Software Updates Monitoring & Anomaly Detection

Imanol Etxezarreta Martinez[a], David García Villaescusa[b], Imanol Mugarza[c], Irune Yarza[d] and Irune Agirre[e]

Ikerlan Technology Research Centre, Basque Research and Technology Alliance (BRTA), Spain

Keywords: Software Update, Patches, Monitoring, Anomaly Detection, Security.

Abstract: Security is becoming a must in the current all-connected paradigm. Software updates are essential to fix any new identified security flaw or vulnerability that may appear as they normally are the fastest and cheapest solution. Nevertheless, a software update targeted to fix a determined issue could end up in a different problem. In order to detect these new issues, systems should be able to gather monitoring data so that possible effects and consequences are observed and characterized. This is specially relevant when upgrades are performed remotely, like in road vehicles, and no prior outcome information is available to the manufacturer. In this paper, a software updates monitoring, an anomaly detection procedure and a proof-of-concept are presented. The monitoring and anomaly detection approach enable the detection of performance anomalies that could result for instance, from malicious code installation during an update. This offline monitoring information can also be used for further system design improvements and to facilitate the review and assessing processes of security issues.

1 INTRODUCTION

Next generation computing systems are expected to offer much more computation capabilities, autonomy and higher levels of interconnection. Data sharing and processing technologies are incorporated to the connected products, which enable information exchange among devices and system over a communication network. Given that in this scenario, cyber-attackers might capture sensible information or tamper the communications with the devices. Therefore, these systems and products should incorporate security mechanisms to mitigate those risks. Besides, software updates management is an element of a complete and sound cybersecurity strategy (Mugarza et al., 2017). Indeed, regulatory requirements related to software updates are being established, for example in the European Cyber Resilience Act (Chiara, 2022),

Runtime monitoring is an useful approach that relies on observing the runtime execution behaviour of a target system in its final environment with different potential applications, such as, verification, error logging, real-time fault detection and advanced maintenance procedures. Furthermore, the ability of replacing or adding new software components to the system causes the number of potential system variants to grow exponentially. As with any other safety system development, these system variants shall be verified and validated. In this case, it is of special interest to guarantee that the software update is compatible with the existing system through integration testing. On this phase monitoring the system at runtime is of paramount importance. In addition, software update mechanisms become a new entry point for security attackers and appropriate security countermeasures shall be deployed to prevent them, which could be improved by monitoring the system at runtime. This monitoring could gather a constant feedback from remote devices and it will be very helpful for decision making of the revision process during the product life cycle, it is possible to improve the design by optimizing it accordingly to the gathered information. In this way, the system can continuously improve the resource usage and avoid oversizing to accommodate new software functionalities if needed.

Regarding anomaly detection, the main focus of this paper, monitoring information is used to identify possible performance anomalies and confirm that the software update does not compromise system relia-

[a] https://orcid.org/0000-0002-3738-8753
[b] https://orcid.org/0000-0003-2497-6553
[c] https://orcid.org/0000-0002-6311-0632
[d] https://orcid.org/0000-0002-3607-7443
[e] https://orcid.org/0000-0002-9507-8841

Etxezarreta Martinez, I., García Villaescusa, D., Mugarza, I., Yarza, I. and Agirre, I.
Software Updates Monitoring Anomaly Detection.
DOI: 10.5220/0011822000003482
In *Proceedings of the 8th International Conference on Internet of Things, Big Data and Security (IoTBDS 2023)*, pages 115-122
ISBN: 978-989-758-643-9; ISSN: 2184-4976

bility and operational features. For this purpose, the system is monitored in two phases, following the approach presented in (Mugarza et al., 2021). Firstly, at design time and before the software update process, an initial system fingerprinting, i.e. profiling, is performed based on execution measurements on the final system. This profile will provide an initial system baseline model. Secondly, at runtime and after update deployment, a new operation time profile will be obtained and compared to the initial one to ensure that it follows its expected behaviour profile and that therefore, the update does not introduce regressions. Based on the result of the comparison, an action can be taken (like raising an alarm or stopping the system).

This paper presents a software updates monitoring and anomaly detection approach developed in the context of the UP2DATE European project (Agirre et al., 2021). After this introduction, the literature review is provided. Next, the software updates process cycle proposed within UP2DATE is shown. Following, the monitoring and anomaly detection approach is introduced and results from initial proof-of-concept results displayed. Lastly, discussions and conclusions are presented.

2 LITERATURE REVIEW

Security monitoring is a wide topic in cybersecurity, which is the process of collecting and analysing indicators of potential security malfunctions, threats, and incidents. For the software update monitoring and fingerprinting, techniques which aim at detecting unknown worms and viruses are used. In the process of analysing and identifying new computer malware, a vulnerability signature is created (Singh et al., 2004). Anomaly detection techniques, by means of identifying unexpected and unusual system patterns, are also used. In case of already distributed and/or speeded worms, multiple monitors can be deployed to detect the malware spread (Kim and Karp, 2004). Different techniques for ransomware fingerprinting and anomaly detection exist, such as: system functional behaviour, traffic analysis and content inspection or performance monitoring. As well, efficient and accurate network monitoring and content inspection is essential to make sure that all systems operate as intended (Lee et al., 2014).

For the network worms and viruses, the networking monitoring data, such as open ports and bandwidth, can be evaluated (Singh et al., 2004). In that paper, S. Singh et al. proposed the network address dispersion estimation as a technique to identify worms and viruses. For the computation of the dispersion, the source and destination IP addresses are analysed. Demilitarized Zone (DMZ)[1] traces might also be monitored and analysed for signature detection, as done in (Kim and Karp, 2004). On the contrary, a different malware detection approach is proposed (Kolbitsch et al., 2009), in which the information flows between the system calls and the malware is modelled. To this end, firstly, by means of a monitor, the system calls are captured, and behaviour graphs generated. Once the behaviour model is constructed, the program is continuously monitored, and its actual behaviour compared to the previously generated model. Similarly, dynamic taint analysis and graph-based techniques for malware detection to detect common malware behaviours is used (Ding et al., 2018). In this case, the Windows Application Programming Interface (API) system calls are monitored.

Online performance modelling and monitoring is vital to identify, detect and address performance issues, which may have a negative impact in the system. Indeed, as the time between new software releases gets significantly short, the problem of thoroughly evaluating the performance of an updated application further exacerbates (Cherkasova et al., 2009). Simulated fault injections corresponding with CPU stresses (Samir and Pahl, 2019; Samir and Pahl, 2020) with infinite loops consuming all CPU, memory leaks using the full memory and workloads that exhaust the system resources. The goal of this activity was to evaluate the presented anomaly detection and prediction model to detect inconsistencies at runtime. Similarly, other experiments performed (Kang et al., 2012) were focused on CPU utilization, memory utilization, and system response time metrics. The authors proposed a Hidden Markov Model based anomaly and prediction model for edge cluster environments. In addition, a review (Ibidunmoye et al., 2015) of the performance anomaly detection and bottleneck identification (PADBI) has presented problems and identified relevant research questions, challenges, contributions, trends and open issues. They highlight different types of commonly observed performance anomalies and bottlenecks in computing systems and conclude that existing PADBI systems operate based on one or more detection strategies and methods, being statistical and machine learning the two predominant ones in literature.

A full-stack monitoring and analysis system is proposed (Jayathilaka et al., 2017; Jayathilaka et al., 2020) for performance anomaly detection and bottleneck identification in cloud Platform-as-a-Service

[1] A DMZ is a perimeter network that protects an organization's internal local-area network (LAN) from untrusted traffic.

(PaaS) systems. The presented system, called Roots, tracks HTTP and HTTPS requests, and applies diverse multiple statistical methods to detect performance anomalies. For this purpose, Roots gathers logs and internal interfaces data, in which high-level metrics (throughput, incoming requests, latency) and PaaS invocations and duration are collected. Moreover, a root cause analysis is performed to identify the performance anomaly root cause by monitoring and analysing workload and PaaS services data. The following data from the PaaS kernel invocations are also captured: timestamp, source application, PaaS service invocation number, request properties, target kernel properties and invocation execution time.

For the anomaly detection, anomaly detectors are deployed, which periodically analyse the collected information. When an anomaly is detected, an action listener is triggered by means of anomaly handlers, such as sending alert emails or displaying dashboard messages. An online anomaly diagnosis framework (Tuncer et al., 2018) is also proposed, which leverages the already monitored performance and resource usage data to learn and detect the signatures of previously observed anomalies. The framework uses the tree-based machine learning techniques: decision tree, random forest and adaptive boosting. Similarly, a scalable infrastructure for continuous monitoring of large-scale computing systems and applications (Agelastos et al., 2014) is proposed, where the information they obtain on a system-wide basis to gain insight into system and application performance includes:

- Network related information: Congestion, Delivered Bandwidth, Operating System Traffic Bandwidth, Average Packet Size and Link Status.
- Shared File System information (e.g. Lustre): Opens, Closes, Reads and Writes.
- Memory related information: Current Free and Active.
- CPU information: Utilization (user, sys, idle and wait).

3 UP2DATE OVER-THE-AIR SOFTWARE UPDATES

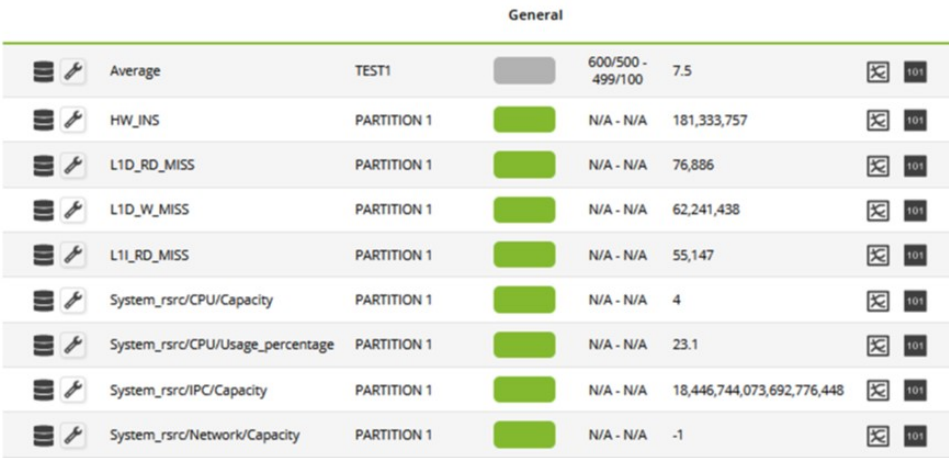
One of the most challenging and relevant steps of an update management procedure in the industrial environment is the definition of a safe and secure process architecture for the execution of updates (Mugarza et al., 2021). The industrial system type monitored in this study is composed by a server, a gateway and an end-device. The upgradable devices are the gateway and the end-device. In the overall system more than one gateway and more than one end-device per gateway could exist. However, as matter of simplification we are only using one of each for the monitoring and anomaly detection approach definition and proof-of-concept validation.

The update cycle is composed by a determined number of steps (Agirre et al., 2021):

1. **New Available Update.** Updatable software components and associated safety and security metadata are stored in the update repository.
2. **Design Time Checks.** Basic checks before update release.
3. **Update Release.** Identification of target systems where the update is applicable, update distribution and user notification.
4. **Virtual Compatibility and Integration Check.** Internal tests before authorizing update installation in particular device.
5. **Download.** Transfer of required software, data and files from the server to the gateway, performed considering security matters.
6. **Installation.** Store the received files in the reprogrammable memory of the gateway or the end-device and set them up to accommodate the new (or rollback) software.
7. **Verification.** Check the correctness of the new software installation, configuration and dependencies with other software updates.
8. **Activation.** Checks if safety conditions for the update are given, invalidates and stores old software and runs new one, considering the needs of dependent updates.
9. **Online Monitoring.** Verify, based on runtime information, that the system meets its specification, and that SASE metrics are within their safe and secure range at system operation: before, during and after an update.
10. **Offline Monitoring.** Send runtime information to a remote server for offline automatic or manual inspection. This is the monitoring performed for the anomaly detection. Is performed continuosly.

4 MONITORING

Security monitoring is an essential activity to carry out for the security management of systems and products, especially in the operation and maintenance phase. In UP2DATE, two different security monitoring methods are applied: security fingerprinting and



General

Average	TEST1		600/500 - 499/100	7.5
HW_INS	PARTITION 1		N/A - N/A	181,333,757
L1D_RD_MISS	PARTITION 1		N/A - N/A	76,886
L1D_W_MISS	PARTITION 1		N/A - N/A	62,241,438
L1I_RD_MISS	PARTITION 1		N/A - N/A	55,147
System_rsrc/CPU/Capacity	PARTITION 1		N/A - N/A	4
System_rsrc/CPU/Usage_percentage	PARTITION 1		N/A - N/A	23.1
System_rsrc/IPC/Capacity	PARTITION 1		N/A - N/A	18,446,744,073,692,776,448
System_rsrc/Network/Capacity	PARTITION 1		N/A - N/A	-1

Figure 1: Monitor values in PandoraFMS server.

anomaly detection, and security auditing. Since the security needs might change through the time, the monitoring infrastructure and methods could also face new necessities and enhancements.

The UP2DATE monitoring architecture supports the possibility to perform application fingerprinting to detect anomalies that might be related to security issues. Figure 2 shows the setup of the UP2DATE fingerprinting approach. The applications that are being monitored include an 'Event Recorder' responsible of measuring the relevant metrics which are then transmitted to the Offline Monitoring partition running on the gateway.

The Offline Monitoring partition will collect all the data and perform a data pre-processing task. This processed data is then send to a remote server for fingerprinting analysis, which consist of a monitoring system and an anomaly detection tool. To this end, a monitoring agent is integrated in the gateway. The key infrastructure for data gathering and communication is Pandora FMS, an IT monitoring tool that collects information and then processes it to determine the state of the monitored platforms (López, 2010). The quantity of variables to collect and the number of possible platforms can both be in the order of hundreds.

On the server side, Pandora stores the data in an internal SQL-type database. All stored data can be queried through a REST API. This means that the anomaly detection engine will be running as an auxiliary service. The developers are free to choose the programming language and environment they desire. Starting from a set of data collected into a time series, these libraries can build a model, that is a fingerprint, of the applications running on a target platform. This model represents the stable state of the platform in secure conditions, and can be used as a reference to detect anomalies during operation. Whenever an update is performed, the fingerprinting model must be generated in a testing environment before the update process is executed in the target system. This feedback mechanism will enable the continuous monitoring of the system, which will help developers and owners to correctly address the maintainability of it.

4.1 Event Collection & Processing

The partitions and devices that can be updated in a system, are monitored with an 'Event Recorder' or observer that is responsible for collecting metrics, which are temporally stored in shared memory. Each observer has its respective monitor in the monitoring partition, which will read the shared memory data and react appropriately in case a value violates its range. The boundaries of each measured metric are defined in the partition metadata file. To make this possible, each partition defines a metadata file that includes information about the shared memory device used to write and read the metrics collected in the partition. By design, each partition will be mapped to a different shared memory device for wide metrics writing.

Some of the metrics used for safety are also used for security. In order to avoid unnecessary overhead looking the same values twice, this shared information is written into a shared memory by the online monitoring partition and then read by the offline monitoring partition. Finally, the collected data is sent upstream to PandoraFMS server once every minute. This architecture scheme provides easy scalability. In Figure 1 it is shown the representations of some measures upstreamed to PandoraFMS in its own Dashboard.

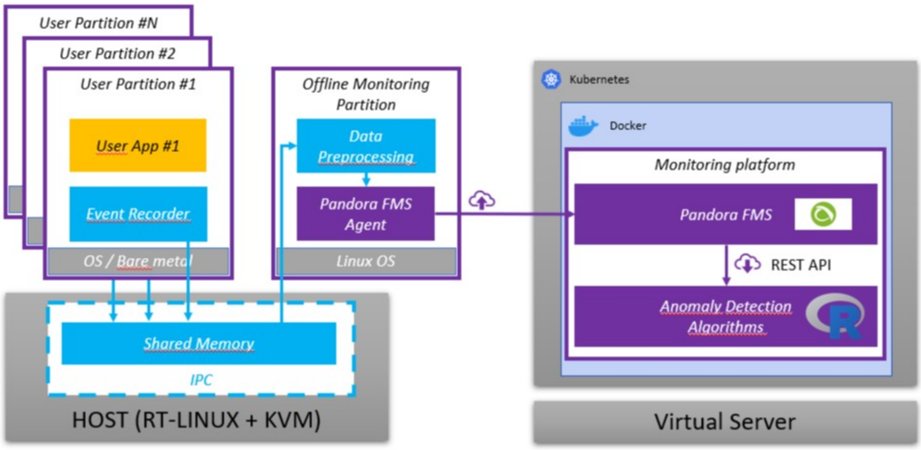


Figure 2: Setup of the Up2Date fingerprinting approach.

4.2 Secure Data Gathering

In order to provide security to the communication over a public network, every communication between host (or gateway if we are considering the host function in the whole system) and server will be operated through a TLS-based VPN tunnel with individual credentials per gateway. As a consequence, both client and server need to be authenticated and the communication is encrypted.

VPNs allow the gateway to provide the capability of accepting incoming connections only from within a trusted environment. Furthermore, as each VPN endpoint can be containerized, it can be assured that compromised devices cannot be used to attack other devices, as they will be imprisoned in the corresponding container.

5 ANOMALY DETECTION

Once the monitor values are available in the Pandora FMS Server, their processing action is enabled with the objective of detecting anomalies by the anomaly detection process that could happen during the execution of the application. The monitored data is stored while the system is running in a safe and secure environment, thus obtaining the expected metric values. The set of these expected values for a particular metric is going to be referred as baseline. A baseline must be obtained for every metric monitored for security.

The selected package to detect anomalies, due to its simplicity and proven efficacy, is *Anomalous*[2], which consists of an R package to detect the most unusual series. This package computes a vector of features on each time series, which represent numeric characteristics of the object in a mathematical way. To continue, a principal component decomposition on the features is performed and finally various bivariate outlier detection methods are applied to the first two principal components. The method is validated by the authors with real-world and synthetic data comprising normal and anomalous time series (Hyndman et al., 2015). The anomalous datasets are based on a malicious activity, new feature deployment or a traffic shift. It is important to keep in mind that this library detects the rarest time-series in the given dataset, and this is why previously obtained normal execution time-series (baseline) are needed to "compare" the normal execution scenario with the runtime values. This comparison is done in the following manner: runtime values are appended to the baseline data and the anomaly detection algorithm is applied to the complete dataset to detect anomalous time-series. The baseline dataset needs to be considerably larger (minimum 5 times bigger) than the runtime data so that the baseline values are considered as the normal time-series.

The Pedestrian Detector application is used to show how the anomaly detection works using the Wide Metrics Observer, which as explained in Section 4.1, writes the wide metrics in a shared memory every second. To provide an illustrative example, in this section we just focus on the CPU usage metric. The offline monitoring partition reads the shared memory of the partition/system-wide metrics once every second and collects the CPU use in a file. The file stores 60 CPU values per line, thus the time-series will have 60 values each. As the application is running in an infinite loop performing the same process for the same input image set, a final baseline of almost an 6000 element time-series is obtained to have a wide dataset of normal operation time-series. Due

[2]https://github.com/robjhyndman/anomalous

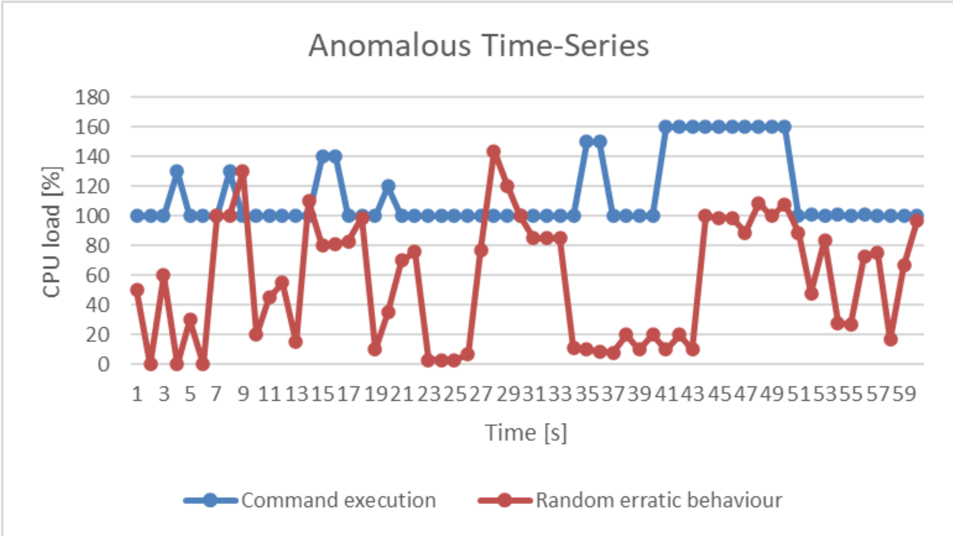


Figure 3: Anomalous time-series examples.

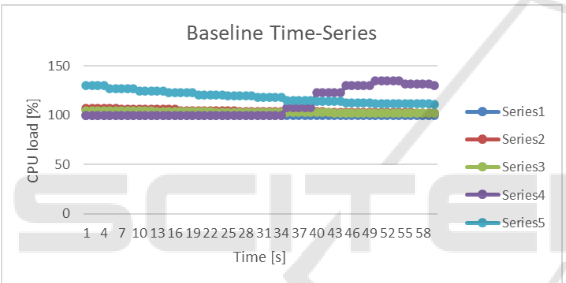


Figure 4: Baseline time-series examples.

to illustrative reasons, only some of the obtained baseline time-series are shown in Figure 4. The shown series are ones that show some typical behaviour of the application: constant CPU values, stepped CPU value increase and stepped CPU value decrease.

The next step is to detect anomalous series in the runtime values. The first step is to insert/append runtime values to the baseline values, which should additionally include anomalies. Looking at the baseline values, the evolution of the CPU load is quite constant or it has some staggered ups and downs. The potential anomaly in the runtime values could have different behaviours, as for example, different spikes in the CPU load triggered by some command execution or some random erratic CPU behaviour. For this example, these two anomalies are artificially introduced in the runtime values with indexes (positions) 50 and 51, represented in Figure 3.

Once the dataset of the baseline plus the runtime values with the anomalies is available, the next step is to pass this dataset to the previously mentioned *Anomalous* anomaly detection library. If constant time-series are passed to the library the feature extrac-

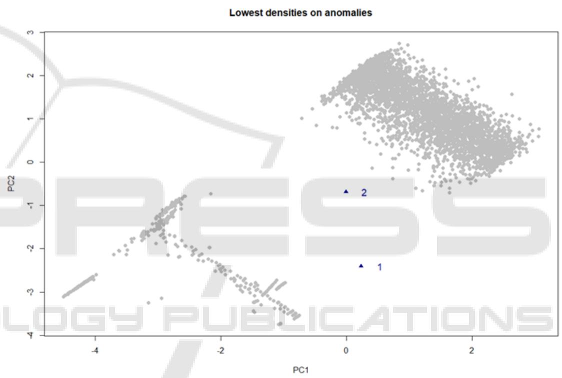


Figure 5: Detection for synthetic anomalies.

tion process fails due to a divide-by-zero operation. In this case, as the computation required by the application is quite heavy, the CPU usage happens to stay at 100% value constantly at least for a minute and thus, for a complete time-series. In order to solve this issue, a very small normal distributed noise is added to the dataset. In this way, the data is prepared to be passed to the library and the following result is obtained.

Table 1: Table to test captions and labels.

Anomaly Order	Index Position
1	51
2	50
3	3594
4	4195
5	3164

As it can be seen from the resulting plot in Figure 5, 2 anomalies are detected, which are marked with blue triangles. But it must be checked that the 2

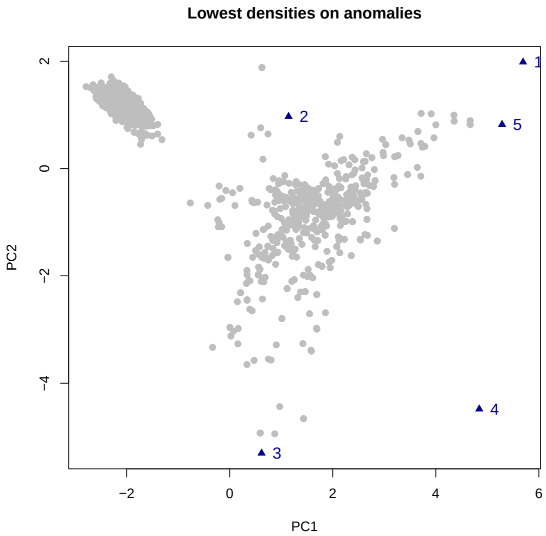


Figure 6: Detection for CPU anomalies.

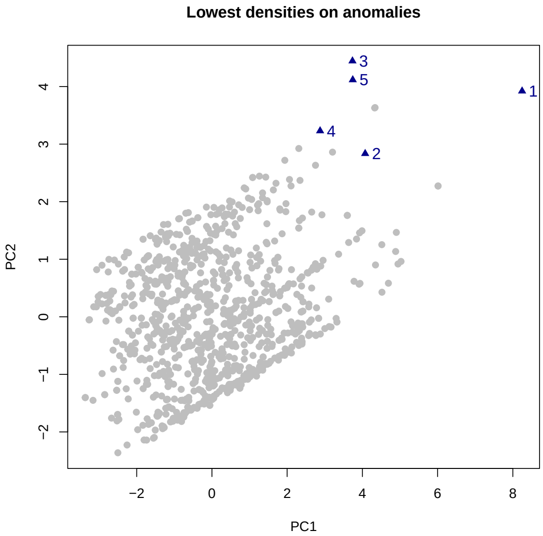


Figure 7: Detection for memory anomalies.

points in the plot represent the 2 anomalous synthetic time-series. For this, the *Anomalous* library computes a table of scores for each time-series, from which the time-series with the smallest score is considered the rarest. Sorting this table, the dataset is ordered from the rarest to the most normal time-series. We can see the anomalous time-series with indexes 50 and 51 in the top 5 sorted results that are shown in Table 1.

For this demo it was previously known that there should be 2 anomalies, because these were enforced for validation purposes. But in real scenarios, there could be more than 2 anomalies or not even one. As already mentioned, the *Anomalous* package indicates which are the most different time-series within the data. Thus, it will always plot at least 1 time-series as a blue triangle, as if it was an anomaly. A post-examination of the result should always be done to verify that the indicated time-series is, in fact, an anomaly. This operation can be done plotting the potential anomalous time-series against some baseline series and assess if it is really an anomalous one.

The anomaly detection used in the system deployed is based on a baseline of 1,000 series, each with 60 values, that are considered not anomalous as those values were recollected during normal runtime. A single anomalous series is introduced to such baseline. The anomaly detector determines then an anomaly score and sorts the series using that score. With the series index sorted as shown in Table 1. Examples of the 5 most anomalous series are shown for CPU in Figure 6 and for memory in Figure 7. If the anomalous series is between the 5 most anomalous scores we consider the anomaly has been detected by the anomaly detector. Table 2 shows the obtained anomalies detection rate.

Table 2: Anomalies detection rate.

Metric	Detection rate
CPU usage	94%
Memory usage	97%
IPC	100%

6 CONCLUSIONS

In this paper, a monitoring and anomaly detection approach for software updates is presented. The monitors have been deployed in a NVIDIA Jetson Xavier platform as a proof of concept with the Pandora Server allocated at the other end of a VPNv6 network. The detection of anomalies has been performed for CPU and memory values. We consider the detection rate of the performed tests to be high enough to have a positive impact in detecting security flaws of an update or attacks performed to the system.

The purpose of offline monitoring is to gather information at the working devices that will be sent over to a remote server for automatic or manual inspection for security fingerprinting and design optimization. We are not making a proposal for automatic responses to the detection apart from the notification as currently the anomaly detection will detect differences provoked by the update itself that are intentional. This could be a very interesting future work for not intrusive automatic reactions on the systems, that implements an exception system for the expected changes of behaviour due to the update itself.

Another lines of future work are the improvement on the detection rate through algorithm optimizations and the analysis of other types of possible anomalies, including also software specific indicators. As expected, the anomaly detection data processing requires a substantial computing power. The optimization in terms or efficiency is an interesting field, that could drive to lower detection rates and could be used to achieve a more reasonable anomaly detection for elements that will achieve lower security levels.

ACKNOWLEDGEMENTS

This work has been funded by the European Union's Horizon 2020 research and innovation programme (grant agreement No 871465 (UP2DATE)).

REFERENCES

Agelastos, A., Allan, B., Brandt, J., Cassella, P., Enos, J., Fullop, J., Gentile, A., Monk, S., Naksinehaboon, N., Ogden, J., et al. (2014). The lightweight distributed metric service: a scalable infrastructure for continuous monitoring of large scale computing systems and applications. In *SC'14: Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, pages 154–165. IEEE.

Agirre, I., Yarza, I., Mugarza, I., Binchi, J., Onaindia, P., Poggi, T., Cazorla, F. J., Kosmidis, L., Grüttner, K., Uven, P., et al. (2021). Safe and secure software updates on high-performance mixed-criticality systems: The up2date approach. *Microprocessors and Microsystems*, 87:104351.

Cherkasova, L., Ozonat, K., Mi, N., Symons, J., and Smirni, E. (2009). Automated anomaly detection and performance modeling of enterprise applications. *ACM Transactions on Computer Systems (TOCS)*, 27(3):1–32.

Chiara, P. G. (2022). The cyber resilience act: the eu commission's proposal for a horizontal regulation on cybersecurity for products with digital elements. *International Cybersecurity Law Review*, pages 1–18.

Ding, Y., Xia, X., Chen, S., and Li, Y. (2018). A malware detection method based on family behavior graph. *Computers & Security*, 73:73–86.

Hyndman, R. J., Wang, E., and Laptev, N. (2015). Large-scale unusual time series detection. In *2015 IEEE International Conference on Data Mining Workshop (ICDMW)*, pages 1616–1619.

Ibidunmoye, O., Hernández-Rodriguez, F., and Elmroth, E. (2015). Performance anomaly detection and bottleneck identification. *ACM Computing Surveys (CSUR)*, 48(1):1–35.

Jayathilaka, H., Krintz, C., and Wolski, R. (2017). Performance monitoring and root cause analysis for cloud-hosted web applications. In *Proceedings of the 26th International Conference on World Wide Web*, pages 469–478.

Jayathilaka, H., Krintz, C., and Wolski, R. (2020). Detecting performance anomalies in cloud platform applications. *IEEE Transactions on Cloud Computing*, 8(3):764–777.

Kang, H., Zhu, X., and Wong, J. L. (2012). {DAPA}: Diagnosing application performance anomalies for virtualized infrastructures. In *2nd USENIX Workshop on Hot Topics in Management of Internet, Cloud, and Enterprise Networks and Services (Hot-ICE 12)*.

Kim, H.-A. and Karp, B. (2004). Autograph: Toward automated, distributed worm signature detection. In *USENIX security symposium*, volume 286. San Diego, CA.

Kolbitsch, C., Comparetti, P. M., Kruegel, C., Kirda, E., Zhou, X., and Wang, X. (2009). Effective and efficient malware detection at the end host. In *Proceedings of the 18th Conference on USENIX Security Symposium*, SSYM'09, page 351–366, USA. USENIX Association.

Lee, S., Levanti, K., and Kim, H. S. (2014). Network monitoring: Present and future. *Computer Networks*, 65:84–98.

López, J. (2010). Monitorización con pandora fms 3. *Todo linux: la revista mensual para entusiastas de GNU/LINUX*, (115):20–23.

Mugarza, I., Parra, J., and Jacob, E. (2017). Software updates in safety and security co-engineering. In *International Conference on Computer Safety, Reliability, and Security*, pages 199–210. Springer.

Mugarza, I., Yarza, I., Agirre, I., Lussiana, F., and Botta, S. (2021). Safety and security concept for software updates on mixed-criticality systems. In *2021 5th International Conference on System Reliability and Safety (ICSRS)*, pages 171–180. IEEE.

Samir, A. and Pahl, C. (2019). Detecting and predicting anomalies for edge cluster environments using hidden markov models. In *2019 Fourth International Conference on Fog and Mobile Edge Computing (FMEC)*, pages 21–28. IEEE.

Samir, A. and Pahl, C. (2020). Detecting and localizing anomalies in container clusters using markov models. *Electronics*, 9(1):64.

Singh, S., Estan, C., Varghese, G., and Savage, S. (2004). Automated worm fingerprinting. In *OSDI*, volume 4, pages 4–4.

Tuncer, O., Ates, E., Zhang, Y., Turk, A., Brandt, J., Leung, V. J., Egele, M., and Coskun, A. K. (2018). Online diagnosis of performance variation in hpc systems using machine learning. *IEEE Transactions on Parallel and Distributed Systems*, 30(4):883–896.