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Patrycja Nędza and Jerzy Domżał *

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Article

Detecting DoS Attacks through Synthetic User Behavior with Long-Short Term Memory Network

Patrycja Nędza [1,†] and Jerzy Domżał [2,*,†]

AGH University of Krakow, Faculty of Computer Science, Electronics and Telecommunications; pnedza@student.agh.edu.pl

* Correspondence: jerzy.domzal@agh.edu.pl

† These authors contributed equally to this work.

Abstract: With the escalation of size and complexity of modern Denial of Service attacks, there is a need for research in the context of Machine Learning (ML) used in attack execution and defense against such attacks. This paper investigates the potential use of ML in generating behavioral telemetry data using Long-Short Term Memory network and spoofing requests for the analyzed traffic to look legitimate. For this research, a custom testing environment was built, that listens for mouse and keyboard events and analyzes them accordingly. While the economic feasibility of this attack currently limits its immediate threat, advancements in technology could make it more cost-effective for attackers in the future. Therefore, proactive development of countermeasures remains essential to mitigate potential risks and stay ahead of evolving attack methods.

Keywords: denial of service; machine learning; behavioral telemetry; long-short term memory

1. Introduction

Modern Denial of Service (DoS) attacks are becoming larger and more sophisticated every year, which imposes the need for robust defense mechanisms utilizing cutting-edge technologies [1], [2], [3]. With ML emerging as a promising tool in not only defence but also attack execution, it becomes necessary to explore its potential usage by attackers and to stay ahead of evolving threats. This study investigates the feasibility of leveraging ML for DoS attack detection by generating behavioral telemetry data using Long-Short Term Memory (LSTM) network [4] and Bezier Curves and crafting spoofing requests to make the analyzed traffic appear legitimate.

While previous research has explored ML-based approaches for DoS attack detection and mitigation [5], [6], few have examined the potential of generating realistic attack traffic through ML itself. Those mainly revolve around adversarial ML attacks using generative adversarial networks (GANs) that can successfully evade an ML-based Intrusion Detection System (IDS) [7], [8]. This gap presents an opportunity to deepen our understanding of attacker capabilities and develop proactive countermeasures.

This research contributes to the field by:

- Demonstrating the potential of LSTM networks to generate realistic behavioral telemetry data that can be used for DoS attack simulations.
- Evaluating the effectiveness of spoofing requests in masking attack traffic and challenging current detection methods.
- Analyzing the economic feasibility of ML-based DoS attacks and highlighting the need for proactive countermeasures despite current limitations.

Our findings aim to advance the development of ML-based DoS attack detection systems by providing valuable insights into attack methodologies and potential blind spots in existing defenses.

2. Related Work

In paper [9], the authors propose an adversarial DBN-LSTM method for detecting and defending DDoS attacks. The key point of the system is the adversarial DBN-LSTM anomaly detection method.

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It can generate several adversarial samples and build adversarial datasets using the GAN model. Moreover, other proposal have been presented to improve the performance of the system:

- implementation of DBN for data dimensionality reduction,
- implementation of LSTM to extract sample timing features to detect IP flow records and identify adversarial DDoS attacks.

The simulation experiments show that the proposed method can effectively detect DDoS attacks and improves system sensitivity to adversarial attacks. In this paper, we propose some new techniques to protect systems against the ML-based DoS attacks.

The authors of [10] presented a CGAN-based intrusion detection system against DDoS attacks on IoT networks. The core of the system is the mechanism which generates synthetic traffic mapping known patterns and completely new network discriminator network to detect anomalies. The obtained results confirm that the generated dataset significantly improved the detection effectiveness. An important element of the entire solution is the mechanism based on deep learning classifiers. In our proposal, we use different ML-based models to detect specific DoS attacs.

In [11], the LSTM-based system was proposed to detect and prevent DDoS attacks in a public cloud networks. The system was designed based on a signature-based attack detection approach. The accuracy rate is on the level of 99.83% according to the CICDDoS2019 data set. The simulation results confirm that the prevention part of the system obtained a performance as good as for the previous studies conducted with different DL algorithms on the same and different datasets. In our approach, we use the LSTM-based system with data generated by behavioral telemetry. This is unique for currently known studies.

The review of currently known deep learning based approaches for detecting DDoS attacks is presented in [12]. The review is provided classifying the papers into five main research areas:

- types of DDoS attack detection deep learning approaches,
- methodologies, strengths, and weaknesses of existing deep learning approaches for DDoS attacks detection,
- benchmarked datasets and classes of attacks in used datasets,
- the preprocessing strategies, hyperparameter values, experimental setups, and performance metrics,
- the research gaps, and future directions.

Another review which presents different approaches to detecting DDoS attacks, using machine learning techniques is presented in [13]. Analyzed techniques, such as k-means, K-Nearest Neighbors, and Naive Bayes used in intrusion detection systems and flow-based intrusion detection systems were considered for review. In the review the high-speed network accuracy evaluation factors are highlighted. They provide a detailed DDoS attack taxonomy, and classifies detection techniques. Sevelat types of attacs were considered, e.g., Zero-Day Attacks, Reflection Attacks, DNS Amplification or SYN Flood.

The mechanism proposed in our paper has not been noticed in the analyzed literature presented in both review papers presented above.

3. Testing Environment

The testing environment simulates a simple login/register website utilizing JavaScript listeners for background data collection. Upon a user's visit to the application, a continuous stream of requests to "telemetry.js" is initiated. This script captures both mouse position and keyboard key press timestamps, sending them to the server via POST requests. The pseudocode in Algorithm 1 outlines the implemented logic.

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Algorithm 1 Telemetry Data Collection

```
upon DOCUMENT IS FULLY LOADED do
    on KEYDOWN EVENT ON WINDOW do
        timestamp ← Current timestamp
        Call SendTelemetryData with 'keyboard' and timestamp
    end on
    on MOUSEMOVE EVENT ON WINDOW do
        timestamp ← Current timestamp
        mouseX ← Mouse X coordinate from event
        mouseY ← Mouse Y coordinate from event
        Call SendTelemetryData with 'mouse', timestamp, mouseX, mouseY
    end on
    function SENDTELEMETRYDATA(eventType, timestamp, x, y)
        Send POST request to '/track_telemetry' with event data
        on RESPONSE RECEIVED do
            Log response message
        end on
    end function
end upon
```

Collected data is stored in two dedicated databases:

1. Telemetry Database, which captures user interactions with the website, including:
    - Event ID (unique identifier),
    - IP address and source port,
    - Event type (keyboard or mouse),
    - Timestamp,
    - Mouse X and Y coordinates (applicable only for mouse events);
2. Request Database, which logs information about individual requests made to the website, such as:
    - Request ID (unique identifier),
    - Telemetry data hash (linking request to interaction),
    - IP address and source port,
    - Timestamp (time of current request),
    - HTTP headers, status code, method, hostname, path,
    - Interaction start time (when was first GET request to critical endpoint sent).

To enhance security, user behavior data (telemetry) is collected only on critical pages like login and register. This allows us to focus verification efforts on areas with heightened risk of bot activity. Specifically, a unique telemetry hash is calculated after credentials are submitted via a POST request.

The hash generation process, outlined in Algorithm 2, considers two key factors:

- Mouse movement: We capture a string representing mouse position points throughout the interaction,
- Keystroke cadence: The average time between key presses is calculated based on timestamps collected since the page loaded successfully.

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Algorithm 2 Telemetry Data Hash

```
function SENDREQUESTDATA
    timestamp ← Current datetime
    resp ← Request headers as dictionary
    telemetry_hash ← 'N/A'
    Initialize database cursor conn
    if Request method is 'POST' then
        Retrieve telemetry data between interaction start and current timestamp
        data ← Fetched data
        if data is not empty then
            Initialize telemetry_str, key_timestamps, total_time_diff, count
            for each entry d in data do
                if d[3] is 'mouse' then
                    Append mouse coordinates to telemetry_str
                else if d[3] is 'keyboard' then
                    Add d[4] to key_timestamps
                end if
            end for
            Calculate average time between key presses
            Append average time to telemetry_str
            Compute hash of telemetry_str
        end if
        Insert request data into the database
    end if
    Commit changes to the database
    Close database connection
end function
```

3.1. Attack Execution

The attack begins by stealthily gathering crucial information about the target login page. This involves pinpointing the exact positions of input boxes and the submit button, as meticulously outlined in Algorithm 3.

Algorithm 3 Get Initial Position of Element

```
function GETINITIALPOSITION(host, path, element_id, offset)
    Initialize headless Chrome browser with fullscreen and SSL error ignore options
    Navigate browser to "https://{host}{path}"
    Find the element on the webpage by its ID
    Get the screen dimensions using PyAutoGUI
    Retrieve browser window position
    Calculate the center coordinates of the element
    Adjust coordinates to be within screen limits and apply offset
    Quit the browser
    return Screen coordinates (screen_x, screen_y)
end function
```

Armed with this knowledge, the attack commences by sending a carefully crafted stream of POST requests. Each request bears a deceptive payload: meticulously crafted mouse position data, designed to mimic genuine human interaction. This process, detailed in Algorithm 4, aims to evade detection by blending seamlessly with typical user behavior.

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Algorithm 4 Send Telemetry Request

function SENDTELEMETRYREQUEST(event_type, timestamp, x (optional), y (optional))
Define path as '/track_telemetry'
Construct data as a JSON string with event_type, timestamp, x, and y
Define headers with necessary information including host, session, and browser details
Call send_post_request with path, data, and headers
end function

Mouse positions are calculated, leveraging Bézier curves, widely used in computer graphics, game development, and image processing, to generate realistic mouse trajectories. These curves offer flexibility and smooth transitions, crucial for mimicking natural user behavior. Important to understand is that those curves can be exchanged with new ML models, such as "SapiAgent", to generate even more human-like mouse trajectories [14]. However, for simplicity, we will operate on the Bézier curves. They are defined by Bernstein polynomials as shown in Equation 1 [15],

$$BZ(t) = \sum_{i=0}^{n} \binom{n}{i} t^i (1-t)^{n-i} P_i, \quad 0 \leq t \leq 1 \tag{1}$$

where:

- n - the degree of the Bézier Curve (number of control points minus one),
- t - the parameter of the Curve (position along the curve ranging between 0 to 1),
- the binomial coefficients are given by Expression 2:

$$\binom{n}{i} = \begin{cases} \frac{n!}{i!(n-i)!}, & \text{if } 0 \leq i \leq n, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

We strategically choose three control points for each curve:

- Start point A
- End point B
- Three random points on the line connecting A and B, with a random perpendicular offset.

This point selection process is elucidated in Algorithm 5.

Algorithm 5 Generate Random Point on Line

function GENERATERANDOMPOINTONLINE(point_a, point_b, randomness)
    $t \leftarrow$ Random number between 0 and 1
    $x \leftarrow (1-t) \times point\_a.x + t \times point\_b.x$
    $y \leftarrow (1-t) \times point\_a.y + t \times point\_b.y$
    Calculate the directional difference dx, dy between $point\_b$ and $point\_a$
    Determine perpendicular direction $perp\_dx$, $perp\_dy$
    Normalize the perpendicular direction
    Calculate $random\_distance$ based on $randomness$
    Adjust x, y coordinates by applying $random\_distance$ in the perpendicular direction
    return x, y
end function

By leveraging Equation 1, we numerically calculate the Bézier curve points, as outlined in Algorithm 6.

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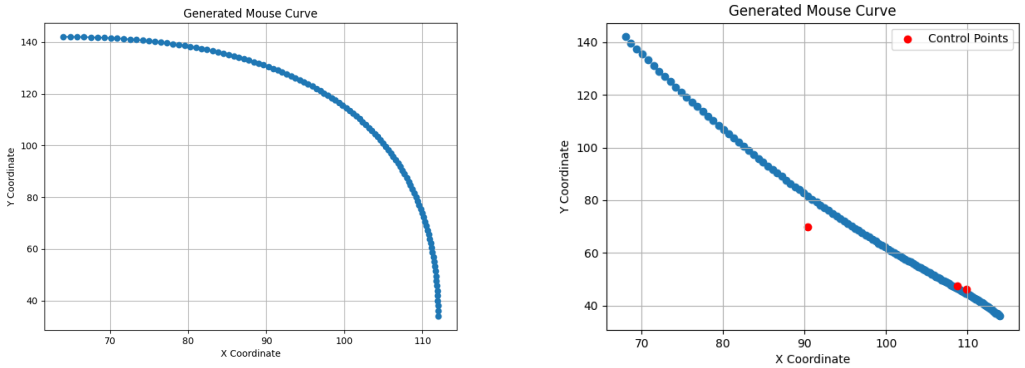
Algorithm 6 Generate Bézier Curve Points

```
function GENERATEBEZIERCURVE(control_points, num_points)
    t ← Create a list of num_points evenly spaced values between 0 and 1
    Initialize curve as a num_points × 2 zero matrix
    n ← Number of control points minus 1
    for i ← 0 to num_points − 1 do
        for j ← 0 to n do
            Calculate Bernstein polynomial bernstein_poly
            curve[i] ← curve[i] + bernstein_poly × control_points[j]
        end for
    end for
    return curve
end function
```

To visualize the generated curves and enhance understanding, we present them in Figure 1.



(**a**) (**b**)

Figure 1. Bézier Curves generated: a by ready python framework with two control points, b by calculating curve points with five control points.

Once the simulated mouse reaches its intended input field, the attack shifts its focus to simulating keyboard activity. This attack leverages the assumption that attackers can readily build a database of keyboard dynamics for their use. To simulate real user behavior, a simple keylogger was implemented. The code samples 128 random passwords from the "rockyou.txt" file [16], one at a time. For each password, it meticulously records every keystroke, capturing both the exact moment the key is pressed (key_down) and released (key_up). This precise timing data continues until the user presses "Enter", signaling the completion of the typed word. Captured data is then stored in a comma-separated values (CSV) file. The structure of this database is outlined in Table 1.

Table 1. Generated database structure

Field Name	Field Type	Key Primary
Timestamp	Date-Time	True
Word_ID	Integer	False
ASCII_Code	Integer	False
Down_Time_MS	Float	False
Up_Time_MS	Float	False

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Each row uniquely identifies a keystroke with a timestamp (recorded in milliseconds), and associates it with the typed word (using an internal Word_ID) and the corresponding ASCII code.

A Long Short-Term Memory (LSTM) model serves as the backbone for predicting the intervals between keystrokes. This choice leverages the inherent sequential nature of keystroke timing data, allowing the model to capture and learn crucial temporal dependencies. Figure 2 visually represents the model's structure. The model loss is shown on the figure number 3.

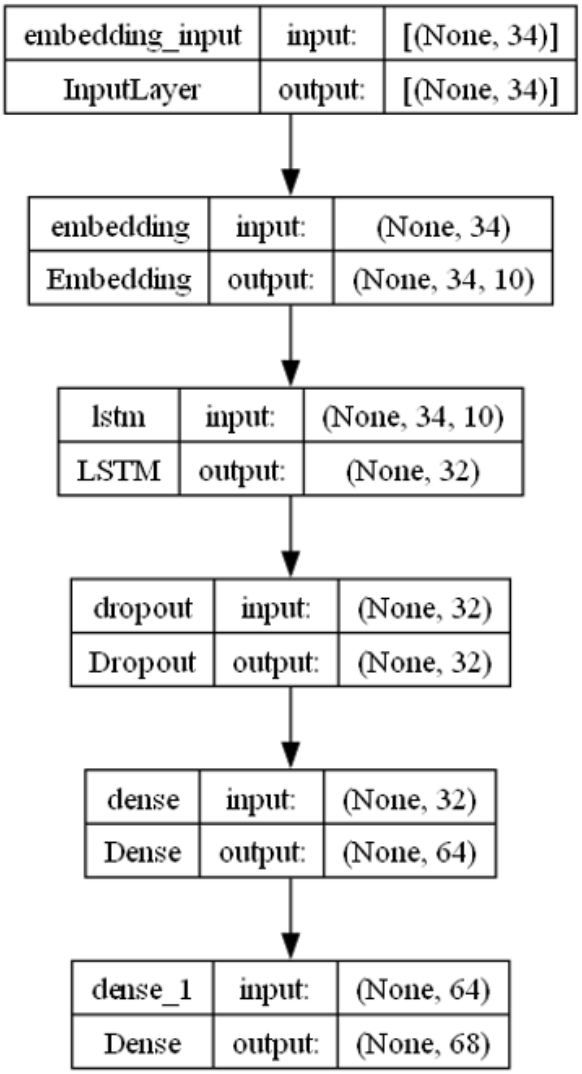

Figure 2. Model architecture.

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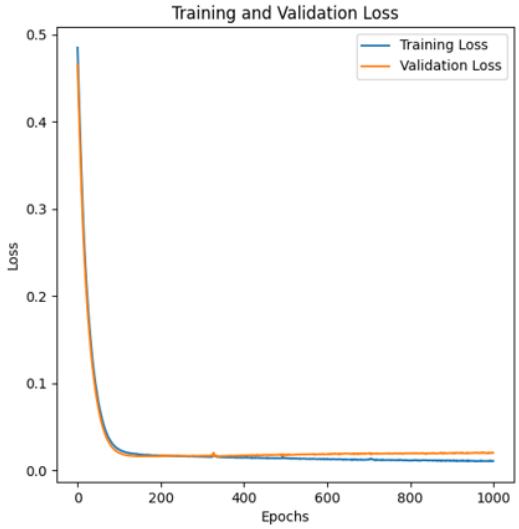

Figure 3. Training and Validation Loss of the model.

Specifically, the model uses 34 input features, representing the maximum password length from the generated database. This allows the model to understand the potential range of keystroke sequences. An LSTM layer then processes this information, effectively extracting relevant patterns and dependencies from the data. Finally, the output layer utilizes these learned patterns to predict the time a key should be held for, as well as the interval between the current and next keystroke.

Algorithm 7 precisely predicts key press and release timings, ensuring a natural typing cadence. These meticulously timed events are then transmitted to the server, further solidifying the illusion of human presence.

Algorithm 7 Type In Current Input Field

```
function TypeInCurrentField(word)
    global timestamp
    times ← predict_hold_and_release_times(word)
    for each time in times do
        offset ← create time delta from time[0]
        send_telemetry_request("keyboard", timestamp + offset)
        increment timestamp by offset and additional time from time[1]
    end for
end function
```

After successfully filling each input field, the attack seamlessly resumes its simulated mouse movements, guiding the cursor towards the submit button. Upon reaching this critical element, the attack culminates in the final submit button click. To maximize the likelihood of success, the attack relentlessly repeats this intricate sequence, relentlessly attempting passwords from the expansive "rockyou.txt" file. This unwavering persistence ensures that no potential password combination is overlooked.

4. Results

We examined the request data, focusing on the following key columns:

- ID,
- Telemetry Hash,
- IP Address,

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- Port,
- Timestamp.

To illustrate the differences introduced by behavioral telemetry, we present excerpts of request data from two sets of simulations:

1. Without Behavioral Telemetry: As shown in Table 2, requests lack unique telemetry hashes. Bot traffic resulted in generating likewise hashes, making it potentially easier to mark as fraudulent.

Table 2. Part of the request data for simulation without behavioral telemetry spoofing used

ID	Telemetry Hash	IP Address	Port	Timestamp
291	e3b0c44298fc1c149afbf4c8996fb92427...	192.168.1.13	64513	2023-11-16 18:19:02
294	e3b0c44298fc1c149afbf4c8996fb92427...	192.168.1.13	64513	2023-11-16 18:19:07
297	e3b0c44298fc1c149afbf4c8996fb92427...	192.168.1.13	64513	2023-11-16 18:19:35
300	e3b0c44298fc1c149afbf4c8996fb92427...	192.168.1.13	64513	2023-11-16 18:19:48
310	e3b0c44298fc1c149afbf4c8996fb92427...	192.168.1.13	64513	2023-11-16 18:22:43

2. With Behavioral Telemetry: Table 3 demonstrates the presence of randomized telemetry hashes, indicating the traffic was more sophisticated in the way behavioral telemetry was used. These unique identifiers, generated based on user behavior simulated during the attack, add a layer of complexity and potentially enhance the attack's ability to evade detection.

Table 3. Part of the request data for simulation with behavioral telemetry spoofing used

ID	Telemetry Hash	IP Address	Port	Timestamp
444	393e9cd505f0a7af71979ffb01e97468d...	192.168.1.13	53546	2023-11-16 18:56:23
446	4d373db4bafae80bddefd995a4d4a6d90...	192.168.1.13	53546	2023-11-16 18:56:27
448	bd970844de692ae66388c6ce161d0d41f...	192.168.1.13	53546	2023-11-16 18:56:30
454	25329f94ba7a792f5d4605cf94bd2240d...	192.168.1.13	53546	2023-11-16 18:58:53
456	a866e3a3fa5ec701b12f242dad5128f92...	192.168.1.13	53546	2023-11-16 18:58:56

Executing the attack yielded several clues about its impact on the server. First one being the frequent number of 500 Internal Server Errors being logged. These responses suggest the server struggled to handle the influx of requests, potentially overloading resources. Another suggestion is the "ConnectionResetError" seen at the peak of traffic received by the server. This error indicates the server actively terminated connections, likely as a defense mechanism.

To gauge the attack's resource consumption, we instrumented the server with dedicated threads. One thread continuously recorded Central Processing Unit (CPU) usage at a specified interval, while the other tracked memory usage. Figure 4 reveals how the attack affected CPU utilization. Unlike legitimate traffic, which exhibits periods of lower usage (subfigure_b), CPU usage during the attack remained consistently high (subfigure_a). This indicates the server struggled to process the influx of requests, likely exceeding its capacity. Furthermore, the lack of clear data at the end of the attack period (subfigure_a) suggests that resources were saturated, preventing complete file writing. As a result, the recorded data had to be truncated.

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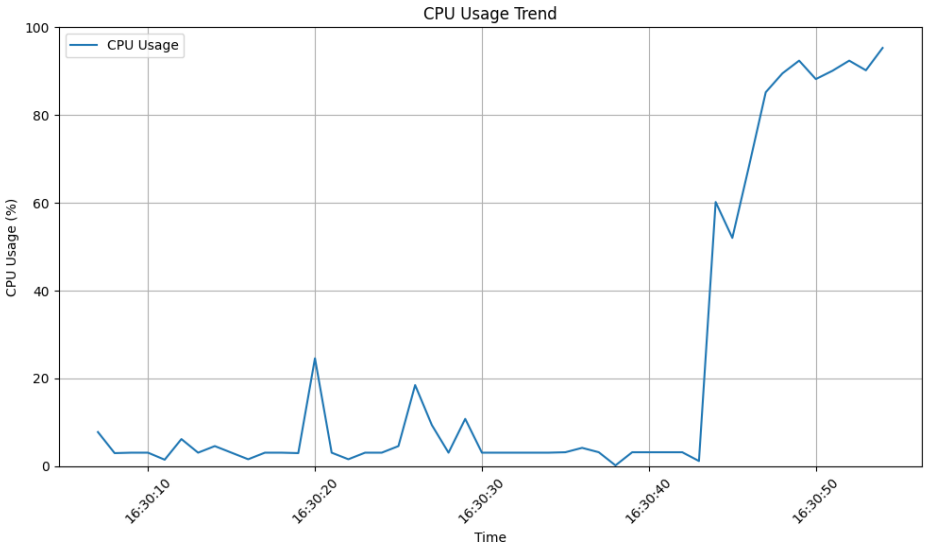
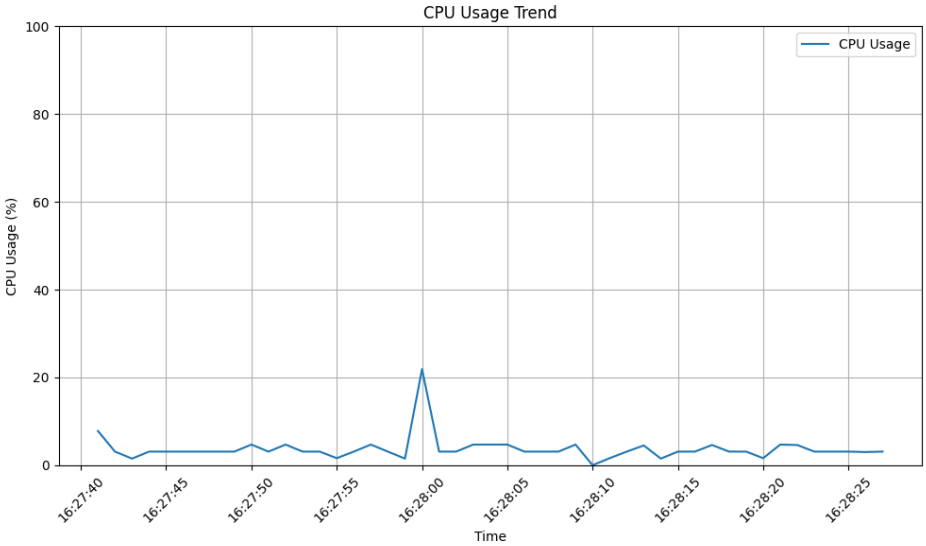


(**a**)



(**b**)

Figure 4. CPU usage trend: a during attack, b during legitimate user interaction

While CPU usage offered clear insights, Figure 5 shows no significant differences in memory consumption on the web application server during the attack (subfigure_a) compared to normal use (subfigure_b). This suggests the attack primarily impacted CPU resources. However, we expect the changes to be reflected in storage utilization on the Windows MySQL server, which requires further investigation.

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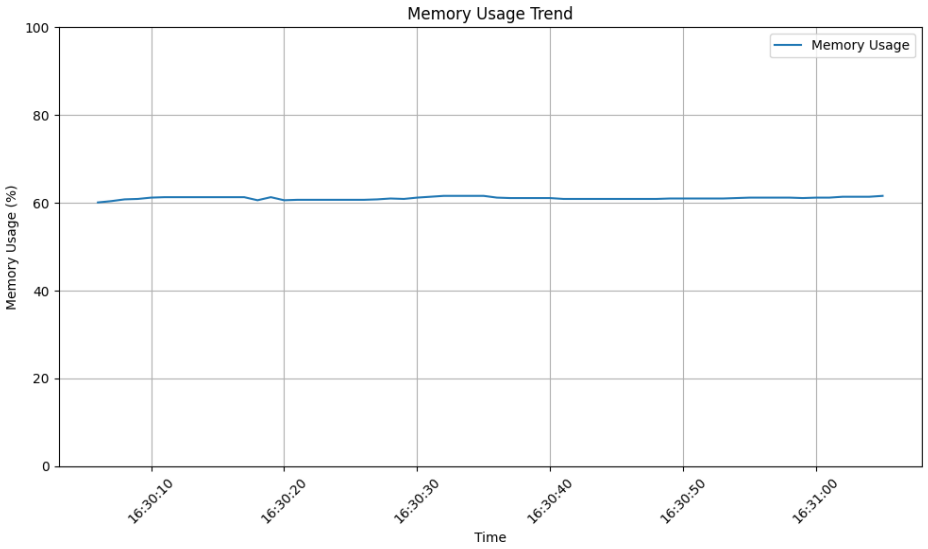
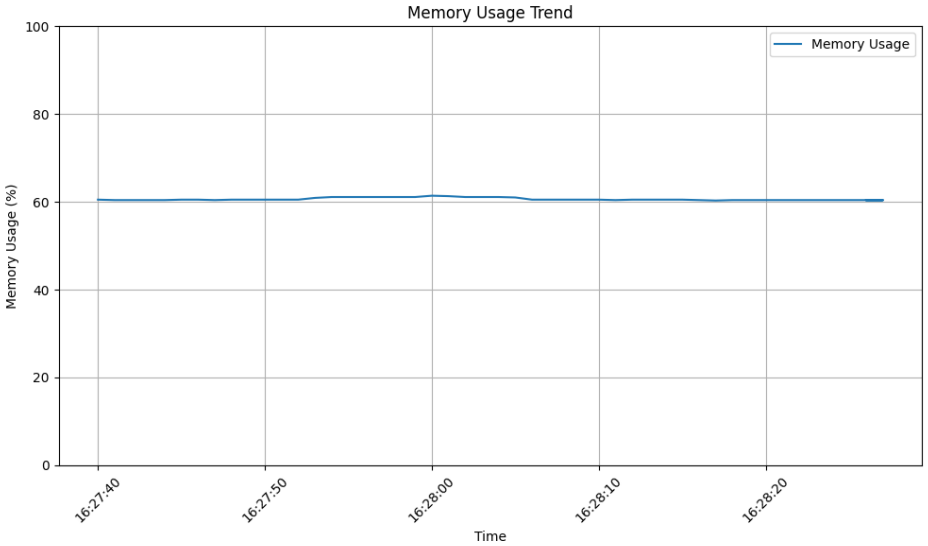


(**a**)



(**b**)

Figure 5. Memory usage trend: a during attack, b during legitimate user interaction

Figure 6 compares the CPU usage of the attacker's machine with the server throughout the attack. While the server experienced sustained high usage, the attacker's CPU usage dropped to 0% just when the server shut down.

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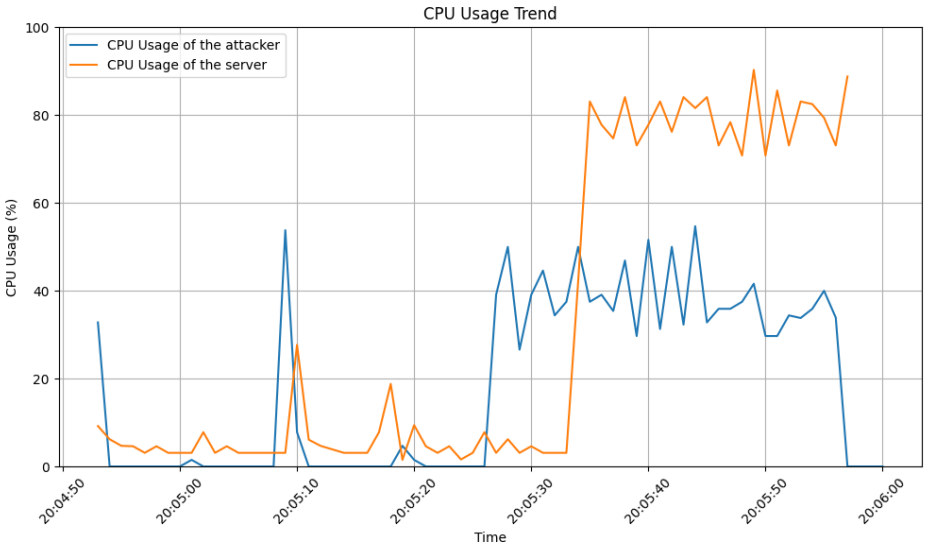

Figure 6. Attacker CPU Usage compared to the server CPU usage

While the attack demonstrably impacted server resources, its efficiency from the attacker's perspective is questionable. Many other DoS techniques offer a better "workload-result ratio," meaning they achieve similar disruption with less resource investment. However, this advantage comes at the cost of easier detection. Table 4 illustrates a captured request sent during the attack. Generally, for the application itself, headers appear legitimate and do not differ from a typical request sent by a legitimate user.

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Table 4. Example attack POST request headers received by the server.

Host	192.168.1.13
Accept	text/html,application/xhtml+xml, application/xml;q=0.9,image/avif, image/webp,image/apng,*/*;q=0.8, application/signed-exchange;v=b3;q=0.7
Cookie	session=.eJwlzLsKwyAARuFXkX8WU VND6guEDC0dsos0NhWsgpcuIe9eoeO Bw3dgeUBDXCUT48QEEwMofKwu22f 1KZpSba7QB8jWx_XdKBEjuacvkVwOR ExaKX1RZL6tOClC2ne3GRhXzYUR9G B2gq05JyiFZeN71JsIfwz2o_r8txcqTh_vp MrnA.ZVZXxw.h1HjL5HRu_cm9I9MK _dJJnbRcqg
Origin	https://192.168.1.13
Referer	https://192.168.1.13/login
Sec-Ch-Ua	Google Chrome;v="119", "Chromium";v="119", "Not?A_Brand";v="24"
Connection	keep-alive
User-Agent	Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/119.0.0.0 Safari/537.36
Content-Type	application/x-www-form-urlencoded
Cache-Control	max-age=0
Content-Length	30
Sec-Fetch-Dest	document
Sec-Fetch-Mode	navigate
Sec-Fetch-Site	same-origin
Sec-Fetch-User	?1
Accept-Encoding	gzip, deflate, br
Accept-Language	en-US,en;q=0.9
Sec-Ch-Ua-Mobile	?0
Sec-Ch-Ua-Platform	Windows
Upgrade-Insecure-Requests	1

5. Discussion

This study examined a DoS attack utilizing spoofed telemetry data, aiming to mimic legitimate user behavior and evade detection. Our analysis revealed:

- Deceptive Nature: The attack exploited the system's reliance on telemetry data for user identification and resource allocation. This highlights the inherent vulnerabilities of trust-based security models in complex systems.
- Challenges in Detection: The attack's ability to blend in with typical user behavior necessitates advanced detection methods that move beyond simple anomaly-based approaches.

However, while using controlled simulations ensured data collection, it may not fully capture the complexities of real-world attack scenarios. Additionally, the analysis focused on a specific attack type, and the effectiveness of deception might vary with different approaches.

Our findings corroborate previous research highlighting the growing sophistication of DoS attacks and their increasing use of deception techniques. Moreover, the challenges in detecting deception-based attacks resonate with calls for advanced threat detection methods that combine behavior analysis with anomaly detection.

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Abbreviations

The following abbreviations are used in this manuscript:

DoS	Denial of Service
ML	Machine Learning
LSTM	Long-Short Term Memory
GAN	Generative Adversarial Network
IDS	Intrusion Detection System
CSV	Comma-Separated Values
CPU	Central Processing Unit

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