

# Joint Security-vs-QoS Framework: Optimizing the Selection of Intrusion Detection Mechanisms in 5G networks

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## ABSTRACT

The advent of 5G technology introduces new - and potentially undiscovered - cybersecurity challenges, with unforeseen impacts on our Economy, Society, and Environment. Interestingly, Intrusion Detection Mechanisms (IDMs) can provide the necessary network monitoring to ensure - in big extent - the detection of 5G-related vulnerability risks and cyberattacks. Yet, how to realize the attack surface of 5G networks in respect to the detected risks, and, consequently, how to optimize the cybersecurity levels of the network, remains an open critical challenge. In respect, this work focuses on deploying multiple distributed Security Agents (SAs) that can run different IDMs over various network components, and proposes a cybersecurity mechanism for optimizing the network's attack surface in respect to the Quality of Service (QoS). The proposed mechanism relies on a new closed-form utility function to describe the trade-off between cybersecurity and QoS, and uses multi-objective optimization to improve the selection of each SA detection level. We demonstrate via simulations that before optimization, an increase in the detection level of SAs brings a direct decrease in QoS as more computational resources are utilized for IDM processing. Thereby, after optimization, we demonstrate that our mechanism can strike a balance between cybersecurity and QoS while showcasing the impact of importance of different objectives of the joint optimization.

## KEYWORDS

5G, cybersecurity, system cost, QoS, multi-objective-optimization, risk detection, risk mitigation

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## 1 INTRODUCTION

5G paves the way for a fully connected world. By blending different types of technologies and advances it offers various types of services such as smart home, V2V communication, smart parking, UAV integrated communication, fog/edge computing, industry 4.0, blockchain-based services to name some [5]. However, apart from the pre-5G security threats (that still need to be addressed), new security challenges have been introduced in 5G mainly due to (i) the utilization of 5G enabling technologies such as software defined networking, network function virtualization, mobile edge computing, network slicing etc; and (ii) high degree of 5G network heterogeneity including internet of things and end-user devices, service requests, new stakeholders and mission-critical applications, etc. [9].

Network-based Intrusion Detection Mechanisms (IDMs) are designed to identify attacks, to generate alerts and to report any detected suspicious behaviour or attacks that jeopardize the integrity, availability and confidentiality of a 5G system network [6]. In this work, we consider the deployment of Security Agent (SA) in a network, where each SA is enabled to execute IDM functionality for monitoring 5G components/nodes against cyberattacks and vulnerability risks. The SAs can perform the system monitoring at different detection levels; hence, they differ on how they identify the potential intrusions. The higher is the detection level, the higher is the efficiency/accuracy of the SA in terms of detecting the

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network vulnerabilities/attacks. However, monitoring the system to identify the potential vulnerabilities or attacks results in increasing the consumption of resources. These resources include, but are not limited to, network bandwidth, computational resources, and monetary cost. On the other hand, maintaining high level of Quality of Service (QoS) when significant amount of data is generated in the network is of high importance to preserve intact the 5G user experience. Thereby, a classical dilemma arises since although IDMs can provide high security services, they can often decrease the QoS performance due to the additional network resources required for IDM processing. [19]. Hence, the system faces a trade-off between maximizing the IDM monitoring performance (i.e. for keeping the network cybersecure) while minimizing the resource cost (i.e. for preserving the user QoS).

We note a large body of literature investigating the problem of intrusion detection in 5G networks, in-vehicle networks, vehicular communication, Internet of things, and small-cells [7, 8, 10–12]. Moreover, there have been several works studying how to secure the system by providing countermeasures considering the security and QoS [4, 15, 16, 18]. These efforts rely on either multi-objective Genetic Algorithm (GA) optimization, or game-theoretic approaches to provide cybersecurity remediation. However, there is no attempt towards addressing the problem of SA detection level selection problem as intended in this work. The significance of such trade-off stands paramount to realize and optimize the cybersecurity network, because it accounts for the network's states/conditions and system preferences at different time instants towards selecting the detection level of the SAs for IDM.

In respect, in this work we approach such trade-off by exploiting multi-objective optimization approaches [2], and by introducing a multi-objective optimization problem which considers both cybersecurity and QoS performances in a single closed-form function. Our contributions are summarized in the following:

- (1) Design of a new utility function in closed-form to correlate the detection level selection problem with the QoS of the network at hand;
- (2) Formulation and justification of the detection level selection problem in the form of joint Security-vs-QoS optimization problem, which, to our knowledge, has not yet been attempted by relevant studies;
- (3) Resolution of the optimal result using *CPLEX* programming and discussion of its feasibility and applicability over small-scale and large-scale network setting;
- (4) Demonstration via simulations to showcase the performance of the multi-objective optimization problem under various utility functions and preference settings.

The rest of the paper is organized as follows. In Section 2, we describe the system model, formulate the problem and discuss the problem solving. In Section 3, we present the simulation results. Section 4 concludes the paper.

## 2 SYSTEM MODEL AND PROBLEM FORMULATION

Let us consider a heterogeneous architecture, which consists of IoT devices, base stations, servers, and different core-level network functions. All these nodes are vulnerable to the cyberattacks. In

order to provide a secure network, we consider some pre-deployed SAs in the network to perform system monitoring. Each SA can perform the system monitoring with a specific security detection level. Each of these security detection levels enable the SA to detect certain vulnerability types in the system. For instance, one security level can be used for signature-based intrusion detection, another one for anomaly-based intrusion detection and another one for complex event processing or hybrid intrusion detection methods. The higher is the detection level, the higher will be the efficiency/accuracy of the SA in detecting the vulnerability/attack types; however, the higher will be the system cost. Hence, there exists a trade-off to be studied for the security detection level selection of each SA, which is what we address in this paper.

Let us show the set of  $M$  SAs as  $\mathcal{A} = \{a_1, \dots, a_m, \dots, a_M\}$ . We denote the security detection level of a SA as  $L_m$  which equals  $l$ , where  $l \in \{1, \dots, N\}$ , representing different detection levels. The problem is assigning the proper detection level to each of the SAs in order to detect the vulnerabilities in the system such that the system utility function is maximized. The system utility function in our joint security-vs-QoS optimization problem is composed of two main functions of  $\Upsilon_m^{\text{sec}}$  and  $\Upsilon_m^{\text{QoS}}$ , which are security and QoS utility functions, respectively.

The efficiency of a security detection level can be evaluated as the number of vulnerabilities it can detect out of the total number of known vulnerabilities. However, we also consider the probability that there might exist certain number of unknown vulnerabilities in the system and define the following as the security utility function:

$$\Upsilon_m^{\text{sec}}(L_m) = \varphi \frac{K'(L_m)}{K + \bar{K}} \quad (1)$$

where  $K'$ ,  $K$ ,  $\bar{K}$ , and  $\varphi$  indicate the number of detected vulnerabilities based on the selected detection level, total number of known vulnerabilities, the number of unknown vulnerabilities, and a coefficient parameter for tuning the range of the values. Number of unknown vulnerabilities are also a portion of the known vulnerabilities  $\bar{K} \in [0 \text{ \%}i] \times K$ .

On the other hand, a high security detection accuracy requires a system to consume resources to enable this functionality for the SAs. We consider that the SAs consume network bandwidth, computational resources and they incur some monetary cost in order to perform the system monitoring. Let us denote the bandwidth that a SA with a specific detection level (i.e.  $L_m$ ) consumes as  $B(L_m)$ . This bandwidth is consumed by the SA in order to perform the system monitoring for the vulnerabilities detection according to the selected level. Similarly, let us show the consumed computational resources by a SA as  $\eta(L_m)$ . Furthermore, as introduced before, higher security detection levels can affect the system in terms of monetary cost as well. Hence, we also consider the system monetary cost and denote it as  $\Psi(L_m)$ . The joint QoS utility function can be written as

$$\Upsilon_m^{\text{QoS}}(L_m) = - \left( \alpha_1 \tilde{B}(L_m) + \alpha_2 \tilde{\eta}(L_m) + \alpha_3 \tilde{\Psi}(L_m) \right) \quad (2)$$

It should be noted that  $\tilde{*}$  represents the normalized value and  $\alpha_*$  represents the weight of each of the QoS objectives ( $\sum_{i=1}^3 \alpha_i = 1$ ). The joint security-vs-QoS utility function for SA detection level

selection can be written as

$$Y_m(L_m) = \beta_1 \Upsilon_m^{\text{sec}}(L_m) + \beta_2 \Upsilon_m^{\text{QoS}}(L_m) \quad (3)$$

where  $\beta_1$  and  $\beta_2$  represent two non-negative weights for the security and QoS utility functions ( $\sum_{i=1}^2 \beta_i = 1$ ). The optimization problem can be written as

$$\text{P1} : \max_{L_m} \left\{ \sum_{m=1}^M Y_m(L_m) \right\} \quad (4)$$

where  $L_m \in \mathbb{R}^M$  represents the detection level decision vector for the SAs. Let us transform P1 and write it as

$$\text{P2} : \max_{\mathbf{X}} \left\{ \frac{\beta_1 \varphi}{K + \bar{K}} \sum_{m=1}^M \sum_{l=1}^L K'_{m,l} x_{m,l} - \beta_2 \sum_{m=1}^M \sum_{l=1}^L (\alpha_1 \tilde{B}_{m,l} + \alpha_2 \tilde{\eta}_{m,l} + \alpha_3 \tilde{\Psi}_{m,l}) x_{m,l} \right\} \quad (5)$$

subject to

$$\text{C2.1} : \sum_{l=1}^L x_{m,l} \leq 1 \quad \forall m, \quad (6)$$

$$\text{C2.2} : \frac{\beta_1}{\beta_2} \geq \frac{(\alpha_1 \tilde{B}_{m,l} + \alpha_2 \tilde{\eta}_{m,l} + \alpha_3 \tilde{\Psi}_{m,l}) \cdot (K + \bar{K})}{K'_{m,l} \cdot \varphi}, \quad (7)$$

$$\text{C2.3} : \beta_1 + \beta_2 = 1, \quad (8)$$

where  $\mathbf{X} \in \mathbb{R}^{M \times L}$  is the decision matrix where each element is binary (i.e.,  $x_{m,l} \in \{0, 1\}$ ). Constraint (6) assures each SA is assigned only one detection level. In order to find the feasibility condition of P2, we set  $\frac{\partial f}{\partial \mathbf{X}} = 0$ , which yields constraint (7). Constraint (8) denotes that the sum of the two objective coefficients equals one.

The optimization problem assigns the detection level to the SAs such that the trade-off between maximizing the security detection efficiency and the QoS is addressed. The optimization problem runs every time the decision needs to be made, which can be every time instant or periodically. P2 is a Binary Integer Programming problem. The problem can be solved by using standard solvers such as *CPLEX* with low execution time on a modest hardware. *CPLEX* is widely used in the literature for problem solving [1, 3]. In the following section, we present the results of our study.

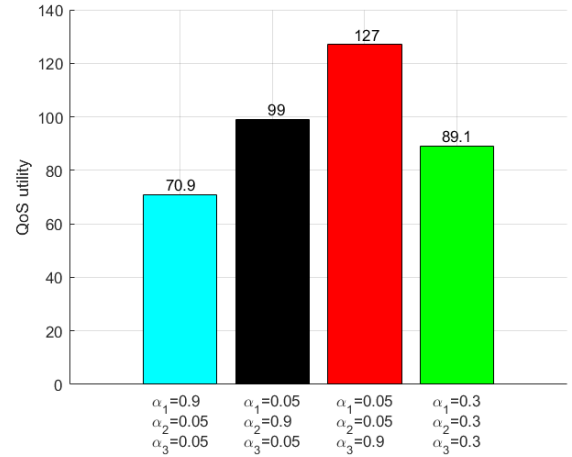
### 3 SIMULATION RESULTS

In this section, we present the numerical results obtained by computer simulations, which are performed in *MATLAB*. Before delving into details about the choice of parameter values, it is important to mention that in the European research project SANCUS [13, 17], a taxonomy is developed to systematically document and assess the impact of various 5G security attacks, which pose a threat to the network. This taxonomy first identifies the security and privacy threats in 5G. Later it introduces efficiency of each of the security levels in identifying the network threats. In this paper, we use synthetic values to demonstrate the performance of the formulated multi-objective optimization problem.

Table 1 summarises the used simulation parameters. Number of detected vulnerabilities for each SA is a value in the range [0

**Table 1: Simulation Parameters**

Parameter	Value
Number of detection levels ( $N$ )	5
Number of SAs ( $M$ )	20
Number of known vulnerabilities ( $K$ )	95
Ratio of unknown to known vulnerabilities ( $t$ )	% 5
Consumed bandwidth for the detection levels ( $B(L_m)$ )	[3.3-33]
Consumed computational resources for the detection levels ( $\eta(L_m)$ )	[3.3-33]
Consumed monetary cost for the detection levels ( $\Psi(L_m)$ )	[3.3-33]



**Figure 1: QoS utility for different  $\alpha$  values**

100] according to the selected level, i.e., the higher/lower detection levels, the higher/lower number of detected vulnerabilities, which also differs across SAs. The values for consumed bandwidth, computational resources and monetary cost are normalized in the range of [3.3 33], where for lower/higher detection levels lower/higher values are selected, where these values vary across the SAs. These upper and lower values are selected for each objective since they allow the three QoS objectives to be in the same range as the security objectives to avoid biased results. It is worth mentioning that the same results can also be obtained by any other ranges.

#### 3.1 Impact of $\alpha$ on the QoS utility

In this section, we evaluate the impact of QoS objectives coefficients i.e.,  $\alpha$ , on the simulation results. We have studied scenarios with different values of  $\alpha$  and the result is depicted in Figure 1. As seen, different values of  $\alpha$  results in different QoS utility values. The impact of the monetary cost on the utility function is the highest and the impact of the bandwidth on the utility function is the lowest according to the generated values for each objective. However, in order to consider all of the objectives with the same level of priority, we select equalizing the objectives coefficients (i.e.,  $\alpha_i = 0.3, i = 1, 2, 3$ ) for the rest of the simulation results.

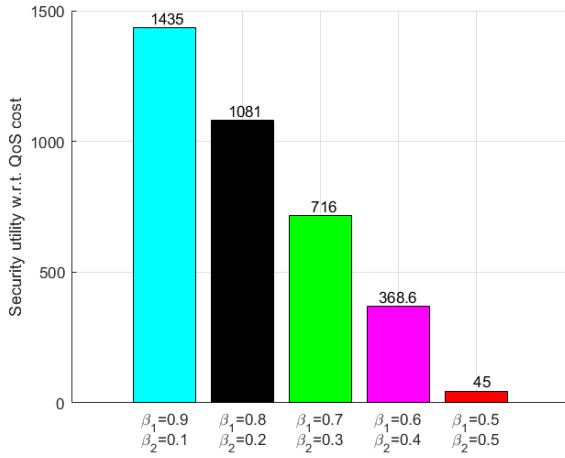


Figure 2: Security-vs-QoS trade-off for different  $\beta$  values

Table 2: SAs detection level selection for  $\beta_1 = 0.8, \beta_2 = 0.2$

Agent	Selected detection level	Agent	Selected detection level
Agent 1	5	Agent 11	5
Agent 2	5	Agent 12	4
Agent 3	5	Agent 13	5
Agent 4	5	Agent 14	5
Agent 5	5	Agent 15	5
Agent 6	4	Agent 16	5
Agent 7	4	Agent 17	5
Agent 8	5	Agent 18	5
Agent 9	5	Agent 19	5
Agent 10	4	Agent 20	5

### 3.2 Impact of $\beta$ on the security-vs-QoS trade-off

In this section, we evaluate the trade-off between the joint objectives coefficients (i.e.,  $\beta$ ). As seen in Figure 2, higher value of  $\beta_1$ , i.e., higher security priority, results in higher efficiency in terms of detecting the vulnerabilities (higher utility). This is due to the fact that the SAs tend to select the highest security levels for monitoring. On the other hand, higher value of  $\beta_2$  (i.e.  $\beta_2 = 0.5$ ) leads to selecting low security levels in order to lower the system costs; however, this decreases the system efficiency in terms of detecting the vulnerabilities and might put the system at higher risk. To conclude, when the system is under high attack, the best case can be setting  $\beta_1 = 0.9$ , and when the system is under low attack a more balanced case by setting  $\beta_1 = \beta_2 = 0.5$  addresses the trade-off better according to the results. Please note that higher values of  $\beta_2$  would not be possible as they violated the feasibility condition in C2.2.

### 3.3 SAs Detection level selection

In this section, we demonstrate the selection of the SAs detection level for different  $\beta$  values.

Table 3: SAs detection level selection for  $\beta_1 = 0.7, \beta_2 = 0.3$

Agent	Selected detection level	Agent	Selected detection level
Agent 1	5	Agent 11	5
Agent 2	4	Agent 12	4
Agent 3	5	Agent 13	4
Agent 4	5	Agent 14	5
Agent 5	5	Agent 15	5
Agent 6	4	Agent 16	5
Agent 7	4	Agent 17	5
Agent 8	5	Agent 18	5
Agent 9	5	Agent 19	5
Agent 10	4	Agent 20	5

Table 4: SAs detection level selection for  $\beta_1 = 0.6, \beta_2 = 0.4$

Agent	Selected detection level	Agent	Selected detection level
Agent 1	5	Agent 11	5
Agent 2	4	Agent 12	4
Agent 3	5	Agent 13	4
Agent 4	5	Agent 14	5
Agent 5	5	Agent 15	4
Agent 6	4	Agent 16	5
Agent 7	4	Agent 17	5
Agent 8	4	Agent 18	5
Agent 9	5	Agent 19	4
Agent 10	4	Agent 20	5

Table 5: SAs detection level selection for  $\beta_1 = 0.5, \beta_2 = 0.5$

Agent	Selected detection level	Agent	Selected detection level
Agent 1	5	Agent 11	1
Agent 2	4	Agent 12	5
Agent 3	2	Agent 13	2
Agent 4	4	Agent 14	4
Agent 5	1	Agent 15	3
Agent 6	1	Agent 16	1
Agent 7	4	Agent 17	4
Agent 8	4	Agent 18	3
Agent 9	1	Agent 19	2
Agent 10	4	Agent 20	1

When prioritizing the security, the SAs select the highest detection level since this maximizes the objective function in P2, as this is the case for scenario where  $\beta_1 = 0.9$ . On the other hand, when the two objectives have equalized coefficients, each of the SAs select a different detection level, depending on the security and QoS values. The results of the detection level selection for 20 SAs

with different values of  $\beta$  coefficients is demonstrated in Tables 2 to 5.

### 3.4 Discussion on large-scale scenario

As demonstrated, the problem P2 can be easily solved using the *CPLEX* optimization solver which exploits the Simplex algorithm as one of the methods for problem solving. However, when the number of variables increases, the number of iterations and complexity grows exponentially which makes it unsuitable for large-scale scenarios [14]. While for large-scale scenarios obtaining the optimal results is difficult, sub-optimal solutions can be easily achieved by exploiting heuristic or meta-heuristic solutions. For instance, by adopting a GA and considering point mutation, one-point crossover and roulette wheel selection, the complexity can be in the order of  $O(gnm)$ , where  $g$  is the number of iterations,  $n$  the population size and  $m$  the individuals size. In our future work, we aim to study larger-scale scenarios and propose heuristic and meta-heuristic solutions. Moreover, we aim to address the SA placement problem in order to optimize the locations of SAs for achieving a higher vulnerability detection efficiency.

## 4 CONCLUSION

In this work, we studied the problem of SA detection level selection where the SAs perform the system monitoring for intrusion detection. We considered a scenario with 20 SAs where each of them can perform the system monitoring with several detection levels. Higher detection levels provide higher vulnerability detection accuracy, however, they also lead to a higher system cost. As a result, there exist a trade-off to be addressed for this problem. We have formulated the joint security-vs-QoS optimization problem and obtained the optimal results using the *CPLEX* optimization solver. Furthermore, we have studied the impact of importance of different objectives of the joint optimization in the simulation results. In our future work, we aim to target larger scale scenarios where we can propose heuristic or meta-heuristic solutions to cope with the network size grows. Moreover, we anticipate to optimize the placement of the SAs for achieving a higher intrusion detection efficiency.

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