Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen
 Published by Research Publishing, Singapore.
doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P3489-cd

System Health Evaluation for Enhanced Resilience of Telecom Networks

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Abstract: In our digital society, the resilience of telecommunications networks is crucial to ensuring reliable connectivity. These networks face growing challenges, including accelerated obsolescence and the unavailability of essential components, often amplified by supply chain issues. These risks threaten network stability and can lead to service disruptions if not properly anticipated and managed. Our research focuses on predicting the risk of obsolescence and unavailability of server components, a major concern for the Orange group. However, the obsolescence risk of a server is not solely determined by its age but also by the age of its components, as each part has its own life cycle, which may vary depending on the manufacturer. Our approach involves using graphs to model the dependencies between components and assess the system's overall obsolescence risk. By leveraging AI and predictive analytics, we aim to anticipate the obsolescence or unavailability of individual components, providing crucial insights for proactive management.

Keywords: Obsolescence, Artificial Intelligence, Machine Learning, Knowledge- graph, Resilience, Telecommunication Networks.

1. Introduction

The resilience of telecommunications networks is essential to maintain client satisfaction in various sectors, including individuals, businesses, and government institutions. This resilience depends not only on the network's ability to recover quickly from failures or cyberattacks Fehling-Kaschek et al. (2020) but also on the immediate availability of replacement components required for corrective and preventive maintenance. However, the progressive obsolescence of equipment and uncertainties around the availability of spare parts pose significant challenges Schulze et al. (2012). If not addressed, these issues can lead to prolonged outages and potentially impact client loyalty.

The aim of this study is to develop predictive models to anticipate the risk of obsolescence or unavailability of critical server components. As outlined by Devereaux (2010), addressing obsolescence issues can involve the following steps:

- Identifying and validating a replacement of a server or component within internal processes.
- Purchasing and payment processing for the new server.
- Awaiting delivery.
- Physical installation of the equipment and the necessary software configuration.

To ensure operational continuity, it is essential to set time thresholds between the estimated obsolescence date of components and the installation of new equipment Devereaux (2010). Proactive planning is crucial to mitigate the risk of stock shortages and prevent sudden activity halts due to resource unavailability. By defining obsolescence scenarios and modeling the dependencies among server components, this research aims to enhance network resilience and ensure service continuity in the event of component failure.

2. State of the Art

2.1. *System Obsolescence*

Obsolescence refers to the process by which equipment, components, or technology become outdated, inefficient, or unsuitable for continued use IEC (2024), typically due to technological advancements, wear and tear, or the unavailability of replacement parts. This phenomenon can have significant consequences, including reduced observed reliability, increased maintenance costs, and possible service interruptions. In many sectors, obsolescence is a major challenge that requires proactive anticipation and management to ensure operational continuity Bartels et al. (2012).

Obsolescence thus affects a wide range of systems, each presenting specific challenges based on their role within various industries. Several examples illustrate the impact of obsolescence across different sectors, including transport, aviation, armaments, and technology Bartels et al. (2012).

In both data centers and telecommunication networks, obsolescence poses significant challenges due to rapid technological advancements and evolving industry standards. Core infrastructure components—such as servers, routers, and switches—face obsolescence as newer, more efficient models are developed. Within servers, critical internal components like processors and RAM also become outdated, further complicating maintenance and upgrade strategies. This progression can lead to higher operating costs and more complex compatibility issues Karagiannopoulos et al. (2024). For data centers, obsolete components risk slowing operations and causing extended downtimes if spare parts or replacements are unavailable during failures Schulze et al. (2021). Similarly, in telecommunications networks, outdated equipment can disrupt connectivity, impacting service continuity and customer satisfaction across sectors. Maintaining these systems involves balancing performance with the ongoing need for compatibility and reliability amidst the pressures of obsolescence.

2.2. *5G Networks*

The deployment of 5G networks represents a significant advancement in telecommunications, offering faster speeds, lower latency, and enabling a wide array of new services Huawei (2016). The 5G infrastructure contains advanced technologies such as dedicated servers, base stations, fiber optics, and edge computing. These components collectively support the surge in connected devices and data, accommodating applications like IoT and augmented reality.

The architecture of the 5G network is based on virtualized or containerized network functions (VNF or CNF), as shown in Fig. 1. User applications, such as calls, video streaming, or web browsing, serve as the primary interface for end users. Cloud-native functions (CNF) handle the essential tasks of the network, including connection and resource management. Each CNF consists of multiple microservices or CNF components, which are small software modules encapsulated in containers and hosted on physical servers BasuMallick (2022). To allocate these microservices to servers, affinity or anti-affinity rules are applied, determining whether certain microservices should be grouped on the same server or distributed across different servers. These microservices communicate with each other through message exchanges, making stable connectivity between physical servers essential. Fig. 1 illustrates an example of CNF deployment in a data center, demonstrating how these elements integrate into the overall 5G network infrastructure.

Next, the hardware consists of physical servers. These servers host the containers and microservices, providing the computational power required to run the network's services BasuMallick (2022). Finally, the connectivity component is built on the spine-leaf architecture. The spine refers to central switches that facilitate communication between different parts of the network. These switches connect to all other network equipment but do not connect directly to each other. Their primary role is to manage data flow between servers and other network resources Gillis (2022). Leaf switches, on the other hand, connect directly to the physical servers and act as entry/exit points for data moving to or from the network's central backbone Gillis (2022). They are responsible for managing data flows intended for end-users.

2.3. *Modeling of complex systems*

Modeling relationships between data is a key area for understanding and leveraging complex dependencies in systems. Various tools and approaches have emerged to model these relationships efficiently, including Graph Neural Networks Wu et al. (2021), knowledge graphs Buchgeher et al. (2021), Bayesian networks Soltan et al. (2019), and Markov chains Borgonovo et al. (2000). In

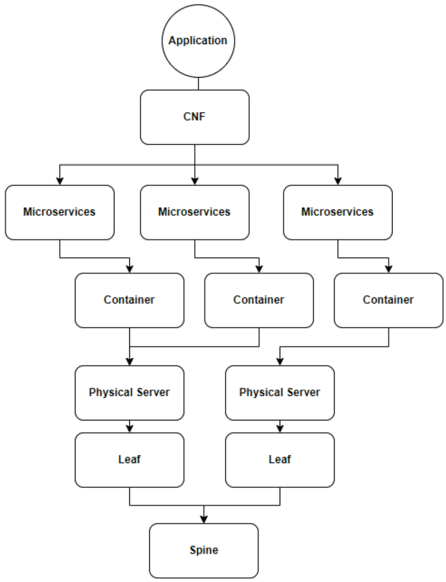

Fig. 1. 5G Network Architecture

this context, we have chosen to focus specifically on knowledge graphs, as they offer a powerful framework for capturing and representing complex interdependencies within systems.

2.3.1. *Graphs for complex systems*

Graphs are a powerful tool for modeling and managing complex systems, particularly in representing the interactions and interdependencies between their components. They enable the depiction of both the constituent elements of a system (as nodes) and the relationships linking them (as edges). This type of representation is widely applied in fields such as systems engineering, critical infrastructure management, and predictive maintenance Chen et al. (2020).

In a graph, nodes represent the components or subsystems within the overall system, while edges symbolize the interactions or dependencies between these components Chen et al. (2020). These edges can be directed or undirected, depending on the nature of the relationship:

- A directed edge (with an arrow) indicates an asymmetric relationship, such as data transfer or functional dependency.
- An undirected edge is suited for a symmetric relationship, such as compatibility between two components.

For instance, a graph could represent a relationship such as:

$$(\mathrm{CPU}, \mathrm{consumes\_power\_from}, \mathrm{Power\_Supply})$$

Where the arrow expresses a unidirectional dependency. Conversely, a relationship like:

$$(\mathrm{RAM}, \mathrm{compatible\_with}, \mathrm{Motherboard})$$

It can be represented by an undirected edge.

In the context of IT systems or networks, several types of dependencies can be modeled using edges:

(1) **Data transfer**: for example, between a processor and a network card.
(2) **Energy dependency**: such as a hard drive depending on the power supply.
(3) **Software compatibility**: the relationship between a firmware version and hardware.
(4) **Interference or contention**: when two components share a common resource.

These dependencies capture critical interactions that influence the overall functioning of the system.

The orientation of edges adds an essential dimension, enabling the modeling of impact directionality. For example:

- An obsolete component may affect another downstream in a processing chain.
- A power supply failure could disrupt all components it powers.

By leveraging the modularity and flexibility of graphs, new relationships can be added, or the structure can be reorganized as the system evolves. This makes graphs particularly suited to dynamic infrastructures such as 5G networks or data centers.

3. Methodology

In the 5G network chain illustrated in Fig. 1, this paper focuses on the physical server. To evaluate the health status of the server, we follow the methodology described in the following paragraphs. We start with data selection, followed by obsolescence prediction, graph representation, and health evaluation based on different scenarios.

3.1. *Component Mapping and Data Sources*

Server components can be classified into two categories: those that remain available on the market (continued components) and those that are already obsolete (discontinued components). For continued components, it is necessary to predict their obsolescence dates. In the literature, obsolescence prediction methods vary from classical statistical techniques to artificial intelligence algorithms, which use historical data, such as component technical characteristics or market introduction dates, as indicators of their future obsolescence Jennings et al. (2016).

In this work, we rely on an internal dataset from Orange, containing information on server components. This dataset enables us to estimate the obsolescence dates for active components.

To assess and predict obsolescence risks, we begin by creating a comprehensive mapping of the components and their associated data sources. The analyzed system consists of AirFrame Rackmount servers. Each hardware component, such as memory (RAM), hard drive, processor (CPU), network card, and chips, is linked to relevant data attributes, including:

- The market introduction date of the components.
- The component's status (whether it has been discontinued or not).
- The obsolescence date for discontinued components.
- The target variable y, which represents the estimated remaining lifetime for each component.

This mapping forms the first step for predictive modeling and dependency analysis, allowing us to collect and organize relevant data for the subsequent steps of the process.

3.2. *Prediction Models*

Obsolescence date prediction is based on polynomial regression, a method that captures the nonlinear relationships between component characteristics and their remaining lifetime Ostertagová (2012). The model uses the data attributes defined during the mapping phase to estimate the obsolescence date of each component. For components without an obsolescence date, the remaining lifetime is calculated as the difference between the predicted obsolescence date and the current date.

An example of RAM obsolescence prediction in 5G servers is shown in Figure 2, illustrating how the model applies these variables to generate actionable insights.

3.3. *Graph Models and Evaluation*

3.3.1. *Graph Model Principle*

After predicting the remaining lifetime of the components, we use a graph model to analyze the dependencies between the different components of the system and understand the overall impact of these predictions on the entire system.

In this model, each component is represented as a node in a graph, and the dependency relationships between hardware components are shown by orange edges. The node size reflects the number of dependencies associated with that component: the larger the node, the more dependencies it has; the smaller the node, the fewer dependencies other components have on it. The component's membership in the system is indicated by a black arrow pointing to the server. Additionally, each component is associated with supplementary information: the "in" represents the number of components it depends on, while the "out" indicates the components it depends upon. This visualization illustrates not only how the obsolescence state of one component can affect the entire system but also how the dependencies between components influence this propagation.

3.4. *Obsolescence Risk Scenarios*

To address the impact of hardware component obsolescence on system functionality, we define three scenarios:

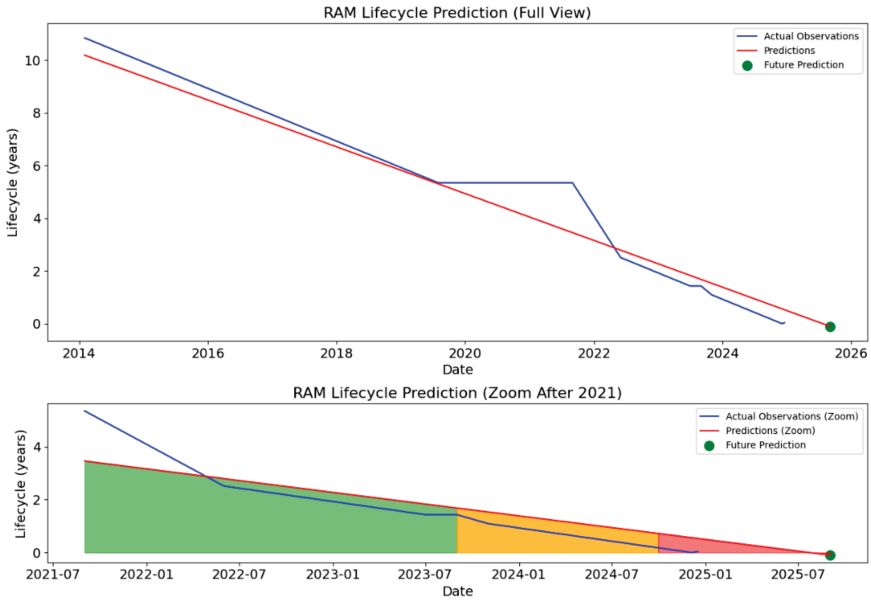

Fig. 2. RAM obsolescence prediction in 5G servers

3.4.1. *Scenario 1: Optimistic Scenario*

In this scenario, the server components are still available on the market, ensuring uninterrupted supply. This situation simplifies the planning of component replacements, providing the organization with enough time to order the necessary parts and manage its inventory efficiently.

One of the main benefits of this scenario is maintaining a stable infrastructure where components remain compatible with existing technologies, as shown in Figure 3.

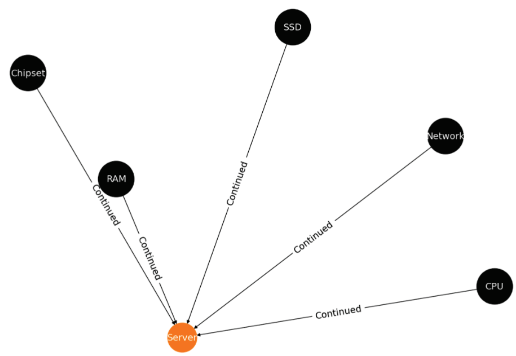

Fig. 3. Optimistic scenario

3.4.2. *Scenario 2: Moderate Scenario*

This scenario describes a situation where some components become obsolete, as shown in Figure 4, but the system as a whole remains operational for some time. However, this obsolescence can lead to a gradual propagation of malfunctions across the system, as discussed in Schulze et al. (2021), affecting the performance of still functional components.

Dependencies between components can be managed as long as only one component becomes obsolete and there is no significant dependence on other components. However, obsolete components require ongoing maintenance and monitoring to limit their potential impact on the system's overall performance. Proactive measures, such as repairing or replacing these components, are essential.

3.4.3. *Scenario 3: Pessimistic Scenario*

The final scenario describes a situation where all components of a system have become obsolete, leading to the risk of being unsupported by the product manufacturer if severe disruptions occur.

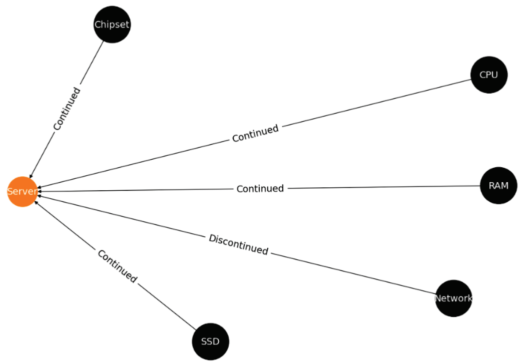

Fig. 4. Moderate scenario

There is also the risk that the system may fail to handle modern tasks. Maintaining the system becomes increasingly difficult, and replacing components within a reasonable time frame becomes complex.

This scenario presents a high risk of server unavailability on the market, as detailed in Figure 5.

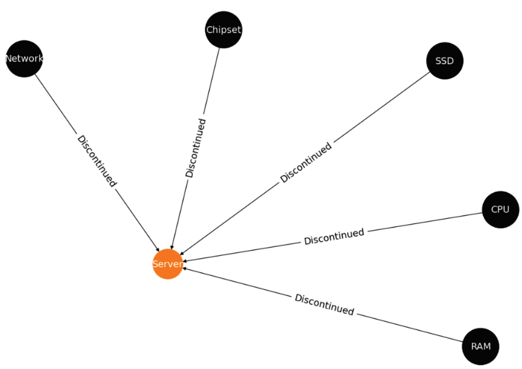

Fig. 5. Pessimistic scenario

3.5. *Health Evaluation and Thresholds*

To classify the system's health based on component obsolescence, specific thresholds are established for each scenario, emphasizing the CPU's critical role due to its high interdependence and impact on overall functionality. These thresholds, guiding the evaluation function of a component's obsolescence, are determined by domain experts. The scenarios are as follows:

Optimistic Scenario

- **Healthy**: Estimated lifetime > 2 years.
- **Warning**: $1 \leq$ lifetime ≤ 2 years.
- **Critical**: Estimated lifetime < 1 year.

Moderate Scenario

- **Critical**: If more than 2 components are obsolete.
- **Warning**: If 2 components are obsolete.
- **Warning**: If 1 component is obsolete.

Pessimistic Scenario

- **Critical**: All components are obsolete.

These thresholds guide the health evaluation of the system and facilitate the identification of critical risks related to obsolescence. For example, Figure 2 illustrates the application of these thresholds to classify the component's state in a clear and actionable manner. In this figure, we are in Scenario 1, where components are still available on the market. The green area represents the "healthy" state, indicating that there are more than 2 years of remaining lifespan for the component (here, the RAM), which is the ideal time to consider alternatives for the server or component. The orange area shows the range where the remaining lifespan is between 1 and 2 years, and the red area indicates the range where there is less than 1 year left before the RAM becomes obsolete.

4. Expected outcome

4.1. *Optimistic Scenario*

In Figure 6, which represents the optimistic scenario where components are still available on the market, the node representing the CPU is noticeably larger. This reflects a strong dependency on other server elements for this component. In this scenario, the components are classified as critical because their estimated remaining lifespan is less than one year (e.g., the CPU with a remaining lifespan of 15 days).

4.2. *Pessimistic Scenario*

In the pessimistic scenario presented in Figure 7, the components are discontinued, meaning they

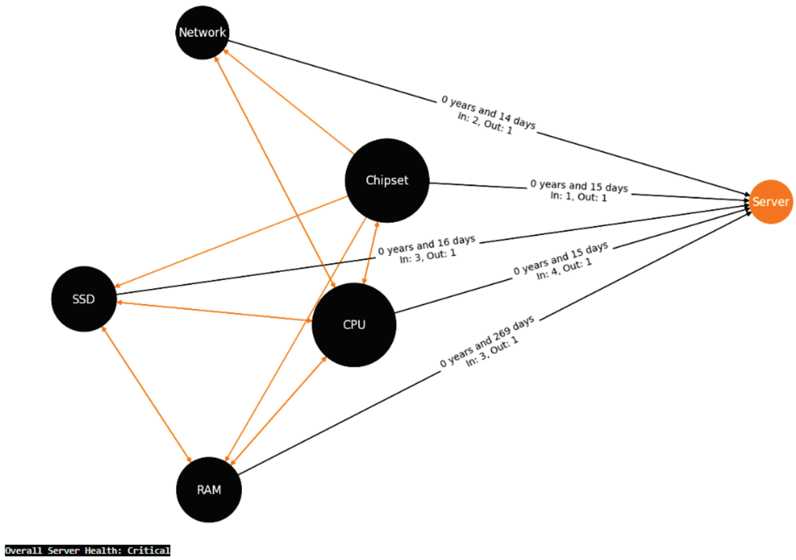

Fig. 6. Graph Representation of the Optimistic Scenario

are no longer available on the market. Consequently, their replacement will take longer, resulting in a "critical" status due to their unavailability (e.g., as shown in Figure 7, a CPU that has been obsolete for 3 years and 80 days). Finding compatible components for the system or a complete server will take time due to the current market shortage. This extended replacement time increases the risk of system downtime, highlighting the importance of proactive planning and timely replacement before the components become critical.

5. Conclusion

This work has focused on developing a predictive model to manage the obsolescence and availability of hardware components in server systems. The next phase of this research will extend the methodology to address software obsolescence. The predictive framework will be adapted to account for factors such as end-of-support timelines, security vulnerabilities, and key elements like cloud computing, virtualization, and operating systems. This approach will enable comprehensive and integrated management of both hardware and software obsolescence across the entire system.

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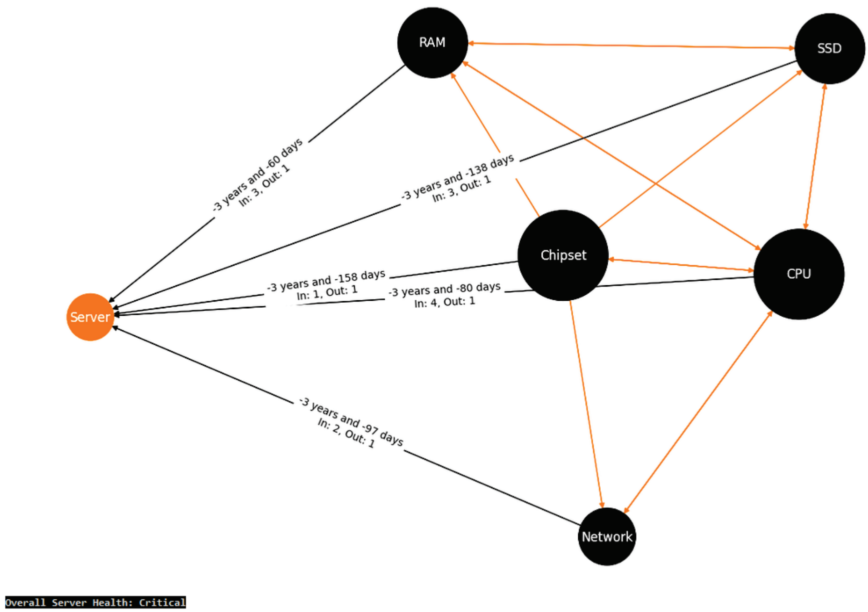

Fig. 7.

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