

# Attack-Defense and Performance Adaptations for Social Virtual Reality Learning Environments

Samaikya Valluripally<sup>a</sup>, Vaibhav Akashe<sup>a</sup>, David Falana<sup>b</sup>, Michael Fisher<sup>c</sup>, Prof. Khaza Anuarul Hope<sup>a</sup>, Prof. Prasad Calyam<sup>a</sup>University of Missouri-Columbia<sup>a</sup>, Rutgers University<sup>b</sup>, Columbia College<sup>c</sup>

## INTRODUCTION

- Social Virtual Reality Learning Environments are 3D spaces designed to educate students remotely via online platforms to enhance learning capabilities.
- Lack of handling performance and security factors can cause a disruption of user's learning experience by inducing cybersickness.
- Our Contributions:** (i) Develop novel model-driven based adaptation framework, to determine the suitable attack-defense or performance adaptation. (ii) Create a full application that allows us to observe the performance and functionality of the systems, architectures, and the developed model behavior.

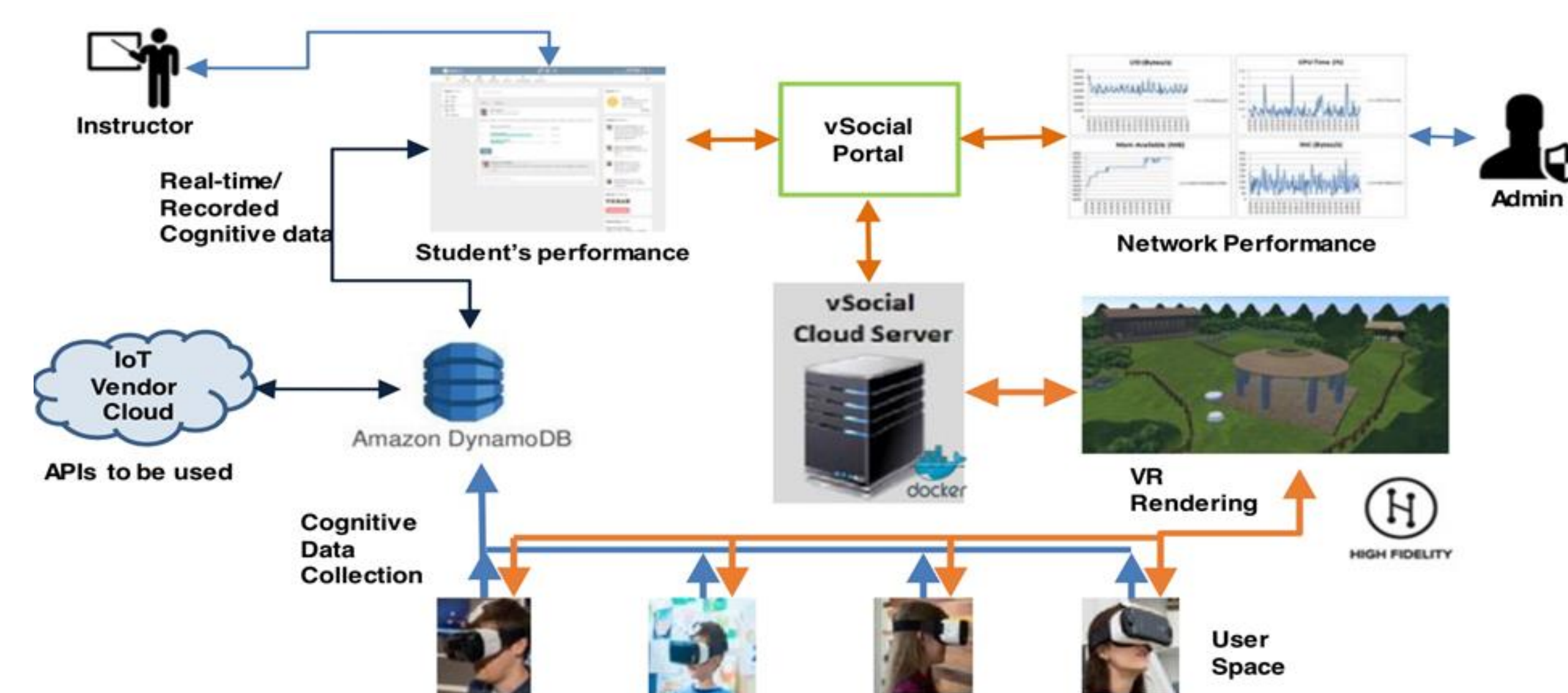


Figure 1: Overview of vSocial, a Social VRLE for training youth with Autism Spectrum Disorder

## CONTROL LOOP ADAPTIVE FRAMEWORK

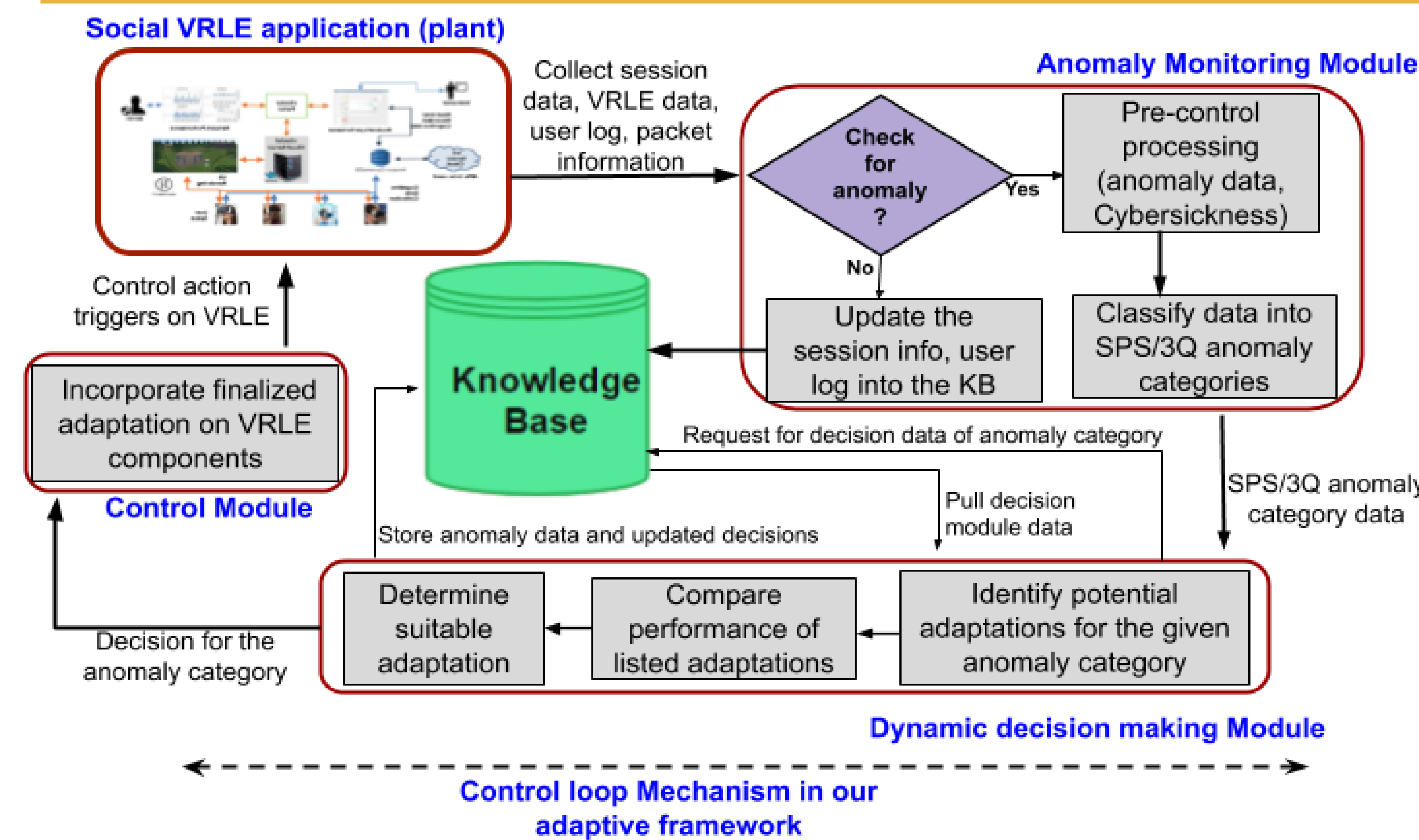


Figure 3: Adaptive Framework

Using our proposed control loop adaptive framework, we implement the real-time adaptations to mitigate cybersickness in social VRLEs.

**Step-1:** VRLE data (user data, session info) is collected to determine any anomalies using our anomaly monitoring tool

**Step-2:** If any anomaly is detected, our framework proceeds to categorize the anomaly into a performance or security issues.

**Step-3:** Using this categorized data, the framework invokes the decision module to determine the suitable adaptation for the detected SPS/3Q anomaly event.

**Step-4:** The dynamic decision-making algorithm updates the determined adaptation and their respective anomaly into the knowledge base.

**Step-5:** Now, the resultant adaptation is incorporated on the VRLE components and further checked if the anomaly still exists.

## EVALUATION RESULTS

Anomalies Detected						
Type	Time	Source	Destination	Protocol	Length	Info
SPS	557.369417	128.206.20.46	128.206.20.43	UDP	92	58222 > 62054 Len=50
SPS	421.962237	128.206.20.43	128.206.20.46	UDP	89	40102 > 58222 Len=47
SPS	553.712925	128.206.20.46	128.206.20.43	UDP	90	58222 > 62054 Len=48
SPS	113.666930	128.206.20.46	128.206.20.43	UDP	78	58222 > 62054 Len=36
SPS	421.248308	128.206.20.43	128.206.20.46	UDP	83	62058 > 58222 Len=41
QoS	82.558665	3.20.240.238	192.168.10.68	UDP	128	48001 > 52766 Len=86
SPS	223.134959	128.206.20.46	128.206.20.43	UDP	90	58222 > 62054 Len=48
SPS	556.242194	128.206.20.46	128.206.20.43	UDP	92	58222 > 62054 Len=50

Figure 4: Anomaly Monitoring tool showing the Detected Anomalies related to SPS/3Q events

Current Solution	Good Solution		Bad Solution	
	12.8			
Solution	Cost(\$)	Runtime (ms)	Resource Cost(mb)	
AWS GuardDuty	1.0	513.0	128	

Active module: SPS  
 [AWS GuardDuty, Higher Resources, Higher Network Bandwidth, Enhanced Networking, Upgrading Instance Type]  
 SPS, 115.244831, 128.206.20.46, 128.206.20.43, UDP, 92, 58222 > 62054 Len=50

Figure 6: Decision Module determine AWS Guard Duty as the suitable solution to implement for an SPS issue

Anomaly Category:	Specific Anomaly Issue:	Adaptation Name:	AWS Service Used:	Threshold Metrics:	Response Time:
QoS	High CPU Utilization	Upgrading Instance Type (A1)	AWS Lambda	(Before) CPU Utilization 9% (After) CPU Utilization 4%	553.066 ms
		Higher Resources (A2)	AWS Autoscaling	(Before) CPU Utilization 9% (After) CPU Utilization 4%	300 s
QoS	Low Network Bandwidth	Enabling Enhanced Networking (A3)	AWS Lambda	(Before) Average Network Packets Out >= 7280 (After) Average Network Packets Out = 7280	900.067 ms
		Higher Network Bandwidth (A4)	AWS Autoscaling	(Before) Average Network Packets Out >= 7280 (After) Average Network Packets Out < 7280	300 s
SPS	Unauthorized Access	Malicious Monitoring Tool (A5)	AWS GuardDuty	Best Practices Suggested By AWS Services	513 ms

Figure 5: Performance of the determined adaptations for the detected anomalies using our framework in terms of response time and threshold Metrics

### Key Findings:

- We determine the cybersickness occurrence can be quantified using certain QoS (packet loss), QoA (visualization delay) metrics from our simulation experiments in vSocial.
- We perform trade-off analysis of our framework for the decision making of the adaptation in terms of different threshold metrics, system response time, resource usage and cost metric.
- With these results, we also show a before after scenario, where we determine that addressing most vulnerable anomaly (Low bandwidth) can aid in mitigating the cybersickness occurrence with the given response time.
- From our QoS adaptation, the CPU Utilization went from 9% to 4% after the adaption occurred, and for the QoS adaptation we observe the Average Packets Per Second is stabilized to meet the threshold value.

## CONCLUSION

- Proposed a novel control loop adaptive framework to address the performance and security issues that induces cybersickness in a social VRLE application.
- We perform real-time adaptations on the identified issues and mitigate them to reduce the cybersickness level of the users.

In the future, we plan to expand our framework to make active decision making for zero-day anomaly events.

## ACKNOWLEDGEMENTS

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## ANOMALY DATA COLLECTION

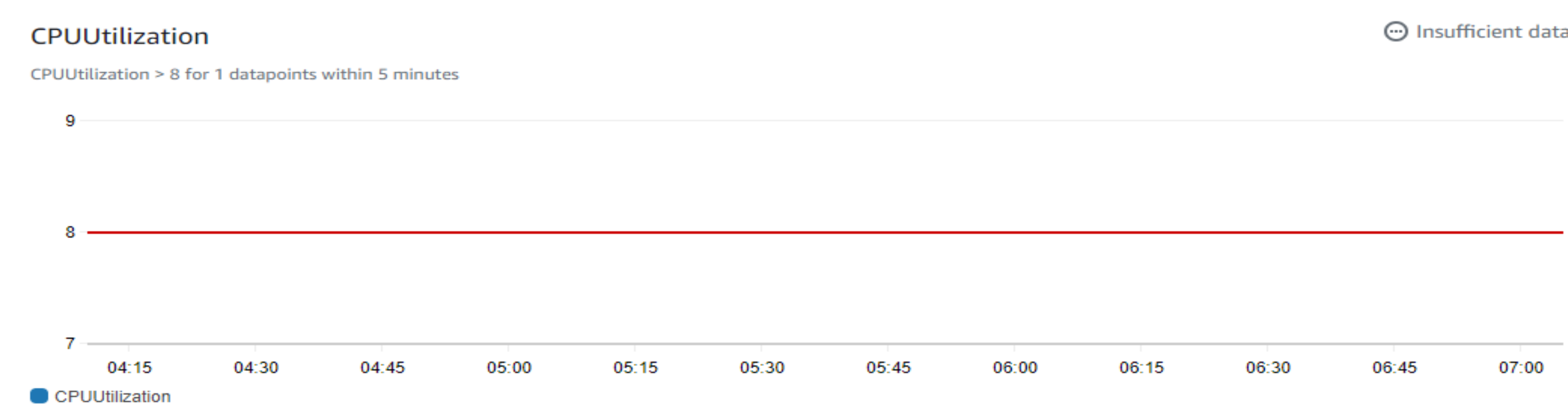
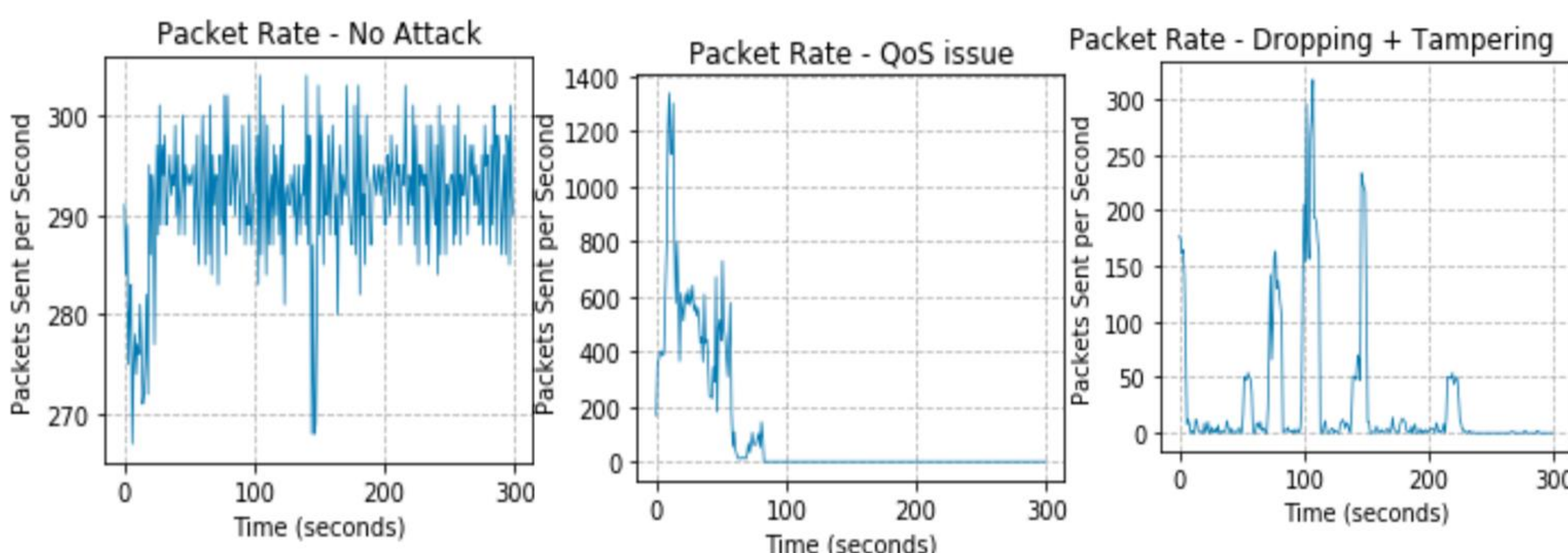


Figure 2: AWS alarm created for Quality of Application anomaly with threshold condition CPU utilization &gt;8%



We collected the relevant SPS/3Q anomaly data, once the alarms created in AWS triggers for the vSocial application.