

A framework for dynamic monitoring of distributed systems featuring adaptive security

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ABSTRACT

Distributed systems play a crucial role in today's information-based society, enabling seamless communication among governmental, industrial, social, and non-governmental institutions. As information becomes increasingly complex, the software industry is highly concerned about the heterogeneity and dynamicity of distributed systems. It is common for various types of information and services to be disseminated on different sites, especially in web 2.0. Since 'information' has become a prime tool for organizations to achieve their vision and mission, a high level of quality of service (QoS) is mandatory to disseminate and access information and services over remote sites, despite an insecure communication system. These systems are expected to have security mechanisms in place, render services within an acceptable response time, dynamically adapt to environmental requirements, and secure key information. This research article proposes a framework for evaluating and determining a threshold up to which distributed systems can collect data to adapt to the environment. The study also proposes a dynamic security metric to determine the level of security disturbance caused by the monitoring system for adaptation and the measures to be implemented. Additionally, the paper details the role of the monitoring system in safeguarding the adaptive distributed system and proposes an adaptive monitoring system that can modify its functionality as per the environment.

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1. INTRODUCTION

Adaptive distributed system (ADS) changes its behavior and setup on the fly based on things like the number of failures, user needs, and communication patterns. ADS, unlike systems that don't adjust, constantly checks and changes what it does to fit the new conditions [1]. ADS gets a lot of data from subsystems, which makes it more flexible but also makes it more vulnerable to intrusion attempts [2], [3]. The monitoring component gathers a lot of information from the environment, which makes ADS more flexible but also offers serious security risks [4]. Intruders can use the detailed information that the tracking system gathers to get ahead of it. Limiting the collection of data makes the system less flexible, so a balance must be kept [5]. By setting limits on how much information can be collected, security measures that were created based on user needs help keep this balance [6]. Threats to security in distributed systems include changing, inspecting, interrupting, and making up information [7], [8]. This is why promises of availability,

privacy, and integrity are needed. Security metrics figure out the amount of risk by looking at things like size, detail, and how important the information is. These measures help improve system security and set priorities for actions that lower risks [9]. The suggested adaptive monitoring system changes how it acts based on how important the data it collects is and how the environment changes. If the security system works well, it lets you look into things more deeply; if an important alert is found, it encrypts the data so that it can be sent safely [10]. Adaptive security metrics figure out the amount of risk and help people make decisions as the environment changes. These measures change dynamically based on how important the information asset is, which shows how important information changes over time [11]. The suggested system makes sure that the right steps are taken based on changing security metrics and the environment, which improves the general security and adaptability of the system.

Almaraz-Rivera *et al.* [12] presents the application of self-supervised learning (S-SL) to improve security in internet of things (IoT) systems. They concentrate on a particular S-SL method that aims to cluster similar examples together in the feature space, while distinguishing dissimilar ones. The study employed the Bot-IoT and LATAM-DDoS-IoT datasets, which contain both attack and normal traffic data pertinent to IoT environments. The effectiveness of S-SL hinges on the quality and diversity of the training data, which can be challenging to maintain in dynamic IoT networks.

Yaras and Dener [13] explore the creation of a hybrid deep learning algorithm designed to detect attacks in IoT networks. The system is engineered to oversee network traffic, identifying suspicious activity and potential threats. This hybrid model utilizes convolutional neural networks (CNNs) for feature extraction and long short-term memory (LSTM) networks to capture temporal dependencies within the data. It is capable of addressing a range of attack types, making it adaptable to various IoT environments. However, the model may demand substantial computational resources, potentially restricting its use in real-time applications within resource-constrained environments.

Javed *et al.* [14] describe the deployment of a lightweight machine learning-based intrusion detection system (IDS) for IoT devices in smart homes features a two-layered architecture that distributes the computational load between the edge and cloud layers. By employing algorithms such as extreme gradient boosting (XGBoost), this approach seeks to attain high accuracy and efficiency in real-time intrusion detection. While the system provides notable benefits in accuracy and scalability, it also introduces challenges related to complexity and reliance on cloud infrastructure. Generating realistic datasets is essential for testing and validating the IDS, as it ensures the system's effectiveness in real-world scenarios.

Algethami and Alshamrani [15] address critical cybersecurity threats in internet of health things (IoHT) environments by proposing a hybrid deep learning-based IDS in their study. The model combines artificial neural network (ANN), bi-directional long short-term memory (BiLSTM), and gated recurrent unit (GRU) architectures and is extensively tested using the ECU-IoHT dataset, demonstrating high accuracy and performance. The findings underscore the potential of advanced artificial intelligent (AI) methodologies in protecting IoHT environments, delivering high-fidelity detection and reducing false positives. However, the complexity of the approach and the necessity for continuous updates present potential challenges that must be addressed.

D'hooge *et al.* [16] offers valuable insights into the challenges associated with achieving robust generalization in machine learning-based IDS. Despite theoretical expectations, the models frequently struggled to generalize effectively to new datasets, highlighting issues with higher-order representation learning. The study critiques existing assumptions in network anomaly detection, advocating for more realistic training data and the adoption of hybrid detection methods. It emphasizes the necessity for improved data quality and more comprehensive evaluation strategies to enhance the practical applicability of these systems in real-world scenarios.

The monitoring system attempts to gain in-depth knowledge about the environment where it works. This is to find any alterations that occur in the distributed environment system, initiate counteractive measures to fulfil the environmental changes and finally provide the required quality of service. Adaptive distributed systems encounter two types of problems as discussed herewith. The first problem is the security issue since the monitoring systems are given free hand to collect data about the environment, with an intention to make the distributed systems, adapt to the changing environment [17], [18]. The monitoring system collects the information regarding the activities of the users, how they communicate among each other and the messages' content. Since all these tasks are performed outside the target system, it threatens the very basis of the system as the latter is vulnerable to intruder attacks. Further, the intruder gains access to vulnerable and confidential information [19], [20]. The scenario becomes crucial in the due course of time as the techniques and mechanisms involved in data collection gains high level of intelligence. So, the monitoring system should be confined to a threshold up to which it can perform the data collection process and prohibited from access to intruders. On the other hand, if a monitoring system is restricted to collect the information, then it may downregulate the performance of the system in terms of adapting to the vibrant environment and ensuring the security mechanism in place [17]. So, the risks of making a crucial distributed

system, adapt to the security threats, are high such that it can compromise the entire security mechanism itself.

So, it is inevitable to have a holistic understanding about the working mechanism of the distributed environment. The knowledge, gained through this process, helps in making the system ready for adaptation to the changing environments. On the other hand, it is also important to focus on the exploitation of this knowledge, by the intruders, in creating a potential unrest upon the security fabric of the system. The following core issues are discussed in this research article.

- The level of knowledge required for a monitoring system, in a distributed environment, to collect information needed for the purpose of adaptation.
- Develop an adaptive distributed monitoring system which has the potential to modify its working mechanism on the basis of environmental changes.
- Identify the mechanisms used by the intruders to exploit this knowledge and cause security threats as in token ring situation.
- Define adaptive security metrics so as to determine the security levels of the adaptive distributed environment.
- In the context of adaptive distributed system, develop and incorporate a framework for an adaptive distributed monitoring system, under the security metrics.

2. PROPOSED METHOD

In the monitoring process, information is extracted from a targeted program during runtime to adapt or reconfigure the distributed system. Adaptation models separate the process into change detection, agreement, and action. The monitoring system identifies changes and collects data during program execution, driven by event-based paradigms. These changes are communicated to a central monitoring system, which then reconfigures the distributed system. Monitoring involves connecting each node's address, data, and control buses to the monitoring node, preventing high perturbation. Events of interest are identified, and changes are reported to the central system, which alerts other nodes and acknowledges the changes. Two triggering methods in hybrid monitoring systems are memory-mapped and co-processor-based monitoring [21]. The former uses predefined addresses to trigger data recording, while the latter uses co-processor instructions.

Components like the bus interface module and event recorder (ER) are part of the monitoring architecture [22]. The ER, containing a control buffer, data collector, trigger recognizer, timer, and overflow counter, triggers events upon changes due to malicious activities. The timer stamps events with the current time, and the overflow counter tracks unrecorded events due to buffer overflow. In co-processor monitoring, data collectors and trigger recognizers verify enabled events based on target processor instructions. If an event is enabled, it is recorded with keywords, overflow control, and current time. Local clocks in monitoring nodes ensure coherent event ordering, while the central monitoring unit adjusts local times based on calculated clock differences.

To secure adaptation data and communication between local and central monitoring systems, an additional layer includes the event analyst (EA), comparator, and repository (R). The repository stores pre-identified events for comparison. The EA assesses the security and criticality of collected data, deciding on secure dissemination methods. The monitoring system adapts based on critical information, known as an adaptive monitoring system [23].

The comparator identifies important events by comparing them against recognized events in the repository. The monitoring system executes its tasks either at the process level or at functional level. It is generally recommended to execute the tasks at process level due to the following reasons. The architecture is shown in Figure 1.

A process can be said as a minimum program unit as it possesses non-deterministic behaviour. So, if the faults can be isolated as individual processes, then it becomes easy to leverage the traditional cyclic debugging method for the next set of fault isolation levels. Furthermore, the execution behaviour can possibly be reconstructed for inter-process communication as well as synchronization operations so as to ensure fault localization as an individual process. The local monitoring system has an EA component which measures the security as well as criticality of the data, gathered by the trigger recognizer and data collector of the ER. Based on the collected data, the monitoring function is adjusted. Every local monitoring system tends to disseminate the information to the central monitoring system via a standalone network so as to mitigate the network traffic or perturbation.

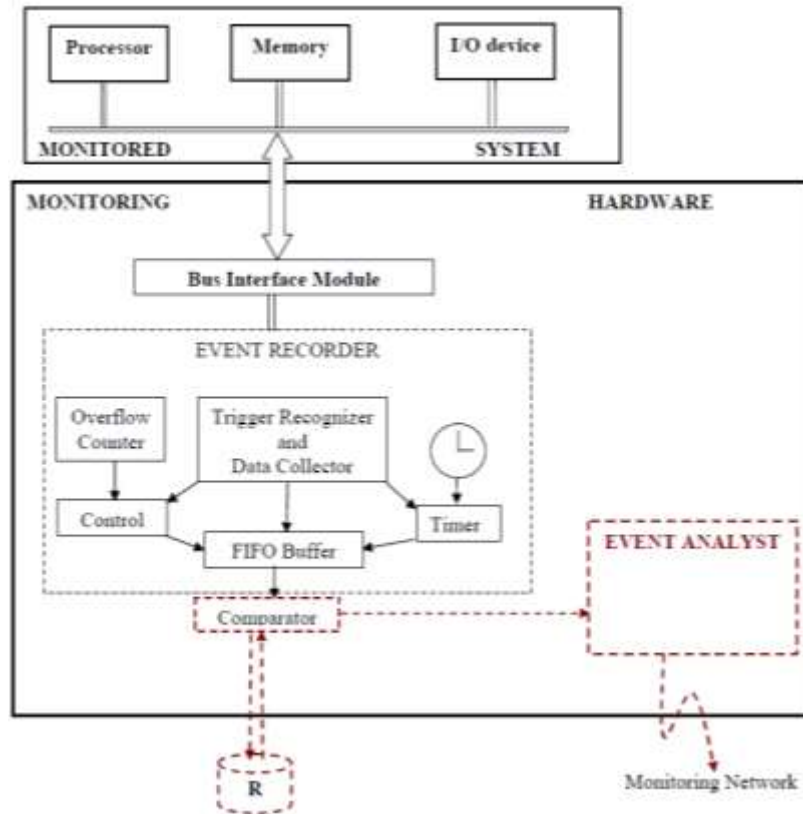


Figure 1. Architecture of adaptive monitoring system

3. METHOD

The study focuses on safeguarding the monitoring system and communicating information between the central and target distributed monitoring systems within an adaptive distributed system. To achieve this, the monitoring architecture has been remodelled. The distributed adaptive monitoring system (DAMS) verifies the criticality and security of the collected information before dissemination. The EA component evaluates events for interest and contrasts them with normal events to ensure system health. A repository of healthy events (R) is used for this comparison. DAMS components are as follows:

- ER: interfaces with the target distributed system and collects data triggered by environmental changes.
- Comparator: helps the ER identify events of interest apart from healthy events.
- EA: analyzes new changes for size, detail, criticality, and infers the information. Verifies security-criticality and validates the effectiveness of the target system’s security mechanisms using proposed metrics.
- Information dissemination: the verified information is sent to the central monitoring system for processing, either with or without SSL, through a monitoring network, based on the information’s security-criticality.
- The proposed DAMS ensures that only secure and critical information is communicated, maintaining the adaptive nature of the distributed system while safeguarding its components.

As mentioned earlier, security-wise, it is risky to allow the monitoring system to collect data so that the distributed system becomes adaptive. This is attributed to the risks caused by the intruders in terms of hijacking the data that is sent to the monitoring systems as shown in Figure 2. So, it is important for the EA (of the adaptive monitoring system) to analyse the data collected, verify whether it fulfils the security metrics, quantify the amount of risks involved if the data is transmitted via unsecured channel and so on. Based on the outcomes from this analysis, the DAMS decides whether the information can be transmitted from the local monitoring system to the central monitoring system. In case, when the results find the collected data to be insecure or possess high risks when transmitted via unsecured channel, then encryption or any other secured channel is used as shown in Figure 3.

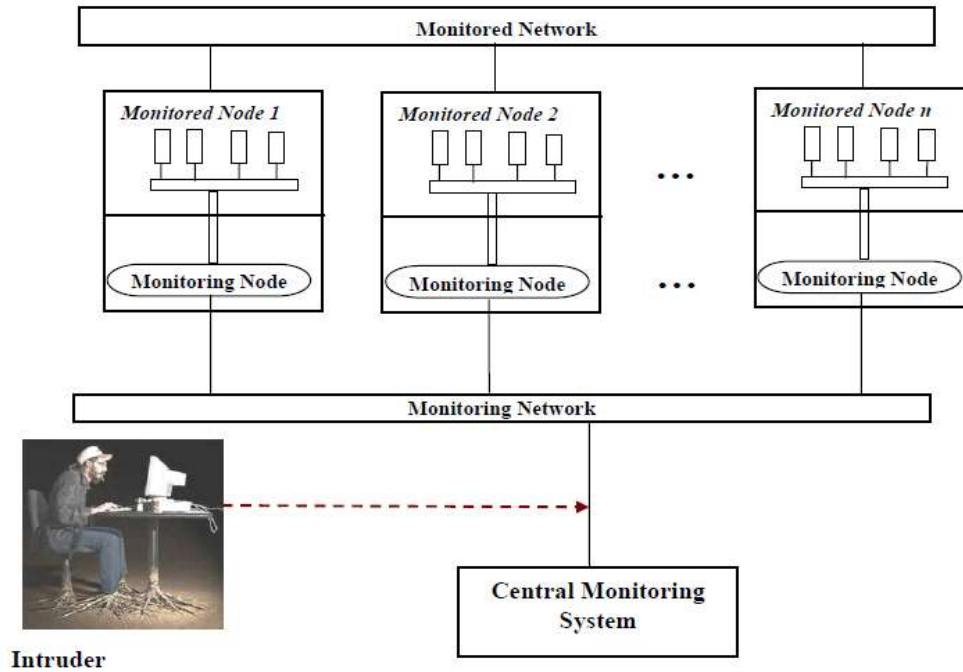


Figure 2. Distributive monitoring architecture

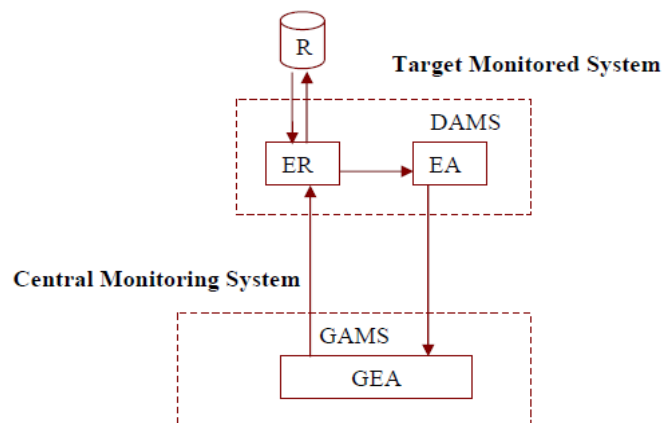


Figure 3. Adaptive monitoring model

Adaptive distributed systems learn from their environments through execution and interaction patterns, enabling them to adapt to changes [24]. Monitoring activities at the process level allows the system to collect data from recognized events and memory addresses where triggered events are stored. The monitoring system measures data complexity using existing security parameters and assesses potential risks if unauthorized agents access the information. Adaptive security metrics aid in this risk assessment. Based on the criticality of the information, the target monitoring system devises a strategy to safeguard and communicate it with the central monitoring system. Implementing the proposed security mechanism requires determining parameters such as detail, size, criticality, and support for inference. These parameters are essential for quantifying the information collected for adaptation. Measurement involves assigning numbers or symbols to attributes based on established rules, providing insights into the models intended for the adaptive monitoring system [25]. Unlike other engineering disciplines, software engineering doesn't strictly adhere to basic physics laws. Figure 4 summarizes the system's functionality through a use case model, offering a high-level overview and Figure 5 shows the activities of the proposed model.

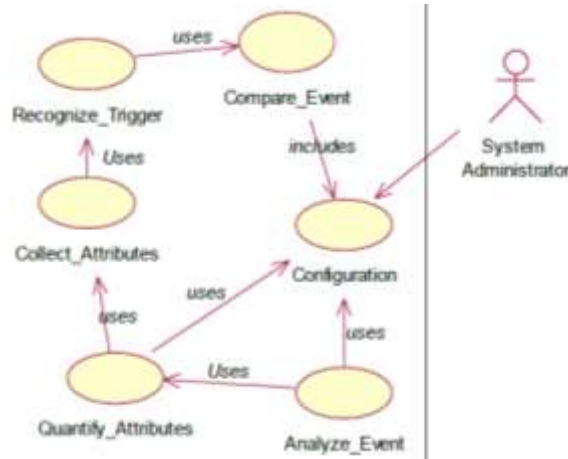


Figure 4. The use case for the adaptive monitoring system

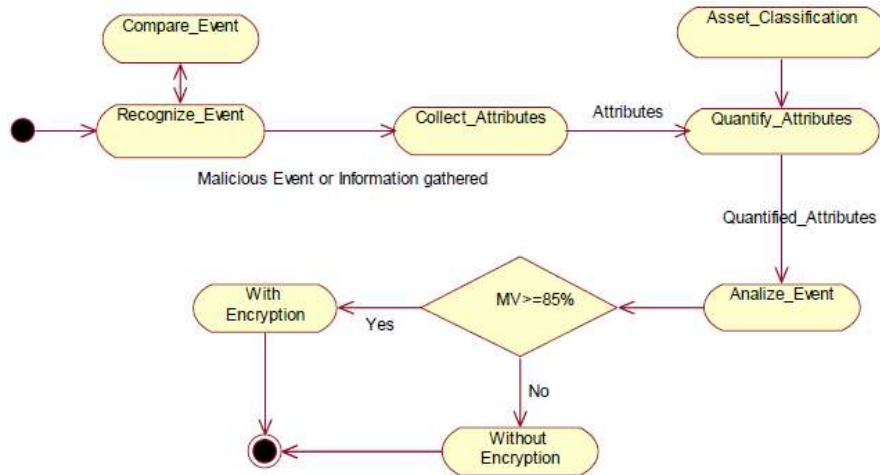


Figure 5. Activity diagram for adaptive monitoring system

4. RESULTS AND DISCUSSION

The performance evaluation of the DAMS, as shown in Table 1, compared to traditional systems demonstrated significant advantages. DAMS demonstrated faster response times, with 150 ms compared to 300 ms under high load. It also achieved higher data processing speeds, handling 10,000 events per second versus 6,000 events per second. Additionally, DAMS exhibited superior intrusion detection and threat mitigation rates, with 95% and 90% compared to 80% and 70%, respectively.

Table 1. Performance evaluation and comparisons of proposed DAMS

Metrics	S-SL [12]	LSTM [13]	XGBoost [14]	BLSTM+GRU [15]	Proposed DAMS
Response time (average under high load)	300 ms	380 ms	320 ms	440 ms	150 ms
Data processing speed (events per second)	6,000	7,200	6,800	8,400	10,000
Intrusion detection rate	80%	90%	88%	89%	95%
Threat mitigation rate	70%	75%	80%	78%	90%
Adaptability (real-time)	Not applicable	Not applicable	Not applicable	Not applicable	Adjusted within 200 ms
Security-criticality accuracy	Not applicable	Not applicable	Not applicable	Not applicable	98%
Service availability	95%	93%	95%	96%	99.50%
User satisfaction (users reported improved reliability)	Not measured	Not measured	Not measured	Not measured	90%

It adapted swiftly to environmental changes, adjusted parameters within 200 ms, and ensured high security-criticality accuracy (98%), as detailed in Table 2. User satisfaction notably improved (90% positive feedback), highlighting DAMS's effectiveness in enhancing service availability and reliability compared to traditional systems, as summarized in Table 3 and Figure 6.

The comparative analysis in Table 3 shows that DAMS markedly surpasses traditional systems in several critical metrics. DAMS demonstrates a 20-40% improvement in response time, enabling faster reactions under load. Its data processing speed is 40-60% faster, showcasing its advanced efficiency in managing extensive data volumes. Additionally, DAMS delivers a 15% higher rate of intrusion detection and a 20% greater threat mitigation rate, underscoring its improved ability to identify and address security threats. With a 4.5% improvement in service availability, DAMS offers enhanced system uptime and reliability. Moreover, the system has received 90% positive feedback from users, indicating high levels of satisfaction and approval.

Figure 6 shows that DAMS greatly exceeds the traditional system in both service availability and user satisfaction. DAMS achieves a service availability of 99.50%, surpassing the traditional system's 95%, and thereby ensuring greater system uptime and reliability. Furthermore, 90% of users reported increased reliability with DAMS, whereas no measurements of user satisfaction were taken for the traditional system. This underscores DAMS's exceptional performance and favourable reception from users. The overall Improvement metrics for DAMS adaptation and security measures presented in Table 4 underscores DAMS's overall superiority, achieving 20-40% improvements across various metrics compared to traditional systems.

Table 2. Behaviour of DAMS

Scenarios	DAMS adaptation and security measures	Results
Sudden environmental changes	Adjusted monitoring parameters within 200 ms	Ensured high-criticality data sent via SSL
Security-criticality analysis	Evaluated data with 98% accuracy	Applied appropriate security measures

Table 3. Comparative analysis of DAMS

Metrics	Improvement with DAMS
Response time	20-40% faster
Data processing speed	40-60% faster
Intrusion detection rate	15% higher detection rate
Threat mitigation rate	20% higher mitigation rate
Service availability	4.5% higher availability
User satisfaction	90% positive feedback from users

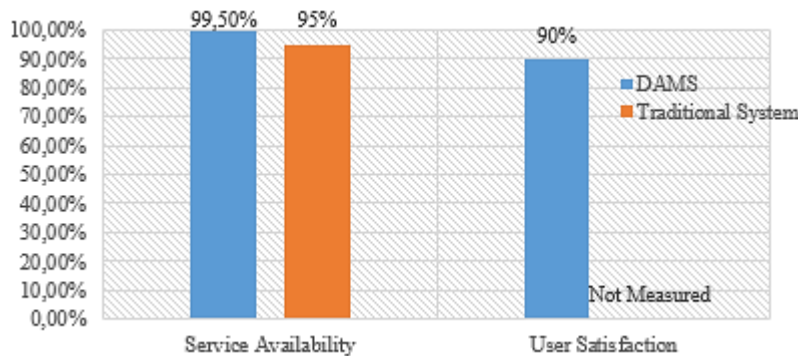


Figure 6. DAMS impact on quality of service (QoS)

Table 4. Overall Improvement metrics for DAMS

Scenario	DAMS adaptation and security measures	Results
Overall improvement	20-40% better across various metrics	Base performan

The performance evaluation of the DAMS highlights its considerable advantages over traditional systems. DAMS delivers quicker response times (150 ms) and processes data at a higher speed (10,000 events per second) compared to traditional methods, which typically average 300 ms and 6,000 events per

second. Furthermore, DAMS excels in security measures, achieving a 95% intrusion detection rate and a 90% threat mitigation rate, compared to 80% and 70% in traditional systems. DAMS swiftly adapts to environmental changes, adjusting parameters within 200 ms, and maintains a high security-criticality accuracy of 98%. User satisfaction is significantly higher, with 90% positive feedback. This comprehensive evaluation highlights DAMS's capability to enhance service availability, user satisfaction, and operational efficiency, making it a compelling choice for robust and adaptable distributed monitoring systems.

5. CONCLUSION

The study addresses security risks in adaptive distributed systems and proposes a system incorporating an adaptive tracking component to enhance security. This component gathers environmental information, increasing flexibility but also potentially exposing sensitive data to hackers. Interceptors can log useful information, enabling hackers to infiltrate modern distributed systems by masquerading as legitimate nodes. The study indicates that because the system collects environmental data, hackers can exploit the tracking component to access private information. To safeguard the distributed system, the proposed adaptive tracking system will transmit crucial data through encrypted channels and less critical data through unencrypted channels. It adapts to its environment to prevent unauthorized access. The study suggests using security metrics to assess data importance and the effectiveness of security measures. These metrics can evolve over time based on the value and weight of the assets. Acknowledging that security systems cannot be 100% effective, the study advocates for a balance between security and quality of service. Protection levels are categorized as excellent (above 85%), above average (71–85%), average (51–70%), below average (26–50%), and poor (below 26%). The innovative approach of the proposed system requires testing to evaluate its efficacy on various real-world scenarios. Future research will explore its impact on system efficiency, enhancement of security measures, real-time applications, and quality of service. The monitoring system collects information during events such as malicious behaviour or significant data gathering, providing opportunities to pre-emptively thwart virus and malware attacks.





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