| Module Entry Point | | Module Exit Point | |
|---|---|---|---|
| **Instruction Sequence** | **Explanation** | **Instruction Sequence** | **Explanation** |
| push ebp | stack frame | move esp,ebp | stack frame |
| mov ebp, esp | setup | pop ebp | cleanup |
| sub esp, *immed* | | ret | |

**Table 8. Funtion Entry/Exit Patterns (x86-64) [8].**

| Module Entry Point | | Module Exit Point | |
|---|---|---|---|
| **Instruction Sequence** | **Explanation** | **Instruction Sequence** | **Explanation** |
| push rbp | stack frame | add rsp, *immed* | stack frame |
| sub rsp, *immed* | | pop rbp | cleanup |
| mov rbp, rdx | setup | ret | |

#### 3.2.3.3 Workload Managmement.

The Workload module creates realistic work for the target system in the sandbox hypervisor to accomplish as a way of generating computational load. Without this module, it could take too long for an injected fault to evolve into a failure. Consider a

[5] `http://www.capstone-engine.org`

missing *free* statement and the consequent memory leak. A production target server may have a considerable amount of memory and the leak could be very small. To accelerate the possibility of failure occurring, realistic load must be generated against the sandbox clone of the production target.

In the original AFP case study, a Windows XP based web-server was used for a target and the load generation was done by a simple web request generator [15]. As previously mentioned, realistic workload is critical in generating realistic failure and consequently training a useful predictor. Initial searches for a load generator suitable for this research yielded a tool developed by MS that initiated remote desktop connections to aid in sizing a terminal services server[6]. By executing a remote desktop session, the authentication and Domain Name System (DNS) functions of the DC would also be loaded. Unfortunately, this tool is no longer maintained and would not execute on the target machine[7]. Further searches for tools that would sufficiently load the DC did not produce any results. Consequently, a tool to produce realistic load for a DC was developed for this research and is introduced here.

The Distributed PowerShell Load Generator (D-PLG) is a collection of MS PowerShell scripts designed to generate realistic traffic that will sufficiently load an MS DC. Other network traffic generators typically work by replaying traffic captured on a live network. Unfortunately, due to the cryptographic nature of authentication, simply replaying traffic will not load a service since the timestamps and challenge responses will no longer be valid. As a result, any replayed traffic will be dropped and ignored by a live DC. D-PLG solves this problem by making native authentication requests by use of built-in PowerShell cmdlets (command-lets). By doing this, realistic authentication requests are sent to the DC and are actually processed. The functions

[6] `http://www.microsoft.com/en-us/download/details.aspx?id=2218`

[7] `https://social.technet.microsoft.com/Forums/windowsserver/en-US/2f8fa5cf-3714-4eb3-a895-c30e2b26862d/debug-assertion-failed-sockcorecpp-line-623`

performed by the DC have been evaluated and D-PLG is designed to sufficiently load each of the services responsible for performing those functions.

In this experiment, the DC is configured as it is in many production environments. After careful analysis, it has been determined that the major roles being performed by the DC in a typical enterprise environment are authentication and DNS. By use of native cmdlets, D-PLG is capable of generating four kinds of traffic designed to stress these services and others: web, mail, file sharing, and MS Remote Desktop Protocol (RDP). D-PLG uses the MS Powershell environment to generate the traffic in an effort to make the traffic as real as possible. After building the tool, an experiment was constructed and executed on a scale model of a production environment. The scaled simulation network was built using the recommendations of the MS community for sizing a DC [18] and tested by running the tool on five client machines against the DC for five rounds of five minutes. The results of this test are shown in Figures 10, 11, 12.

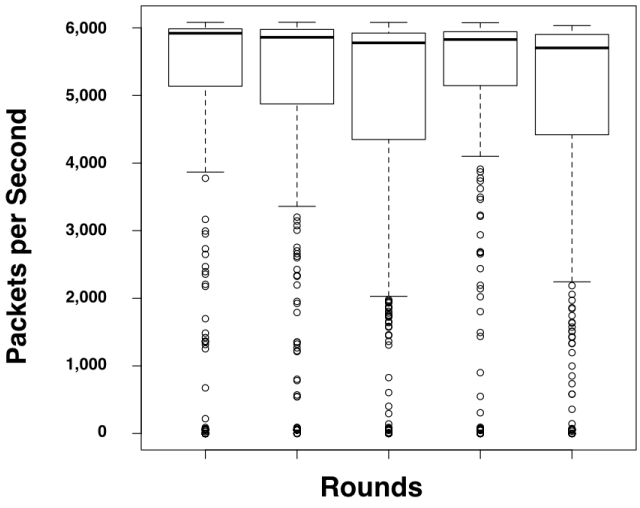



**Figure 10. How many packets per second were sent or received by the domain controller across all five rounds of the first test. In each test, we captured approximately 1.8 million packets.**

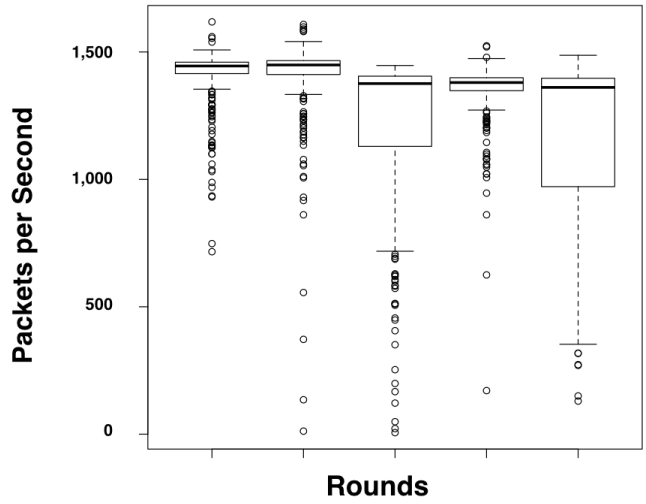



**Figure 11. How many packets per second were sent or received by one of the clients across all five rounds of the first test.**

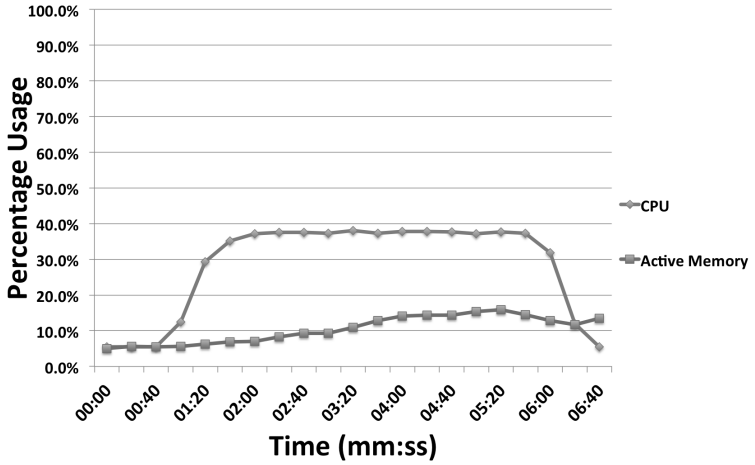



**Figure 12. Domain controller CPU and memory utilization during the first test.**

D-PLG makes use of client machines running a Windows operating system with PowerShell version 4.0 or newer. The controller asks each machine to generate a configurable list of requests at evenly spaced intervals for a configurable duration of time. While this may not be realistic network traffic, it does produce realistic load against a DC. Since D-PLG depends on the use of client machines, it is recommended that

any load generation be conducted during off-peak hours if spare client sized machines are not available. It should be noted however, that even with poorly resourced client machines (shown in 4), D-PLG was able to generate fifteen thousand authentication sessions over a five minute period; approximately 10 authentication sessions per machine, per second. With modern workstations, the impact on these client machines is negligible and they can be in use during load generation.

Based on these results, and that a production DC should be at approximately 40% CPU utilization during peak utilization [18], D-PLG is capable of sufficiently loading the DC over a sustained period of time for the purposes of implementing the AFP framework and is used in this research. Further, D-PLG is capable of scaling to provide load against higher capacity DCs by using only a few client machines. D-PLG is available on Github[8] for others to use.

#### 3.2.3.4 Events Manager.

This module is responsible for receiving and managing log messages and other events that may be used to train the failure prediction algorithm. Irrera, et al. [15] use the *Logman* tool for event management in their original case study. Since the experimental environment was modelled after the Air Force enterprise environment, the *Solar Winds* log forwarding tool is used to perform the functions in this module as it is already present on many of the Air Force DCs. The DCs on the Sandbox and Target hypervisors forward all events to the Ubuntu VM with the *rsyslog* server daemon configured to receive all messages. These messages are then processed and added to a Structured Query Language (SQL) database for training and prediction.

[8]https://github.com/paullj1/AFP-DC/tree/master/D-PLG

#### 3.2.3.5 Sandbox Management.

The purpose of the sandbox management module is to supervise the virtual cloning of the production system that is made when a new predictor is to be trained. As Irrera, et al. [11, 15] point out, it is typically inappropriate to inject faults and cause failures in production systems, so a virtual clone must be created for that purpose.

The sandbox is managed manually using VM snapshots. After an initial stable state was configured, snapshots of every component of the architecture were taken so that they could be reset after iterations of the experiment. It is important to note here that because VMWare has documented Application Programming Interface (API)s, in future work, this function could be automated.

### 3.2.4 Sandbox Hypervisor.

The sandbox hypervisor hosts the virtual clone of the production environment where faults will be injected and from which failure data will be collected. Cloning the production environment ensures that the production system will not be affected and service will be maintained during the training phase. For the purposes of this experiment, the sandbox is constructed on a single hypervisor implemented as shown in Table 4. The following sections outline each module within this module.

#### 3.2.4.1 Fault Injection.

This module is responsible for causing the target application to fail so that labelled failure data can be generated in a short period of time. As described in Section 3.2.3.2, W-SWFIT has been developed to serve this purpose and implements the G-SWFIT technique developed by Duraes, et al. [8] for fault injection. The execution is controlled by the Windows Server VM on the Controller hypervisor through PowerShell remote execution to reduce the interaction and potential to introduce bias into the

training data. The tool allows us to inject a comprehensive list of faults into the AD Services processes and binary libraries which are mostly contained within the 'lsass.exe' process. Since many of the critical functions performed by the AD Services processes are performed in one library called 'ntdsa.dll', it is the focus of fault injection.

This function is extended by this research to include failure as a result of excessive load and failure as a result of a corrupt database. Section 3.3 covers these extensions in more depth.

#### 3.2.4.2 Monitoring.

The purpose of this module is to capture some evidence or indication of pending failure so that it may be used to train a prediction algorithm. Irrera, et al. [15] use the *Logman* tool in their original study but because the experimental infrastructure used in this research is modelled after production Air Force networks, the *Solar Winds* log forwarding tool is used because it is already present in the Air Force architecture. The tool is a lightweight application that simply forwards Windows events to a syslog server.

#### 3.2.4.3 Sandbox Workload.

The sandbox workload module is likely the most critical module in the entire framework. Its purpose is to create realistic work for the target application to do before faults are injected. If the workload is not realistic, then the failures that occur after fault injection will not be representative of real failures and any data or indicators collected cannot be used to train an effective prediction algorithm [6,15,17].

Irrera, et al. [15] used a web traffic generator called TPC-W installed on a single machine in their original study because their target was a web server. Because the

DC does not respond to web-requests and a tool had not previously been written for this application, a tool was developed for this research called D-PLG. D-PLG is a tool that generates approximately ten full-stack authentication sessions requests per second in order to sufficiently load the DC. D-PLG is a distributed tool and requires the use of client machines as a result. This module is represented by those client machines. In this experiment, the client portion of D-PLG is installed on five client machines managed by the central workload manager as discussed in Section 3.2.3.3.

### 3.2.5 Target Hypervisor.

The target hypervisor was constructed as a clone of the sandbox hypervisor shown in Table 4. The following section outlines the monitoring tool installed on the DC on this hypervisor. It should be noted here that while the client machines were cloned as well for convenience, they were not used in this experiment.

#### 3.2.5.1 Monitoring.

The monitoring module is exactly the same as the sandbox monitoring module and for this experiment, the *Solar Winds* syslog forwarding tool is used. To ensure that the messages that are sent are uniquely identified by the controller, the hostname of the target machine must be different from the hostname of the sandbox target machine.

## 3.3 Extenstions to the AFP

This section outlines a few extensions to the AFP Framework specifically with respect to the fault load. Given that fault injection isn't always considered representative [17], this experiment explores three other faults that may occur in a production environment: an under-resourced CPU, not enough memory, and heap-space corrup-

tion.

Under some circumstances these faults may not be considered to lead to realistic failure. However, one reason an organization may wish to implement the AFP may be that monetary resources are not available to implement an adequately redundant or sized DC. Consequently, load based failure may be a realistic challenge faced by some organizations and knowing that such a failure may occur might be valuable. Furthermore, in some cases, third-party applications or hardware drivers may be responsible for memory leaks or accidental heap-space corruption. Since the Windows operating system implements shared library linking, hardware drivers that operate in kernel space are able to overwrite areas of memory that are in use by critical system processes [22]. The result is typically a system crash.

By adding these additional faults when generating failure data used to train a prediction algorithm, the resulting algorithm will be able to predict a wider range of realistic failures.

# IV. Experimental Results and Analysis

This chapter reports results after conducting the experiments laid out in Chapter III. First, common reporting techniques and measures of performance are reviewed. These measures and reporting techniques are then used to report the results of the experiments conducted. The chapter concludes with a short summary.

## 4.1 Performance Measures

This section reviews the performance measures used in this chapter to demonstrate the efficacy and quality of the statistical models trained in this research. These measures are commonly used in the field of machine learning to compare and assess predictors and are taken from a survey of Online Failure Prediction (OFP) methods written by Salfner et al. [23].

This research utilizes a technique called cross-validation in which a set of labelled training data are broken into three parts as follows:

1. Training Set: A data set that allows a prediction model to establish and optimize its parameters

2. Validation Set: The parameters selected in the training phase are then validated against a separate data set

3. Test Set: The predictor is finally run against a final previously unevaluated data set to assess generalizability

During the test phase, true positives (negatives) versus false positives (negatives) are determined in order to compute the performance measures in this section. The following terms and associated abbreviations are used: True Positive (TP) is when failure has been predicted and then actually occurs; False Positive (FP) is when failure

has been predicted and then does not occur; True Negative (TN) is when a state has been accurately classified as non-failure prone; False Negative (FN) is when a state has been classified as non-failure prone and a failure occurs.

### 4.1.1 Precision and Recall:.

Precision and recall are the most popular performance measures used when for comparing OFP approaches. The two are related and often times improving precision results in reduced recall. Precision is the number of correctly identified failures over the number of all predicted failures. In other words, it reports, out of the predictions of a failure-prone state that were made, how many were correct. In general, the higher the precision the better the predictor. Precision is expressed as:

$$Precision = \frac{TP}{TP + FP} \in [0, 1]$$

Recall is the ratio of correctly predicted failures to the number of true failures. In other words, it reports, out of the actual failures that occurred, how many the predictor classified as failure-prone. In conjunction with a higher precision, higher recall is indicative of a better predictor. Recall is expressed as:

$$Recall = \frac{TP}{TP + FN} \in [0, 1]$$

F-Measure, as defined by [30], is the harmonic mean of precision and recall and represents a trade-off between the two. A higher F-Measure reflects a higher quality predictor. F-Measure is expressed as:

$$F\text{-}Measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \in [0, 1]$$

### 4.1.2 False Positive Rate (FPR) and Specificity:.

Precision and recall do not account for true negatives (correctly predicted non-failure-prone situations) which can bias an assessment of a predictor. The following performance measures take true negatives into account to help evaluators more accurately assess and compare predictors.

FPR is the number of incorrectly predicted failures over the total number of predicted non-failure-prone states. A smaller FPR reflects a higher quality predictor. The FPR is expressed as:

$$FPR = \frac{FP}{FP + TN} \in [0, 1]$$

Specificity the number of times a predictor correctly classified a state as non-failure-prone over all non-failure-prone predictions made. In general, specificity alone is not very useful since failure is rare. Specificity is expressed as:

$$Specificity = \frac{TN}{FP + TN} = 1 - FPR$$

### 4.1.3 Negative Predictive Value (NPV) and Accuracy:.

In some cases, it may be desirable to show that a prediction approach can correctly classify non-failure-prone situations. The following performance measures usually can not stand alone due to the nature of failures being rare events. In other words, a highly "accurate" predictor could classify a state 100% of the time as non-failure-prone and still fail to predict every single true failure. This predictor would be highly accurate, but ultimately ineffective.

NPV is the number of times a predictor correctly classifies a state as non-failure-prone to the total number all non-failure-prone states during which a prediction was made. Higher quality predictors have high NPVs. The NPV is expressed as:

$$NPV = \frac{TN}{TN + FN}$$

Accuracy is the ratio of all correct predictions to the number of predictions made. Accuracy is expressed as:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

### 4.1.4 Precision/Recall Curve:.

Much like with other predictors, many OFP approaches implement variable thresholds to sacrifice precision for recall or vice versa. That trade-off is typically visualized using a precision/recall curve as shown in Figure 13.

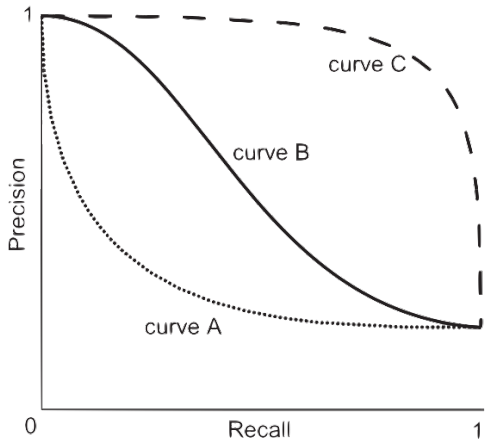



**Figure 13. Sample precision/recall curves [23]. Curve $A$ represents a poorly performing predictor, curve $B$ an average predictor, and curve $C$ an exceptional predictor.**

Another popular visualization is the Receiver Operating Characteristic (ROC) curve. By plotting True Positive Rate (TPR) over FPR one is able to see the predictors ability to accurately classify a failure. A sample ROC curve is shown in Figure 14.

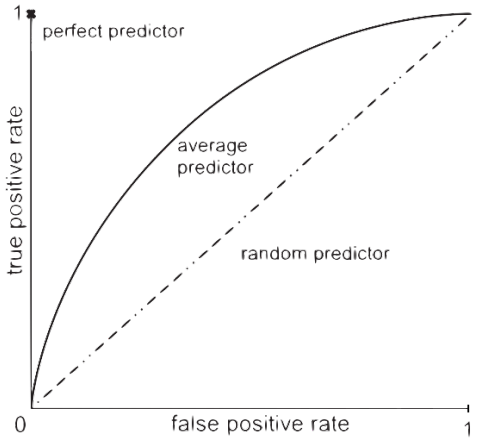



**Figure 14. ROC plots of perfect, average, and random predictors [23].**

The ROC curve relationship can be further illustrated by calculating the Area Under the Curve (AUC). Predictors are commonly compared using the AUC which is calculated as follows:

$$AUC = \int_0^1 TPR(FPR)\, d\, FPR \in [0, 1],$$

.

A pure random predictor will result in an AUC of 0.5 and a perfect predictor a value of 1. The AUC can be thought of as the probability that a predictor will be able to accurately distinguish between a failure-prone state and a non-failure-prone state, over the entire operating range of the predictor.

The results of the experiments conducted in this research will report all of the above described measures of performance in the next section.

## 4.2 Results

The experiments designed in Chapter III were executed in a virtual environment to produce failure data. The failure data generated was used to train statistical learning models using the open source statistical learning software suite: *R*. The parameters used to train each model were selected using cross-validation on a subset of the failures generated. Finally, each model was evaluated using a held-out test set. The results of this evaluation for each fault load are reported here.

The rest of this chapter is organized by the different fault loads that were used to generate the corresponding failure data: fault injection, under-resourced Central Processing Unit (CPU), under-resourced memory, and heap space corruption. In each sub-section, the results after training a machine learning model on failure data generated using that type of fault are detailed.

### 4.2.1 Fault Injection.

This fault-load was quite effective at creating a failure, but unfortunately, each failure observed occurred immediately after introducing the fault. Because there was no delay between injection and failure, there did not exist any indicators of failure. Consequently, machine learning cannot help in this situation. According to Russinovich, et al. [22] the *lsass.exe* process is at the top of the structured exception handling stack and does not actually handle any exceptions. When faced with an exception, the process exits and the system reboots.

### 4.2.2 Under-Resourced CPU.

This fault-load never resulted in a failure. To test this fault-load, the virtual domain controllers resources were reduced. The CPU went from a dual-core to a single virtual CPU, and the memory was reduced from 2 Gb to 512 Mb. This reduction was

well beneath the recommended capacity [18] for a domain controller. The workload generator was then allowed to run against this configuration for seven days. For the duration of the test, the CPU load was 100%, and physical memory was 90% utilized on average. While the service did experience reduced response time, failure did not occur.

### 4.2.3 Under-Resourced Memory.

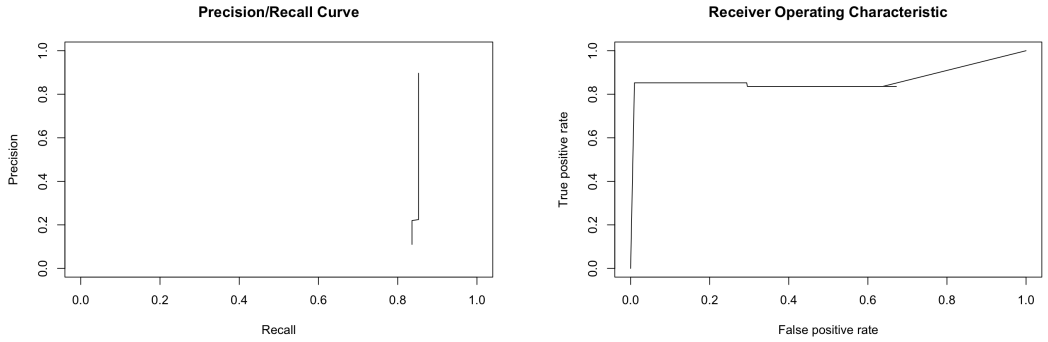
The under-resourced memory fault load was the first that created observable indicators of failure with any lead time. This fault load produced the best performing predictor and the largest sliding time window for prediction of sixty seconds. Two machine learning models were tested against the data generated using this type of fault: Support Vector Machine (SVM), and boosting using the multinomial distribution. According to James, et al. [16], the SVM is closely related to traditional machine learning methods like logistic regression. For this reason, this experiment explores the use of both prediction techniques.

#### 4.2.3.1 Support Vector Machine.

For this prediction method, the *e1071* package was used to train an SVM. The *tune* function was used to run a 5-fold cross-validation a total of 48 times to select the optimal parameters (gamma, cost, and degree polynomial) using: four kernels, four sliding time windows, and three training/test data splits. Additionally, in order to offset the imbalanced data, classification weights were used at 0.99 for failure, and 0.01 for non-failure.

The optimal model was selected with the Radial kernel with $\gamma = 0.1$, $cost = 1$, time window = 60 seconds, and the split of data = 4 of the observed failures used for training.

The test data was then evaluated in sequential order using a threshold. After two sequential windows were predicted as failure-prone, the next $w$ windows were also predicted as failure-prone, where $w = \textit{window size} - \textit{threshold size}$. The resulting confusion matrix for the optimal F-Measure, ROC curve, and precision/recall curve are shown in Table 9, and Figure 15 respectively.




(a) Precision/Recall Curve.

(b) Receiver Operating Characteristic (ROC) Curve (AUC = 0.8664).

**Figure 15. Test data performance of the SVM prediction method on failure data obtained by consuming all available memory until target application fails.**

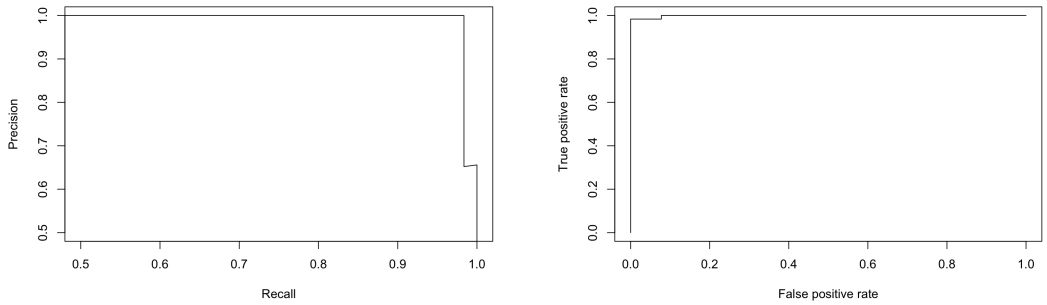
**Table 9. Confusion matrix on test data created before software updates on threshold with highest F-Measure (0.8739) using SVM.**

| | | **Actual** | |
|---|---|---|---|
| | | **Fail** | **No-Fail** |
| **Predicted** | **Fail** | 52 | 6 |
| | **No-Fail** | 9 | 607 |

#### 4.2.3.2 Boosting.

The precision/recall, and ROC curves on a sixty second time window are shown in Figure 16. The confusion matrix at the optimal threshold for F-measure is shown in Table 10.

After the software update, the same prediction model was used on a generated failure. A list of updates that were applied are shown in Appendix C. The preci-




(a) Precision/Recall Curve.

(b) Receiver Operating Characteristic (ROC) Curve (AUC = 0.9984).

**Figure 16. Test data performance of the boosting prediction method on failure data obtained by consuming all available memory until target application fails.**

**Table 10. Confusion matrix on test data created before software updates on threshold with highest F-Measure (0.9917) using boosting.**

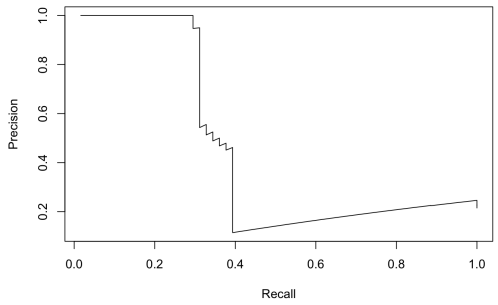
| | | **Actual** | |
|---|---|---|---|
| | | **Fail** | **No-Fail** |
| **Predicted** | **Fail** | 60 | 0 |
| | **No-Fail** | 1 | 412 |

sion/recall and ROC curves on data generated after the software update using the old model are shown in Figure 17. The confusion matrix at the optimal threshold for F-measure is shown in Table 10

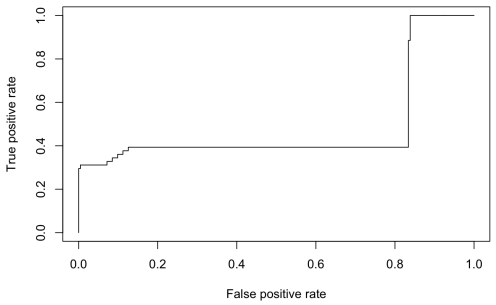
**Table 11. Post-update failure data confusion matrix on threshold with highest F-Measure (0.4691) using model trained on failure data generated before software update.**

| | | **Actual** | |
|---|---|---|---|
| | | **Fail** | **No-Fail** |
| **Predicted** | **Fail** | 19 | 1 |
| | **No-Fail** | 42 | 222 |

Finally, a new predictor was trained using more generated failures as was done before the update. The precision/recall, and ROC curves on the held-out test data are shown in Figure 18 and the confusion matrix at the optimal threshold for F-measure is shown in Table 12.

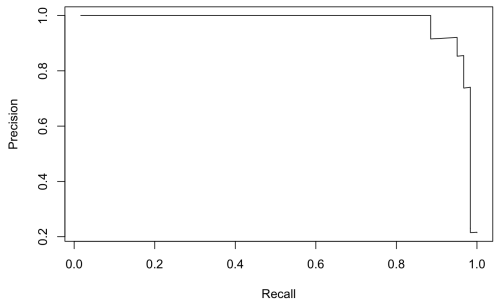



(a) Precision/Recall Curve.

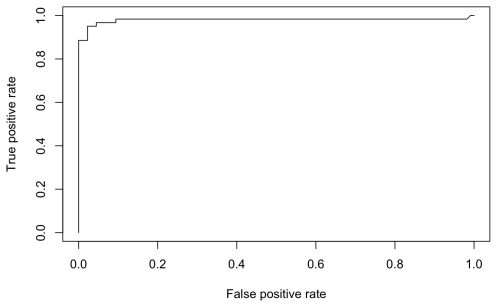



(b) Receiver Operating Characteristic (ROC) Curve (AUC = 0.4854).

**Figure 17. Performance of the boosting prediction method trained on failure data created before the software upate obtained by consuming all available memory until target application fails.**




(a) Precision/Recall Curve.




(b) Receiver Operating Characteristic (ROC) Curve (AUC = 0.9801).

**Figure 18. Performance of the boosting prediction method trained on failure data created after the software upate obtained by consuming all available memory until target application fails.**

**Table 12. Post-update failure data confusion matrix on threshold with highest F-Measure (0.9355) using model trained on failure data generated after software update.**

| | | **Actual** | |
|---|---|---|---|
| | | **Fail** | **No-Fail** |
| **Predicted** | **Fail** | 58 | 5 |
| | **No-Fail** | 3 | 218 |

### 4.2.4 Heap Space Corruption.

### 4.2.5 Summary.

# V. Conclusion and Future Work

This research has shown that it is possible to predict failure in modern computer operating systems given a representative fault load.

## 5.1 Future Work

Future lines of research should include the following...

- More automation using VMWare APIs
- Implement more of the operators from G-SWFIT and better automate injection/training phases
- Automate the event checking process... need a way to better determine when underlying system has changed
- Implement more predictors?
- Better define method for determining when to run AFP? Sliding time window? Machine learngin?
- Continuously running AFP? Let it run continuously in the background to capture new failures. The same way our tool reports failure, have a health checking daemon running in the background that will report to syslog when failure has occured so that it gets labelled
- More data. Use variables as recommended by Irrera et al.
- Realistic data. Get real failure data from 83/561 NOS
- Implement and use the AFP to predict failure in production environment!

- More features. Solve volume/velocity problem using solutions like STORM, CAPSA, SPARK, and OS Query
- Try new fault-loads on another service (like web-server)
- This works in a small environment, but may face challenges when scaling

## 5.2 Conclusion

This research explored the use of the AFP to predict failure in MS domain controllers... unaltered, did not work... not enough lead time.

Memory leak did provide useful results if the user isn't concerned with false positives. Noticed that there are axiomatic predictors in log messages as well that may precede SVM appraoch.

CPU leak did not provide any useful information. Failure was not achieved. Service just became very slow.

Heap space was not very consistent. Domain controller will go back to disk if heap is corrupted. Maybe in the future, consider corrupting both disk and memory.

Bottom line: when a process is designed to handle these types of faults, then failure prediction will not be possible.

# Appendix A. Windows Software Fault Injection Tool (W-SWFIT) Source Code

```
// FaultInjection.cpp : Defines the entry point for the console application.
//

#include "stdafx.h"
#include "globals.h"

#include "Operators.h"
#include "Operator.h"
#include "Library.h"

using namespace std;

bool SendSyslog();

int _tmain(int argc, _TCHAR* argv[]) {

	// Declarations
	DWORD aProcesses[1024], cbNeeded, cProcesses;
	TCHAR szProcessName[MAX_PATH] = TEXT("<unknown>");
	unsigned int i;

	// Get All pids
	if (!EnumProcesses(aProcesses, sizeof(aProcesses), &cbNeeded)){
		cerr << "Failed to get all PIDs: " << GetLastError() << endl;
		return -1;
	}

	// Get screen width
	CONSOLE_SCREEN_BUFFER_INFO csbi;
	GetConsoleScreenBufferInfo(GetStdHandle(STD_OUTPUT_HANDLE), &csbi);
	int dwidth = csbi.srWindow.Right - csbi.srWindow.Left;

	cout << "Running Processes" << endl;
	printf("%-6s %-*s\n", "PID", dwidth-7, "Process");
	cout << string(3, '-') << " " << string(dwidth - 7, '-') << endl;
	cProcesses = cbNeeded / sizeof(DWORD);
	for (i = 0; i < cProcesses; i++) {
		if (aProcesses[i] != 0) {
			HANDLE hProc = OpenProcess(PROCESS_QUERY_INFORMATION | PROCESS_VM_READ, FALSE,
			     aProcesses[i]);
			if (hProc != NULL) {
				HMODULE hMod;
				DWORD cbNeededMod;
				if (EnumProcessModules(hProc, &hMod, sizeof(hMod), &cbNeededMod)) {
					GetModuleBaseName(hProc, hMod, szProcessName, sizeof(szProcessName
					     ) / sizeof(TCHAR));
				}

				_tprintf(TEXT("%6u %-*s\n"), aProcesses[i], dwidth-7, szProcessName);
				CloseHandle(hProc);
			}
		}
	}

	// Which process?
	string s_pid = "";
	cout << endl << "Into which process would you like to inject faults? [PID]: ";
	getline(cin, s_pid);
	int pid = stoi(s_pid);

	HANDLE hTarget = OpenProcess(PROCESS_ALL_ACCESS, FALSE, pid);
```

```
        if (!hTarget) {
                cerr << "Failed␣to␣open␣process␣(check␣your␣privilege):␣" << GetLastError() << endl;
                return -1;
        }

        // Enumerate modules within process
        HMODULE hmods[1024];
        cout << "DLLs␣currently␣loaded␣in␣target␣process:" << endl;
        printf("%-4s␣%-*s\n", "ID", dwidth-5, "Module␣Name:");
        cout << string(4, '-') << "␣" << string(dwidth - 5, '-') << endl;
        if (EnumProcessModules(hTarget, hmods, sizeof(hmods), &cbNeeded)) {
                for (i = 0; i < (cbNeeded / sizeof(HMODULE)); i++) {
                        TCHAR szModName[MAX_PATH];
                        if (GetModuleFileNameEx(hTarget, hmods[i], szModName, sizeof(szModName) / sizeof
                             (TCHAR))) {
                                _tprintf(TEXT("%4d␣%-*s\n"), i, dwidth-5, szModName);
                        } else {
                                cerr << "Failed␣to␣Print␣enumerated␣list␣of␣modules:␣" << GetLastError()
                                     << endl;
                        }
                }
        } else {
                cerr << "Failed␣to␣enum␣the␣modules:␣" << GetLastError() << endl;
        }

        // Which Module?
        string s_mod_id = "";
        cout << "Into␣which␣module␣would␣you␣like␣to␣inject␣faults?␣[ID]:␣";
        getline(cin, s_mod_id);
        int mod_id = stoi(s_mod_id);

        MODULEINFO lModInfo = { 0 };
        cout << "Dll␣Information:" << endl;
        if (GetModuleInformation(hTarget, hmods[mod_id], &lModInfo, sizeof(lModInfo))){


                cout << "\t␣Base␣Addr:␣" << lModInfo.lpBaseOfDll << endl;
                cout << "\t␣Entry␣Point:␣" << lModInfo.EntryPoint << endl;
                cout << "\t␣Size␣of␣image:␣" << lModInfo.SizeOfImage << endl << endl;

        } else {
                cerr << "Failed␣to␣get␣module␣information:␣" << GetLastError() << endl;
                return -1;
        }

        // Get module name
        TCHAR szModName[MAX_PATH] = TEXT("<unknown>");
        GetModuleFileNameEx(hTarget, hmods[mod_id], szModName, sizeof(szModName) / sizeof(TCHAR));

        // Build library object
        Library *library = new Library(hTarget, (DWORD64)lModInfo.lpBaseOfDll,
                                                                lModInfo.SizeOfImage, string((char *)
                                                                     &szModName));

        // Save library for future static analysis
        library->write_library_to_disk("C:\\memdump.dll");

        library->inject();

        // Send syslog message
        SendSyslog();

        return 0;
}

bool SendSyslog() {
```

```
	WSADATA wsaData;
	int iResult = WSAStartup(MAKEWORD(2, 2), &wsaData);
	if (iResult != NO_ERROR) {
		cerr << "Couldn't send syslog message" << endl;
		return false;
	}

	SOCKET ConnectSocket;
	ConnectSocket = socket(AF_INET, SOCK_STREAM, IPPROTO_TCP);
	if (ConnectSocket == INVALID_SOCKET) {
		cerr << "Couldn't send syslog message" << endl;
		WSACleanup();
		return false;
	}

	sockaddr_in clientService;
	clientService.sin_family = AF_INET;
	clientService.sin_addr.s_addr = inet_addr("192.168.224.7");
	clientService.sin_port = htons(514);

	iResult = connect(ConnectSocket, (SOCKADDR *)&clientService, sizeof(clientService));
	if (iResult == SOCKET_ERROR) {
		cerr << "Couldn't send syslog message" << endl;
		closesocket(ConnectSocket);
		WSACleanup();
		return false;
	}

	char *sendbuf = "FAULT_INJECTED_SUCCESSFULLY";
	iResult = send(ConnectSocket, sendbuf, (int)strlen(sendbuf), 0);
	if (iResult == SOCKET_ERROR) {
		cerr << "Couldn't send syslog message" << endl;
		closesocket(ConnectSocket);
		WSACleanup();
		return false;
	}
	cout << "Successfully sent syslog message" << endl;

	closesocket(ConnectSocket);
	WSACleanup();
	return true;
}

// Class definition for the Funciton object

#ifndef FUNCTION_H
#define FUNCTION_H

#include "stdafx.h"
#include "globals.h"

#include "Operator.h"

#include <map>

using namespace std;

class Function {

	public:
		Function(HANDLE _target, DWORD64 _start, DWORD64 _end, byte *_code);
		~Function();

		bool inject();

	private:
```

```
        map < DWORD64, Operator *> local_injection_points; // Address -> NOP Sequence
        DWORD64 start_addr = 0;
        DWORD64 end_addr = 0;
        byte *buf;
        DWORD64 size = 0;
        HANDLE hTarget; // Managed by Library (don't close it here)

        // Capstone Buffer
        cs_insn *code_buf;
        size_t cs_count = 0;
        csh cs_handle;

        bool build_injection_points();
        bool perform_injection(DWORD64 addr);
        bool inject(Operator *op, DWORD64 addr);

        // Build map of injectable points
        bool find_operators_mfc();

};

#endif

// Class definition for the Library object (contains single DLL)

#ifndef LIBRARY_H
#define LIBRARY_H

#include "stdafx.h"
#include "globals.h"

#include "Operators.h"
#include "Operator.h"
#include "Function.h"

#include <vector>
#include <map>

using namespace std;

class Library {

    public:
        Library(HANDLE _target, DWORD64 _start, DWORD _size, string _path);
        ~Library();

        bool write_library_to_disk(string path);
        bool inject();

    private:
        string name; // Name of library
        vector < Function * > functions; // Vector (list) of functions in library
        map < Operator *, Operator * > function_patterns; // Vector of function patterns
        byte *buf; // Buffer for memory contents
        DWORD64 start_addr = 0;
        DWORD image_size = 0;
        HANDLE hTarget;

        bool read_memory_into_bufer();
        bool build_operator_map();
        bool find_functions();
        bool find_pattern(Operator *op, DWORD64 start, DWORD64 stop, DWORD64 *location);
};

#endif
```

```
// Class definition for the Operator object
// This object contains a byte array and a size

#ifndef OPERATOR_H
#define OPERATOR_H

#include "stdafx.h"
#include "globals.h"

using namespace std;

class Operator {

	public:
		Operator(const byte *pattern, DWORD64 size);
		~Operator();

		DWORD64 size() { return _size; }
		const byte *pattern() { return (const byte *)_pattern; }

	private:
		byte *_pattern;
		DWORD64 _size;
};

#endif

// Operators.h : Defines the operators to search and replace
//

#ifndef OPERATORS_H
#define OPERATORS_H

#include "stdafx.h"
#include "globals.h"

const byte start_pattern_1[] = { 0x55, 0x48, 0x83, 0xec, 0x20, 0x48, 0x8b, 0xea };
const byte end_pattern_1[] = { 0x48, 0x83, 0xc4, 0x20, 0x5d, 0xc3 };
/*	Begin Function:
	PUSH RBP
	SUB RSP, 0x20
	MOV RBP, RDX

   End Function:
	ADD RSP, 0x20
	POP RBP
	RET
*/

const byte start_pattern_2[] = { 0xff, 0xf3, 0x48, 0x83, 0xec, 0x20, 0x48, 0x8b, 0xd9 };
const byte end_pattern_2[] = { 0x48, 0x83, 0xc4, 0x20, 0x5b, 0xc3 };
/*	Begin Function:
	PUSH RBX
	SUB RSP, 0x20
	MOV RBX, RCX

	End Function:
	ADD RSP, 0x20
	POP RBX
	RET
*/

const byte start_pattern_3[] = { 0xff, 0xf3, 0x48, 0x83, 0xec, 0x20, 0x8b, 0xd9 };
const byte end_pattern_3[] = { 0x48, 0x83, 0xc4, 0x20, 0x5b, 0xc3 };
/*	Begin Function:
	PUSH RBX
```

```
       SUB RSP, 0x20
       MOV EBX, ECX

       End Function:
       ADD RSP, 0x20
       POP RBX
       RET
*/

const byte start_pattern_4[] = { 0x57, 0x48, 0x83, 0xec, 0x20, 0x48, 0x8b, 0xf9 };
const byte end_pattern_4[] = { 0x48, 0x83, 0xc4, 0x20, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x20
       MOV RDI, RCX

       End Function:
       ADD RSP, 0x20
       POP RDI
       RET
*/

const byte start_pattern_5[] = { 0x57, 0x48, 0x83, 0xec, 0x20, 0x8b, 0xf9 };
const byte end_pattern_5[] = { 0x48, 0x83, 0xc4, 0x20, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x20
       MOV EDI, ECX

       End Function:
       ADD RSP, 0x20
       POP RDI
       RET
*/

const byte start_pattern_6[] = { 0x57, 0x48, 0x83, 0xec, 0x20, 0x8b, 0xf1 };
const byte end_pattern_6[] = { 0x48, 0x83, 0xc4, 0x20, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x20
       MOV ESI, ECX

       End Function:
       ADD RSP, 0x20
       POP RDI
       RET
*/

const byte start_pattern_7[] = { 0xff, 0xf3, 0x48, 0x83, 0xec, 0x20, 0x48, 0x8d, 0x0d };
const byte end_pattern_7[] = { 0x48, 0x83, 0xc4, 0x20, 0x5b, 0xc3 };
/*     Begin Function:
       PUSH RBX
       SUB RSP, 0x20
       LEA RCX, 'immed'

       End Function:
       ADD RSP, 0x20
       POP RBX
       RET
*/

const byte start_pattern_8[] = { 0x57, 0x48, 0x83, 0xec, 0x40, 0x48, 0x8b, 0xe9 };
const byte end_pattern_8[] = { 0x48, 0x83, 0xc4, 0x40, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x40
```

```
       MOV RBP, RCX

       End Function:
       ADD RSP, 0x40
       POP RDI
       RET
*/

const byte start_pattern_9[] = { 0x57, 0x48, 0x83, 0xec, 0x20, 0x48, 0x8b, 0xf1 };
const byte end_pattern_9[] = { 0x48, 0x83, 0xc4, 0x20, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x20
       MOV RSI, RCX

       End Function:
       ADD RSP, 0x20
       POP RDI
       RET
*/

 const byte start_pattern_10[] = { 0x57, 0x48, 0x83, 0xec, 0x20, 0x48, 0x8b, 0xe9 };
 const byte end_pattern_10[] = { 0x48, 0x83, 0xc4, 0x20, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x20
       MOV RBP, RCX

       End Function:
       ADD RSP, 0x20
       POP RDI
       RET
*/

 const byte start_pattern_11[] = { 0x57, 0x48, 0x83, 0xec, 0x30, 0x48, 0x8b, 0xe9 };
 const byte end_pattern_11[] = { 0x48, 0x83, 0xc4, 0x30, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x30
       MOV RBP, RCX

       End Function:
       ADD RSP, 0x30
       POP RDI
       RET
*/

 const byte start_pattern_12[] = { 0x57, 0x48, 0x83, 0xec, 0x20, 0x48, 0x8b, 0x05 };
 const byte end_pattern_12[] = { 0x48, 0x83, 0xc4, 0x20, 0x5f, 0xc3 };
/*     Begin Function:
       PUSH RDI
       SUB RSP, 0x20
       MOV RAX, 'immed'

       End Function:
       ADD RSP, 0x20
       POP RDI
       RET
*/

 const byte omva_1[] = { 0x48, 0x8b, 0x5c, 0x24, 0x30 }; // MOV RBX, [RSP+0x30]
 const byte omva_2[] = { 0x48, 0x8b, 0x74, 0x24, 0x38 }; // MOV RSI, [RSP+0x38]

#endif
```

```
#ifndef GLOBALS_H
#define GLOBALS_H

#include <stdio.h>
#include <tchar.h>

#include <windows.h>
#include <string>
#include <psapi.h>
#include <iostream>
#include <fstream>
#include <io.h>

#include <capstone.h>
#include <inttypes.h>

#endif

// stdafx.h : include file for standard system include files,
// or project specific include files that are used frequently, but
// are changed infrequently
//

#pragma once

#include "targetver.h"

#include <WinSock2.h>
#include <Ws2tcpip.h>
#pragma comment(lib, "Ws2_32.lib")

#include <stdio.h>
#include <tchar.h>

#include "Library.h"
#include "Function.h"
#include "Operator.h"

#pragma once

// Including SDKDDKVer.h defines the highest available Windows platform.

// If you wish to build your application for a previous Windows platform, include WinSDKVer.h and
// set the _WIN32_WINNT macro to the platform you wish to support before including SDKDDKVer.h.

#include <SDKDDKVer.h>

// FaultInjection.cpp : Defines the entry point for the console application.
//

#include "stdafx.h"
#include "globals.h"

#include "Operators.h"
#include "Operator.h"
#include "Library.h"

using namespace std;

bool SendSyslog();

int _tmain(int argc, _TCHAR* argv[]) {

	// Declarations
	DWORD aProcesses[1024], cbNeeded, cProcesses;
	TCHAR szProcessName[MAX_PATH] = TEXT("<unknown>");
```

```
unsigned int i;

// Get All pids
if (!EnumProcesses(aProcesses, sizeof(aProcesses), &cbNeeded)){
	cerr << "Failed to get all PIDs: " << GetLastError() << endl;
	return -1;
}

// Get screen width
CONSOLE_SCREEN_BUFFER_INFO csbi;
GetConsoleScreenBufferInfo(GetStdHandle(STD_OUTPUT_HANDLE), &csbi);
int dwidth = csbi.srWindow.Right - csbi.srWindow.Left;

cout << "Running Processes" << endl;
printf("%-6s %-*s\n", "PID", dwidth-7, "Process");
cout << string(3, '-') << " " << string(dwidth - 7, '-') << endl;
cProcesses = cbNeeded / sizeof(DWORD);
for (i = 0; i < cProcesses; i++) {
	if (aProcesses[i] != 0) {
		HANDLE hProc = OpenProcess(PROCESS_QUERY_INFORMATION | PROCESS_VM_READ, FALSE,
		    aProcesses[i]);
		if (hProc != NULL) {
			HMODULE hMod;
			DWORD cbNeededMod;
			if (EnumProcessModules(hProc, &hMod, sizeof(hMod), &cbNeededMod)) {
				GetModuleBaseName(hProc, hMod, szProcessName, sizeof(szProcessName
				    ) / sizeof(TCHAR));
			}

			_tprintf(TEXT("%6u %-*s\n"), aProcesses[i], dwidth-7, szProcessName);
			CloseHandle(hProc);
		}
	}
}

// Which process?
string s_pid = "";
cout << endl << "Into which process would you like to inject faults? [PID]: ";
getline(cin, s_pid);
int pid = stoi(s_pid);

HANDLE hTarget = OpenProcess(PROCESS_ALL_ACCESS, FALSE, pid);
if (!hTarget) {
	cerr << "Failed to open process (check your privilege): " << GetLastError() << endl;
	return -1;
}

// Enumerate modules within process
HMODULE hmods[1024];
cout << "DLLs currently loaded in target process:" << endl;
printf("%-4s %-*s\n", "ID", dwidth-5, "Module Name:");
cout << string(4, '-') << " " << string(dwidth - 5, '-') << endl;
if (EnumProcessModules(hTarget, hmods, sizeof(hmods), &cbNeeded)) {
	for (i = 0; i < (cbNeeded / sizeof(HMODULE)); i++) {
		TCHAR szModName[MAX_PATH];
		if (GetModuleFileNameEx(hTarget, hmods[i], szModName, sizeof(szModName) / sizeof
		    (TCHAR))) {
			_tprintf(TEXT("%4d %-*s\n"), i, dwidth-5, szModName);
		} else {
			cerr << "Failed to Print enumerated list of modules: " << GetLastError()
			    << endl;
		}
	}
} else {
	cerr << "Failed to enum the modules: " << GetLastError() << endl;
}
```

```
        // Which Module?
        string s_mod_id = "";
        cout << "Into␣which␣module␣would␣you␣like␣to␣inject␣faults?␣[ID]:␣";
        getline(cin, s_mod_id);
        int mod_id = stoi(s_mod_id);

        MODULEINFO lModInfo = { 0 };
        cout << "Dll␣Information:" << endl;
        if (GetModuleInformation(hTarget, hmods[mod_id], &lModInfo, sizeof(lModInfo))){


                cout << "\t␣Base␣Addr:␣" << lModInfo.lpBaseOfDll << endl;
                cout << "\t␣Entry␣Point:␣" << lModInfo.EntryPoint << endl;
                cout << "\t␣Size␣of␣image:␣" << lModInfo.SizeOfImage << endl << endl;

        } else {
                cerr << "Failed␣to␣get␣module␣information:␣" << GetLastError() << endl;
                return -1;
        }

        // Get module name
        TCHAR szModName[MAX_PATH] = TEXT("<unknown>");
        GetModuleFileNameEx(hTarget, hmods[mod_id], szModName, sizeof(szModName) / sizeof(TCHAR));

        // Build library object
        Library *library = new Library(hTarget, (DWORD64)lModInfo.lpBaseOfDll,
                                                                lModInfo.SizeOfImage, string((char *)
                                                                    &szModName));

        // Save library for future static analysis
        library->write_library_to_disk("C:\\memdump.dll");

        library->inject();

        // Send syslog message
        SendSyslog();

        return 0;
}

bool SendSyslog() {
        WSADATA wsaData;
        int iResult = WSAStartup(MAKEWORD(2, 2), &wsaData);
        if (iResult != NO_ERROR) {
                cerr << "Couldn't␣send␣syslog␣message" << endl;
                return false;
        }

        SOCKET ConnectSocket;
        ConnectSocket = socket(AF_INET, SOCK_STREAM, IPPROTO_TCP);
        if (ConnectSocket == INVALID_SOCKET) {
                cerr << "Couldn't␣send␣syslog␣message" << endl;
                WSACleanup();
                return false;
        }

        sockaddr_in clientService;
        clientService.sin_family = AF_INET;
        clientService.sin_addr.s_addr = inet_addr("192.168.224.7");
        clientService.sin_port = htons(514);

        iResult = connect(ConnectSocket, (SOCKADDR *)&clientService, sizeof(clientService));
        if (iResult == SOCKET_ERROR) {
                cerr << "Couldn't␣send␣syslog␣message" << endl;
                closesocket(ConnectSocket);
```

```
                WSACleanup();
                return false;
        }

        char *sendbuf = "FAULT_INJECTED_SUCCESSFULLY";
        iResult = send(ConnectSocket, sendbuf, (int)strlen(sendbuf), 0);
        if (iResult == SOCKET_ERROR) {
                cerr << "Couldn't send syslog message" << endl;
                closesocket(ConnectSocket);
                WSACleanup();
                return false;
        }
        cout << "Successfully sent syslog message" << endl;

        closesocket(ConnectSocket);
        WSACleanup();
        return true;
}


#include "stdafx.h"
#include "Function.h"
#include "Operators.h"

Function::Function(HANDLE _target, DWORD64 _start, DWORD64 _end, byte *_code) {
        hTarget = _target;
        start_addr = _start;
        end_addr = _end;
        size = end_addr - start_addr;
        buf = _code;
        local_injection_points = map < DWORD64, Operator *>();

        // Build Capstone (CS) Array of code
        if (cs_open(CS_ARCH_X86, CS_MODE_64, &cs_handle) != CS_ERR_OK)
                cerr << "Error disassembling code." << endl;

        // Enable op details
        cs_option(cs_handle, CS_OPT_DETAIL, CS_OPT_ON);
        //cs_option(cs_handle, CS_OP_DETAIL, CS_OPT_ON);

        cs_count = cs_disasm(cs_handle, buf, size, start_addr, 0, &code_buf);
        if (cs_count == 0)
                cerr << "Error disassembling code." << endl;


        // Build Injection points based on disassembled code
        build_injection_points();
}

Function::~Function() {
        cs_close(&cs_handle);
        cs_free(code_buf, size);
}

// Public Functions
bool Function::inject() {
        // For each injection point in the funciton, ask the user if they would like to inject
        for (map<DWORD64, Operator *>::iterator it = local_injection_points.begin();
                it != local_injection_points.end(); ++it) {

                // If the user injects, return true;
                if (inject(it->second, it->first))
                        return true;
        }
        return false;
}
```

```
// Private Functions
bool Function::build_injection_points() {
	find_operators_mfc();

	// TODO: Other operators

	return true;
}

// Returns address of injection point for "Operator for Missing Function Call (OMFC)"
bool Function::find_operators_mfc() {

	// Constraint 2 (CO2): Call must not be only statement in the block (size > size of entry +
	    size of exit + 16)
	if (cs_count < 6) return false;

	for (size_t j = 0; j < cs_count; j++) {
		if (string(code_buf[j].mnemonic).find("call") != string::npos){
			// Constraint 1 (CO1): Return value of the function (EAX) must not be used.
			bool constraint01 = false;
			for (size_t i = j + 1; i < cs_count; i++) {
				cs_detail *details = code_buf[i].detail;
				if (code_buf[i].detail) {
					for (size_t k = 0; k < details->regs_read_count; k++) {
						string modreg = string(cs_reg_name(cs_handle, details->
						    regs_read[k]));
						if (modreg.find("eax") != string::npos || modreg.find("rax
						    ") != string::npos)
							constraint01 = true;
					}
				}
			}

			// Doesn't violate any of the OMFC constraints, add it
			if (!constraint01) {
				Operator *op = new Operator(code_buf[j].bytes, code_buf[j].size);
				local_injection_points[code_buf[j].address] = op;
			}
		}
	}
		//printf("0x%"PRIx64":\t%s\t\t%s\n", code_buf[j].address, code_buf[j].mnemonic, code_buf
		    [j].op_str);
	return true;
}

bool Function::inject(Operator *op, DWORD64 addr) {

	// Ready to continue?
	string cont = "";
	printf("Ready␣to␣inject␣%d␣bytes␣at:␣0x%X\n\n", op->size(), addr);
	cout << "Continue?␣[Y|n]:␣";
	getline(cin, cont);

	if (cont.find("n") != string::npos || cont.find("N") != string::npos) {
		cout << "Aborting" << endl;
		return false;
	}

	byte *nop_array = (byte *)malloc(op->size());
	fill_n(nop_array, op->size(), 0x90);

	SIZE_T mem_bytes_written = 0;
	if (WriteProcessMemory(hTarget, (LPVOID)addr, nop_array, op->size(), &mem_bytes_written) != 0)
	    {
		cout << "Bytes␣written:␣" << mem_bytes_written << endl;
```

```
		cout << "Successful injection." << endl;
		return true;
	} else {
		cerr << "Failed to inject fault into memory: " << GetLastError() << endl;
		return false;
	}
	return false;
}

#include "stdafx.h"
#include "Process.h"

Library::Library(HANDLE _target, DWORD64 _start, DWORD _size, string _path) {
	hTarget = _target;
	start_addr = _start;
	image_size = _size;
	name = _path;
	buf = (byte *)malloc(image_size);
	function_patterns = map < Operator *, Operator * >();
	functions = vector < Function *>();

	if (!buf) {
		cerr << "Failed to allocate space for memory contents: " << GetLastError() << endl;
		CloseHandle(hTarget);
		return;
	}
	read_memory_into_bufer();
	build_operator_map();
	find_functions();
}


Library::~Library() {
	free(buf);
	CloseHandle(hTarget);
}

// PUBLIC FUNCTIONS
bool Library::write_library_to_disk(string path) {

	cout << "Writing static copy of memory contents for analysis to " << path << endl;
	FILE *fp;
	fopen_s(&fp, path.c_str(), "w");
	SIZE_T bytes_written = 0;
	while (bytes_written < image_size) {
		bytes_written += fwrite(buf, 1, image_size, fp);
	}
	fclose(fp);
	cout << "Wrote " << bytes_written << " bytes." << endl << endl;
	return true;
}

bool Library::inject() {
	// For each function in the module, call public inject funciton
	for (vector< Function *>::iterator it = functions.begin(); it != functions.end(); ++it) {
		if ((*it)->inject())
			return true;
	}
	return true;
}

// PRIVATE FUNCTIONS
bool Library::read_memory_into_bufer() {
	SIZE_T num_bytes_read = 0;
	int count = 0;
```

```
        if (ReadProcessMemory(hTarget, (DWORD64 *)start_addr, buf, image_size, &num_bytes_read) != 0)
             {
                cout << "Buffered␣memory␣contents.␣Got␣" << num_bytes_read << "␣bytes." << endl << endl
                     ;
                return true;
        }
        else {
                cout << "Failed␣to␣read␣memory:␣" << GetLastError() << endl;
                return false;
        }
        return false;
}

bool Library::build_operator_map() {
        function_patterns[new Operator(start_pattern_1, sizeof(start_pattern_1))] =
                new Operator(end_pattern_1, sizeof(end_pattern_1));
        function_patterns[new Operator(start_pattern_2, sizeof(start_pattern_2))] =
                new Operator(end_pattern_2, sizeof(end_pattern_2));
        function_patterns[new Operator(start_pattern_3, sizeof(start_pattern_3))] =
                new Operator(end_pattern_3, sizeof(end_pattern_3));
        function_patterns[new Operator(start_pattern_4, sizeof(start_pattern_4))] =
                new Operator(end_pattern_4, sizeof(end_pattern_4));
        function_patterns[new Operator(start_pattern_5, sizeof(start_pattern_5))] =
                new Operator(end_pattern_5, sizeof(end_pattern_5));
        function_patterns[new Operator(start_pattern_6, sizeof(start_pattern_6))] =
                new Operator(end_pattern_6, sizeof(end_pattern_6));
        function_patterns[new Operator(start_pattern_7, sizeof(start_pattern_7))] =
                new Operator(end_pattern_7, sizeof(end_pattern_7));
        function_patterns[new Operator(start_pattern_8, sizeof(start_pattern_8))] =
                new Operator(end_pattern_8, sizeof(end_pattern_8));
        function_patterns[new Operator(start_pattern_9, sizeof(start_pattern_9))] =
                new Operator(end_pattern_9, sizeof(end_pattern_9));
        function_patterns[new Operator(start_pattern_10, sizeof(start_pattern_10))] =
                new Operator(end_pattern_10, sizeof(end_pattern_10));
        function_patterns[new Operator(start_pattern_11, sizeof(start_pattern_11))] =
                new Operator(end_pattern_11, sizeof(end_pattern_11));
        function_patterns[new Operator(start_pattern_12, sizeof(start_pattern_12))] =
                new Operator(end_pattern_12, sizeof(end_pattern_12));
        return true;
}

bool Library::find_functions() {
        for (map < Operator *, Operator * >::iterator it = function_patterns.begin();
                        it != function_patterns.end(); ++it ) {

                DWORD64 begin = 0;
                while (find_pattern(it->first, begin, image_size, &begin)) {

                        DWORD64 end = 0;
                        if (find_pattern(it->second, begin, image_size, &end)) {
                                functions.push_back(new Function(hTarget, start_addr + begin + (it->first
                                     )->size(),
                                                                                start_addr +
                                                                                     end - (it
                                                                                     ->second)
                                                                                     ->size(),
                                                                                     &buf[begin
                                                                                     ]));

                        }
                        begin++;
                }
        }
        return true;
}

// Search 'buf' for 'pattern' at 'start'. If found, sets 'offset', and returns true.
```

```
bool Library::find_pattern(Operator *op, DWORD64 start, DWORD64 stop, DWORD64 *location) {

	const byte *pattern = op->pattern();
	for (DWORD64 i = start; i < stop; i++) {
		if (buf[i] == pattern[0]) {
			for (int j = 1; j < op->size(); j++) {
				if (buf[i + j] != pattern[j])
					break;
				if (j < op->size() - 1)
					continue;

				*location = i;
				return true;
			}
		}
	}
	return false;
}

#include "stdafx.h"
#include "Operator.h"

Operator::Operator(const byte *pattern, DWORD64 size) {
	_size = size;
	_pattern = (byte *)malloc(_size);
	memcpy(_pattern, pattern, size);
}

Operator::~Operator() {
	free(_pattern);
}

// stdafx.cpp : source file that includes just the standard includes
// FaultInjection.pch will be the pre-compiled header
// stdafx.obj will contain the pre-compiled type information

#include "stdafx.h"

// TODO: reference any additional headers you need in STDAFX.H
// and not in this file
```

# Appendix B. ResourceLeak Source Code

```
##############################################################################
#                                                                            #
# W-SWFIT: Resource Leak                                                     #
# Authors: Paul Jordan                                                       #
# Date Created: 8 May 2016                                                   #
# Description: Makefile for the W-SWFIT Resource Leak project.               #
#                                                                            #
# Copyright (c) 2016                                                         #
#                                                                            #
##############################################################################
PROGRAM=resourceleak
C_FILES:=$(shell find . -iname "*.cpp")
OBJS:=$(patsubst %.cpp, %.o, $(C_FILES))
CFLAGS=-Wall -ffast-math -O3 -std=c++11 -I./incl/
LDFLAGS=
SRC=src

native: CC=g++
windows: CC=/usr/local/gcc-4.8.0-qt-4.8.4-for-mingw32/win32-gcc/bin/i586-mingw32-g++

all: native

windows: $(OBJS)
	$(CC) $(CFLAGS) $(OBJS) $(LDFLAGS) -o $(PROGRAM).exe

native: $(OBJS)
	$(CC) $(CFLAGS) $(OBJS) $(LDFLAGS) -o $(PROGRAM)

%.o: %.cpp
	$(CC) $(CFLAGS) -c $< -o $@

%: %.cpp
	$(CC) $(CFLAGS) -o $@ $<

clean:
	$(RM) $(PROGRAM) *.o $(SRC)/*.o $(PROGRAM).exe
```

```
/*****************************************************************************/
/*                                                                           */
/* resourceleak.cpp                                                          */
/* Project: W-SWFIT: Resource Leak                                           */
/* Authors: Paul Jordan                                                      */
/* Date Created: 8 May 2016                                                  */
/*                                                                           */
/* Description: Small app designed to fill up memory, disk, or CPU at a */
/* configurable rate in order to force a system to fail. This application */
/* simulates a poorly written third-party application which might cause */
/* failure in an underlying system.                                          */
/*                                                                           */
/* Copyright (c) 2016                                                        */
/*                                                                           */
/*****************************************************************************/

#include "globals.hpp"
#include "memory.hpp"
#include "cpu.hpp"
//#include "disk.hpp"

using namespace std;

int main(int argc, char *argv[]) {
  // Process Command Line Args
  if ( argc < 3 ) {
```

```
    cerr << "Need␣to␣specify␣which␣type␣of␣leak␣[m]emory,␣or␣[c]pu." << endl;
    cerr << "usage:␣"<< argv[0] <<"␣-[m|c]␣<rate>" << endl;
    return 1;
  }

  Resource *leak = NULL;
  if      ( string(argv[1]).compare("-m") == 0 )
    leak = new Memory();
  else if ( string(argv[1]).compare("-c") == 0 )
    leak = new CPU();
  else {
    cerr << "Unrecognized␣leak␣type.␣Specify␣[m]emory,␣or␣[c]pu." << endl;
    return 1;
  }

  int rate;
  string str_rate = string(argv[2]);
  if ( ! (istringstream(str_rate) >> rate) ) rate = 0;

  if (rate <= 0 || rate > 100) {
    cerr << "Unrecognized␣rate.␣Specify␣rate␣between␣1-100." << endl;
    return 1;
  }

  if (leak)
    leak->start(1);

  while(true) { this_thread::sleep_for(chrono::seconds(1)); }
  return 0;
}

/*****************************************************************************/
/*                                                                           */
/* cpu.cpp                                                                */
/* Project: W-SWFIT: Resource Leak                                           */
/* Authors: Paul Jordan                                                      */
/* Date Created: 8 May 2016                                                  */
/* Description: Implementation file for the CPU leak class.               */
/*                                                                           */
/* Copyright (c) 2016                                                        */
/*                                                                           */
/*****************************************************************************/

#include "cpu.hpp"

bool CPU::start(int rate) {
  _running = true;
  _rate = rate;
  __rate = rate; // mutable (degrading) rate
  _leak = thread(&CPU::leak, this);
  return true;
}

void CPU::leak() {
  while(_running) {

    if (__rate > 1) { __rate *= .99; }
    else { __rate = 0; }

    this_thread::sleep_for(chrono::milliseconds((int)__rate));
  }
}

bool CPU::stop() {
  _running = false;
  return true;
```

```
}

/*************************************************************************/
/*                                                                       */
/* Memory.cpp                                                            */
/* Project: W-SWFIT: Resource Leak                                       */
/* Authors: Paul Jordan                                                  */
/* Date Created: 8 May 2016                                              */
/* Description: Implementation file for the Memory leak class.           */
/*                                                                       */
/* Copyright (c) 2016                                                    */
/*                                                                       */
/*************************************************************************/

#include <math.h>
#include "memory.hpp"

Memory::Memory() {
  storage = vector<void *>();
}

Memory::~Memory() {
  storage.clear();
}

bool Memory::start(int rate) {
  _running = true;
  _rate = rate;
  _leak = thread(&Memory::leak, this);
  return true;
}

void Memory::leak() {
  while(_running) {
    void *buf = malloc(pow(10,6)); // Allocate 1MB at rate
    storage.push_back(buf);
    this_thread::sleep_for(chrono::milliseconds(_rate));
  }
}

bool Memory::stop() {
  _running = false;
  return true;
}

/*************************************************************************/
/*                                                                       */
/* cpu.hpp                                                             */
/* Project: W-SWFIT: Resource Leak                                       */
/* Authors: Paul Jordan                                                  */
/* Date Created: 8 May 2016                                              */
/* Description: Header file for the CPU leak class.                    */
/*                                                                       */
/* Copyright (c) 2016                                                    */
/*                                                                       */
/*************************************************************************/

#ifndef CPU_H
#define CPU_H

#include "globals.hpp"
#include "resource.hpp"

using namespace std;

class CPU : public Resource {
```

```
  public:
    CPU() {}
    ~CPU() {}

    bool start(int rate); // smaller number = faster leak
    bool stop();

    bool running() const { return _running; }
    int rate() const { return _rate; }

  private:
    void leak();

    bool _running = false;
    int _rate = 0;
    double __rate = 0;
    thread _leak;

};

#endif

#ifndef GLOBALS_H
#define GLOBALS_H

#ifdef __MINGW32__
#include "mingw.thread.h"
#endif

#include <stdlib.h>
#include <chrono>
#include <vector>
#include <thread>
#include <iostream>
#include <sstream>

#endif

/*****************************************************************************/
/*                                                                           */
/* Memory.hpp                                                                */
/* Project: W-SWFIT: Resource Leak                                           */
/* Authors: Paul Jordan                                                      */
/* Date Created: 8 May 2016                                                  */
/* Description: Header file for the Memory leak class.                       */
/*                                                                           */
/* Copyright (c) 2016                                                        */
/*                                                                           */
/*****************************************************************************/

#ifndef MEMORY_H
#define MEMORY_H

#include "globals.hpp"
#include "resource.hpp"

using namespace std;

class Memory : public Resource {
  public:
    Memory();
    ~Memory();

    bool start(int rate); // # of milliseconds to sleep
                          // before allocating more memory
                          // (smaller number = faster leak)
```

```
    bool stop();

    bool running() const { return _running; }
    int rate() const { return _rate; }

  private:
    void leak();

    vector<void *> storage;
    bool _running = false;
    int _rate = 0;
    thread _leak;

};

#endif

/*****************************************************************************/
/*                                                                           */
/* Resource.hpp                                                              */
/* Project: W-SWFIT: Resource Leak                                           */
/* Authors: Paul Jordan                                                      */
/* Date Created: 8 May 2016                                                  */
/* Description: Abstract resource header file. Each resource implements */
/* abstract class.                                                           */
/*                                                                           */
/* Copyright (c) 2016                                                        */
/*                                                                           */
/*****************************************************************************/

#ifndef RESOURCE_H
#define RESOURCE_H

#include "globals.hpp"

class Resource {
  public:
    virtual bool start(int rate) = 0;
    virtual bool stop() = 0;
    bool running() const { return _running; }
    int rate() const { return _rate; }

  private:
    bool _running = false;
    int _rate = 0;

};

#endif
```

# Appendix C. Windows Updates

**Table 13. Updates applied to Windows Server 2008 R2 x64 Edition.**

| Description | HotFixID | Description | HotFixID |
|---|---|---|---|
| Update | 982861 | Security Update | KB2676562 |
| Security Update | KB2032276 | Security Update | KB2685939 |
| Security Update | KB2207559 | Security Update | KB2690533 |
| Security Update | KB2296011 | Security Update | KB2691442 |
| Security Update | KB2305420 | Security Update | KB2698365 |
| Update | KB2345886 | Security Update | KB2705219 |
| Security Update | KB2347290 | Security Update | KB2706045 |
| Security Update | KB2387149 | Security Update | KB2712808 |
| Security Update | KB2393802 | Update | KB2718704 |
| Security Update | KB2419640 | Security Update | KB2729451 |
| Security Update | KB2423089 | Security Update | KB2736418 |
| Security Update | KB2425227 | Security Update | KB2742598 |
| Security Update | KB2442962 | Security Update | KB2743555 |
| Update | KB2454826 | Update | KB2748349 |
| Security Update | KB2483614 | Update | KB2749655 |
| Update | KB2506014 | Security Update | KB2753842 |
| Security Update | KB2506212 | Security Update | KB2756920 |
| Security Update | KB2509553 | Security Update | KB2757638 |
| Security Update | KB2511455 | Security Update | KB2758857 |
| Update | KB2533552 | Security Update | KB2765809 |
| Security Update | KB2535512 | Security Update | KB2769369 |
| Security Update | KB2536275 | Security Update | KB2770660 |
| Security Update | KB2536276 | Security Update | KB2772930 |

| | | | |
|---|---|---|---|
| Security Update | KB2544893 | Update | KB2779562 |
| Update | KB2552343 | Security Update | KB2785220 |
| Security Update | KB2560656 | Security Update | KB2789644 |
| Security Update | KB2564958 | Security Update | KB2790113 |
| Security Update | KB2570947 | Security Update | KB2790655 |
| Security Update | KB2584146 | Security Update | KB2807986 |
| Security Update | KB2585542 | Security Update | KB2813170 |
| Security Update | KB2604114 | Security Update | KB2813347 |
| Security Update | KB2618451 | Security Update | KB2840149 |
| Security Update | KB2620704 | Security Update | KB972270 |
| Security Update | KB2621440 | Update | KB974431 |
| Security Update | KB2631813 | Security Update | KB974571 |
| Security Update | KB2643719 | Hotfix | KB975467 |
| Security Update | KB2644615 | Security Update | KB975560 |
| Security Update | KB2645640 | Update | KB977074 |
| Security Update | KB2647170 | Security Update | KB978542 |
| Security Update | KB2653956 | Security Update | KB978601 |
| Security Update | KB2654428 | Security Update | KB979309 |
| Security Update | KB2655992 | Security Update | KB979482 |
| Security Update | KB2656355 | Security Update | KB979687 |
| Security Update | KB2656410 | Security Update | KB979688 |
| Security Update | KB2658846 | Update | KB979900 |
| Security Update | KB2659262 | Update | KB980408 |
| Update | KB2661254 | Security Update | KB982132 |
| Security Update | KB2667402 | Security Update | KB982799 |

# Appendix D. Glossary

| | |
|---|---|
| AD | Active Directory |
| AFP | Adaptive Failure Prediction |
| API | Application Programming Interface |
| ASLR | Address Space Layout Randomization |
| AUC | Area Under the Curve |
| CPU | Central Processing Unit |
| CRISP-DM | Cross Industry Standard Process for Data Mining |
| CSCS | Cyber Security and Control System |
| D-PLG | Distributed PowerShell Load Generator |
| DC | Domain Controller |
| DNS | Domain Name System |
| DOD | Department of Defense |
| FN | False Negative |
| FP | False Positive |
| FPR | False Positive Rate |
| G-SWFIT | General Software Fault Injection Technique |
| GB | Gigabyte |
| GHSMM | Generalized Hidden Semi-Markov Model |
| GHz | Gigahertz |
| IP | Internet Protocol |
| MS | Microsoft |

| | |
|---|---|
| NOS | Network Operation Squadrons |
| NPV | Negative Predictive Value |
| OFP | Online Failure Prediction |
| PFM | Proactive Fault Management |
| RDP | Remote Desktop Protocol |
| ROC | Receiver Operating Characteristic |
| SQL | Structured Query Language |
| SVM | Support Vector Machine |
| TN | True Negative |
| TP | True Positive |
| TPR | True Positive Rate |
| VM | Virtual Machine |
| W-SWFIT | Windows Software Fault Injection Tool |

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As society becomes more dependent upon computer systems to perform increasingly critical tasks, ensuring those systems do not fail also becomes more important. The Air Force, much like many other organizations, depends heavily on desktop computers for day to day operations. Unfortunately, the software that runs on these desktop computers is still written by humans and as such, is still subject to human error and consequent failure. A natural solution is to use statistical machine learning to predict failure. However, since failure is still a relatively rare event, obtaining labelled training data to train these models is not trivial. This work explores predicting failure in the Microsoft enterprise authentication service using realistically generated failure data in an effort to increase up-time in desktop computers and improve mission effectiveness.

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