Dependability Analysis of Weather Monitoring Systems Considering Different Redundancy Mechanisms

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Abstract. *The increasing occurrence of extreme weather events makes precipitation forecasting essential for disaster mitigation. The Internet of Things (IoT) has enhanced weather monitoring, but ensuring system availability and reliability remains a challenge. This study evaluates the impact of redundancy on system dependability, focusing on availability and reliability. Models were developed to compare a system without redundancy to one incorporating redundancy in critical components. Using Stochastic Petri Nets (SPNs), we analyzed their behavior under different failure and repair scenarios. Results show that redundancy significantly improves availability, reduces the probability of failures, and minimizes downtime, reinforcing its importance in the resilience of climate monitoring systems.*

1. Introduction

The increasing frequency and intensity of extreme weather events have generated growing concerns regarding the socioeconomic and environmental impacts of climate change. Meteorology and weather forecasting have proven to be valuable allies in decision-making across various application domains. In response to this scenario, the application of emerging technologies, such as IoT and AI, has shown promise in improving the prediction and mitigation of risks associated with these events [7]. However, ensuring the reliability and availability of these systems remains a challenge.

Northeast Brazil has great interannual variability in precipitation, with some years being extremely dry and others being rainy. According to [4], among the main climatic factors that determine the distribution of these elements and their seasonal variation are its geographic position, topography, surface characteristics, and the pressure systems influencing the region [9]. As a result, it is crucial to perform climate forecasts that help mitigate potential disasters arising from high interannual variability.

Weather forecasting is a global activity that plays a crucial role in various sectors of society, including government agencies, the military, media, industries, agriculture, and personal use [2]. In Brazil, weather forecasts provided by competent agencies focus on timeframes longer than one hour and are typically available only at the city or metropolitan region level. The main data sources for local weather information are the National Institute of Meteorology (INMET)[1] and the Pernambuco Water and Climate

[1]https://tempo.inmet.gov.br/TabelaEstacoes/

Agency (APAC)[2]). However, there is a gap in short-term weather forecasting (with resolutions under 60 minutes) and at the geographic level of specific locations within a city.

Accurate forecasts with intervals shorter than one hour offer several benefits, including enabling swift response actions to prevent damage, providing real-time warnings, facilitating evacuations, and allowing for better preparedness in the face of severe weather events. In this study, we employ an alternative IoT architecture for weather forecasting based on low-cost weather stations. Specifically, we use the Ambient Weather WS-2902D climate monitoring system, a solar-powered, wireless weather station that includes sensors to monitor climate variables such as temperature, humidity, atmospheric pressure, precipitation, and wind speed [11].

One of the main challenges of such systems is ensuring their operational continuity, particularly in scenarios where data availability is critical. Evaluating availability and reliability is crucial to understanding system dependability under various conditions, as it helps identify vulnerabilities, optimize maintenance, and improve system design. To address this challenge, this study focuses on modeling the availability and reliability of the monitoring system, using SPNs to evaluate and ensure the system remains operational even in the face of failures or interruptions. To the best of our knowledge, no previous studies have analyzed the availability and reliability of low-cost climate monitoring stations using formalisms such as Stochastic Petri Nets.

The proposed models were evaluated using a real-world monitoring system based on the Ambient Weather WS-2902D station. The results demonstrate that incorporating redundancy can significantly enhance system availability, reduce downtime, and improve overall reliability. Specifically, our analysis showed that applying the redundancy model increased operational availability from 95.69% (approximately 377.7 hours of unavailability per year) to 99.99% (approximately 0.71 hours of unavailability per year). These findings show the potential of the proposed approach to strengthen the resilience of low-cost climate monitoring infrastructures, ensuring more reliable data collection for informed decision-making in extreme weather scenarios.

The remainder of this work is organized as follows: Section 2 presents the related work. Section 3 describes the adopted architecture and infrastructure. Section 4 discusses the proposed models. Section 5 presents the results obtained. Finally, Section 6 concludes the work and suggests directions for future research.

2. Related Works

Weather forecasting traditionally relies on complex models that consider various atmospheric factors, such as temperature, humidity, and wind patterns. However, these models often neglect the dependability aspects of the systems used for monitoring and prediction. Recent studies, such as the work by Chang et al. [5], highlight the growing interest in machine learning (ML) techniques as a promising alternative or complement to traditional weather forecasting methods. These techniques can capture complex, nonlinear patterns in atmospheric data, enabling more accurate and adaptive modeling of meteorological conditions. Albuquerque et al. [1] applied machine learning algorithms to classify critical rainfall volumes in Recife. Their methodology included models like Logistic

[2]https://www.apac.pe.gov.br/

Regression, KNN, SVM, Decision Tree, and Random Forest, with Logistic Regression achieving 94.12% accuracy and 100% recall, proving to be the most effective. While the focus of these works is on rainfall prediction, they do not address aspects related to the dependability of the weather monitoring systems

On the other hand, SPNs have been explored to model critical systems, particularly for analyzing metrics such as availability and reliability. For example, Andrade et al. [3] used SPNs to evaluate the dependability of Cyber-Physical Systems (CPSs) in smart environments, applying the technique in a case study of a water treatment plant. While significant, the study has limitations in modeling real-world systems and the accuracy of the data required for the analysis. Silva et al. [10] applied SPNs to assess availability and reliability in the textile Industry 4.0, with a focus on enhancing the competitiveness of industries in the Agreste region of Pernambuco. However, none of these works focus on monitoring weather systems, which is the main focus of this study.

3. Adopted Weather Monitoring System

Figure 1 illustrates the topology of our weather monitoring system. This architecture is designed for flexibility and resilience, with each device operating independently to ensure continuous operation, even in the event of failures. The monitored region is assumed to have internet connectivity, either through Wi-Fi or 4G, to enable real-time data transmission and remote access.

The system includes a camera that records real-time weather conditions in video format. The captured data is then sent to a controller using designated communication protocols. The controller processes and forwards this information to a central server, where the data is further analyzed and stored. In addition, the weather monitoring system is equipped with a WS-2902D weather station, as detailed in [11], which includes internal sensors and is powered by a battery. The weather station continuously collects essential climate data, such as temperature, humidity, pressure, and wind speed, and sends it directly to the server for processing.

All the collected information is securely stored on the central server and can be accessed remotely through connected devices. This approach provides users with convenient, centralized access to real-time climate data, facilitating more accurate and timely decision-making, especially in critical scenarios such as extreme weather events.

4. Proposed Models

In this section, we present the models developed using SPNs to analyze system availability and reliability. Petri nets are a family of formalisms well-suited for modeling various types of systems, as they can effectively represent concurrency, synchronization, communication mechanisms, and both deterministic and probabilistic delays. Essentially, they are composed of transitions, which represent events or actions that change the state of the system, places, which represent conditions or states, and tokens, which are used to indicate the system's current state. By incorporating time, SPNs extend traditional Petri nets with timed transitions, which represent events that occur with exponentially distributed delays, and immediate transitions, which represent instantaneous events. This combination allows SPNs to more accurately model the dynamic behavior of real-world systems.

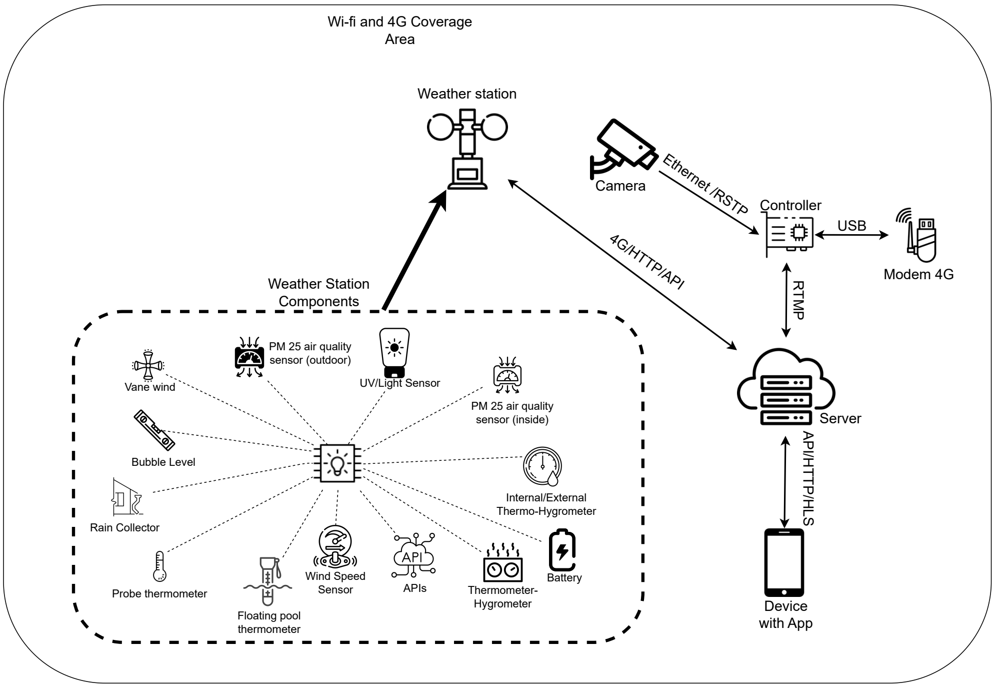

Figure 1. Adopted weather monitoring system.

The modeling was performed using Mercury 5.3.1 tool, as described in [8], which has been applied in other studies, such as [6], to generate results. The study considers four scenarios for system availability and reliability: (i) with redundancy, and (ii) without redundancy. These scenarios aim to evaluate the impact of redundancy on the system's dependability under different operational conditions, highlighting how the presence of redundancy can improve availability and reliability by mitigating the effects of failures or interruptions in the system.

4.1. Availability Model Without Redundancy

Figure 2 shows the model without redundancy, while Table 1 describes the places, transitions, and tokens used in this work. In this case, each component was configured with the minimum number of tokens necessary to ensure the basic functioning of the system. No redundant elements capable of replacing the components in case of failure were included, which leaves critical components without support mechanisms. This configuration illustrates that the failure of a single critical component directly compromises the operation of the system as a whole. This highlights the negative impacts of the lack of redundancy on overall availability and highlights the vulnerability of the system to failures in essential elements.

Each component of the system presented in Figure 1 is represented by elements composed of places and transitions. It is important to note that the sensors of the WS-2902D weather station are considered identical, with each having the same mean failure and repair times, and are represented by the place *PsensorsAvailable*. The failure and

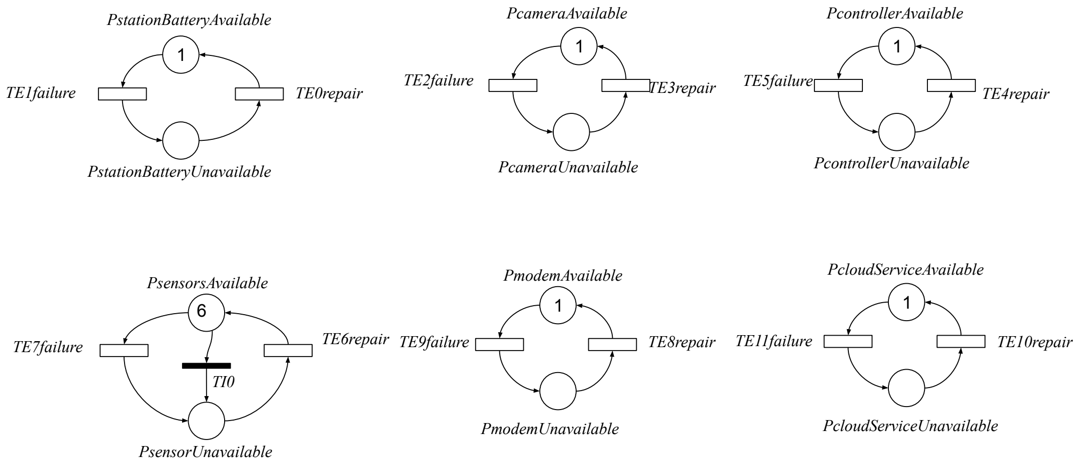

Figure 2. Model Without Redundancy.

repair behavior of all components is similar. For instance, the place *PstationBatteryAvailable* indicates that the station battery is functioning normally. After a predefined time, configured in the transition *TE1failure*, the failure event is triggered, moving the token to the place *PstationBatteryFailure*, signaling that the component has failed and requires repair. The repair process is carried out through the transition *TE0repair*, which, after a defined time interval, returns the token to the place *PstationBatteryAvailable*, indicating that the component has been restored to normal operation.

One exception to the failure and repair behavior is the model related to the sensors, which is the fourth model. In this model, if the battery is unavailable, the sensors also become unavailable. The transition *TI0* is instantaneous (not associated with time) and takes precedence over timed transitions. When activated, it triggers a priority state if necessary. In the proposed model, the *TI0* transition follows the guard expression from Table 2, which is based on the number of tokens in *PstationBatteryAvailable*. If this place reaches zero tokens, it indicates that the battery is unavailable. As a result, the tokens in *PsensorsAvailable* transition to *PsensorUnavailable*, signaling the unavailability of the weather station's sensors.

4.2. Availability Model With Redundancy

Figure 3 shows the components of the system in the redundancy scenario. In this model, each critical component is configured with additional tokens, representing redundant elements capable of assuming their functions in case of failure. For example, while the weather station can operate with only 6 sensors, redundancy allows it to have up to 12 sensors, ensuring greater resilience. This approach is designed to ensure that even in the event of component failures, the system remains available and functional, avoiding significant interruptions in operation. In this way, redundancy plays a fundamental role in maintaining availability and mitigating negative impacts that could compromise the reliability of the system.

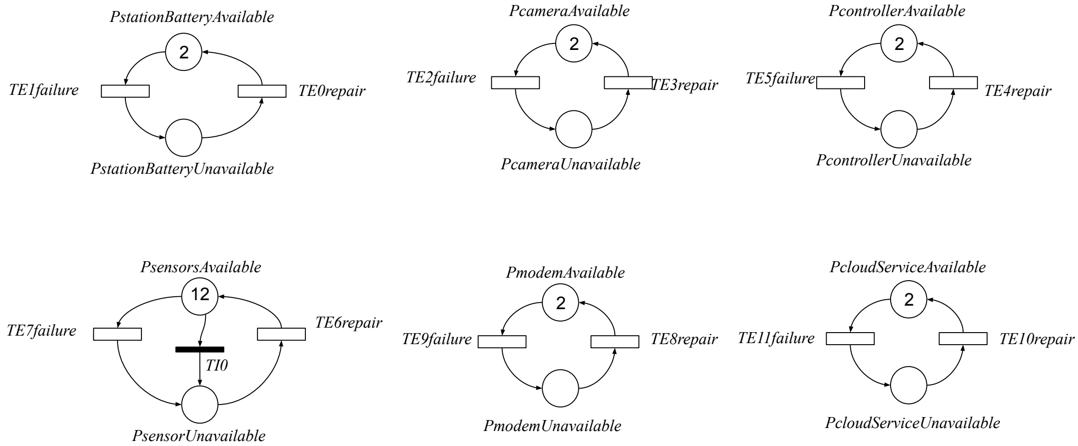

Figure 3. Model With Redundancy.

Table 1. Transitions and places in the adopted environment.

Transition	Description	Value	Place	Description	Tokens
TE0repair	Battery repair time	48(h)	PstationBatteryAvailable	Available battery	1-2
TE1failure	Battery failure time	13149(h)	PstationBatteryUnavailable	Unavailable battery discharged	0
TE3repair	Camera repair time	72(h)	PcameraAvailable	Available camera	1-2
TE2failure	Camera failure time	30681(h)	PcameraUnavailable	Unavailable camera	0
TE4repair	Controller repair time	72(h)	PcontrollerAvailable	Available controller	1-2
TE5failure	Controller failure time	43830(h)	PcontrollerUnavailable	Unavailable Controller	0
TE6repair	Sensor repair time	72(h)	PsensorsAvailable	Available Sensors	6-12
TE7failure	Sensor failure time	32872.5(h)	PsensorsUnavailable	Unavailable Sensors	0
TE8repair	Modem repair time	96(h)	PmodemAvailable	Available modem	1-2
TE9failure	Modem failure time	43830(h)	PmodemUnavailable	Unavailable Modem	0
TE10repair	Cloud repair time	4(h)	PcloudServiceAvailable	Available cloud service available	1-2
TE11failure	Cloud failure time	48213(h)	PcloudServiceUnavailable	Unavailable cloud service	0
TI0	Instantaneous transition	-	-	-	-

Table 2. Guard expressions of availability models.

Guard	Expression
TE6repair	(#PstationBatteryAvailable>=1)
TI0	(#PstationBatteryAvailable = 0)

4.3. Reliability Models

Reliability is the probability that a system, component, or asset will perform its function correctly over a specified period, under defined operational conditions. With this, reliability models have been developed, as illustrated in Figures 4 and 5. This model was derived from the models presented in Figures 3 and 2, with the difference that it does not include repair transitions.

In these models, if any component fails, the system is considered to have failed as well. This failure is represented by the number of tokens in specific places within the SPN, which indicates the system's unavailability. This behavior is modeled through guard functions assigned to the transitions. Due to space constraints, we only present the guard function for the reliability models with redundancy, as shown in Table 3. For instance, in Figure 5, if the place *PstationBatteryUnavailable* contains two tokens, it signifies that both batteries of the meteorological stations have failed, leading to a system failure. As a result, no other transitions can be triggered. This logic applies to other components, with the exception of the sensors, where the system failure occurs only when the place *PsensorUnavailable* contains seven tokens, indicating the failure of all sensors.

From these models, one key metric collected is the probability of failure, as shown in Table 5. This metric represents the likelihood that the system will experience a failure within a given period, providing a crucial measure of its reliability. In this study, we analyzed two reliability models: one with redundancy and the other without, to assess the impact of redundancy on system dependability. By comparing the failure probabilities of both models, we can evaluate how redundancy enhances the system's ability to maintain operations despite component failures, thus improving overall resilience and reliabilit.

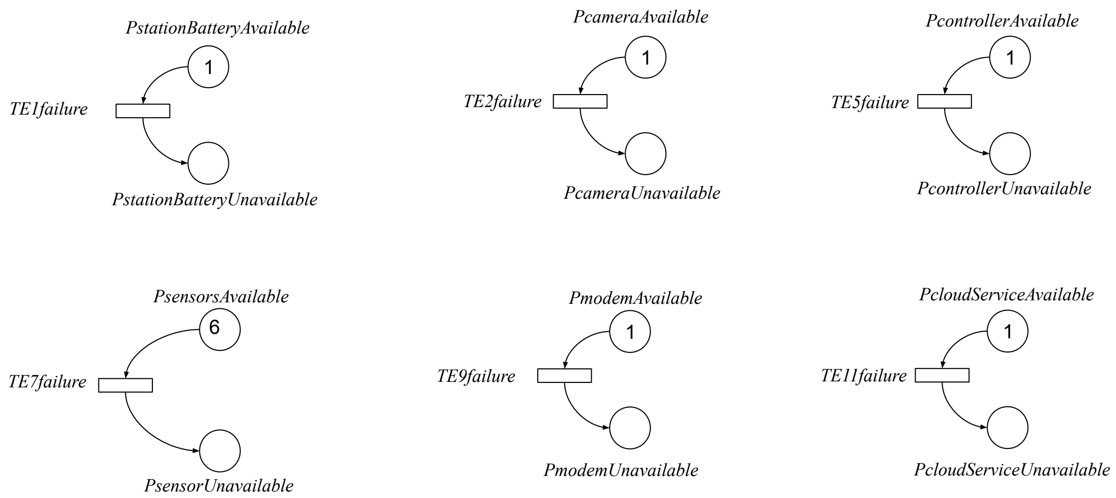

Figure 4. Reliability model without redundancy.

5. Results

In this section, we present the results derived from analyzing the models introduced in the previous section. The parameters used in our analysis, as shown in Table 1, were derived from the actual infrastructure available to us, or gathered from the literature [11]. The analysis was conducted using the Mercury 5.3.1 tool [8]. Table 4 presents the metrics

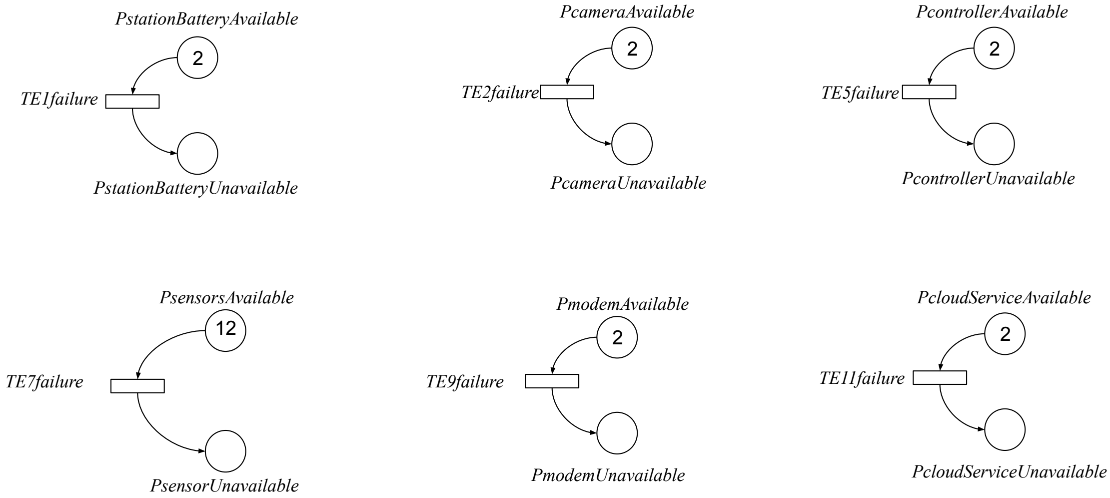

Figure 5. Reliability model with redundancy.

Table 3. Guard expressions for the reliability models with redundancy.

Guard	Expression
TE1failure	$(\#PcameraUnavailable \leq 1) AND (\#PsensorsUnavailable \leq 6) AND$ $(\#PcontrollerUnavailable \leq 1) AND (\#PmodemUnavailable \leq 1) AND$ $(\#PcloudServiceUnavailable \leq 1)$ $AND (\#PstationBatteryUnavailable \leq 1)$
TE2failure	$(\#PstationBatteryUnavailable \leq 1) AND (\#PsensorUnavailable \leq 6) AND$ $(\#PcontrollerUnavailable \leq 1) AND (\#PmodemUnavailable \leq 1) AND$ $(\#PcloudServiceUnavailable \leq 1) AND (\#PcameraUnavailable \leq 1)$
TE5failure	$(\#PstationBatteryUnavailable \leq 1) AND (\#PsensorUnavailable \leq 6) AND$ $(\#PcameraUnavailable \leq 1) AND (\#PmodemUnavailable \leq 1) AND$ $(\#PcloudServiceUnavailable \leq 1) AND (\#PcontrollerUnavailable \leq 1)$
TE7failure	$(\#PstationBatteryUnavailable \leq 1) AND (\#PcameraUnavailable \leq 1 AND$ $(\#PcontrollerUnavailable \leq 1) AND (\#PmodemUnavailable \leq 1) AND$ $(\#PcloudServiceUnavailable \leq 1) AND (\#PsensorUnavailable \leq 6)$
TE9failure	$(\#PstationBatteryUnavailable \leq 1) AND (\#PsensorUnavailable \leq 6) AND$ $(\#PcontrollerUnavailable \leq 1) AND (\#PcameraUnavailable \leq 1) AND$ $(\#PcloudServiceUnavailable \leq 1) AND (\#PmodemUnavailable \leq 1)$
TE11failure	$(\#PstationBatteryUnavailable \leq 1) AND (\#PsensorUnavailable \leq 6) AND$ $(\#PcontrollerUnavailable \leq 1) AND (\#PmodemUnavailable \leq 1) AND$ $(\#PcameraUnavailable \leq 1) AND (\#PcloudServiceUnavailable \leq 1)$

adopted to evaluate system availability and downtime, both with and without redundancy. Meanwhile, Table 5 provides the metrics for calculating the probability of failure.

Table 4. Availability metrics.

Metrics	Functions
Availability without redundancy	$P\{(\#PcameraAvailable \geq 1)AND(\#PcontrollerAvailable \geq 1)AND$ $(\#PmodemAvailable \geq 1)AND(\#PcloudServiceAvailable \geq 1)AND$ $(\#PstationBatteryAvailable \geq 1)AND(\#PsensorsAvailable \geq 6)\}$
Availability with redundancy	$P\{(\#PcameraAvailable \geq 1)AND(\#PcontrollerAvailable \geq 1)AND$ $(\#PmodemAvailable \geq 1)AND(\#PcloudServiceAvailable \geq 1)AND$ $(\#PstationBatteryAvailable \geq 1)AND(\#PsensorsAvailable \geq 6)\}$
Downtime without redundancy	$(1 - P\{(\#PcameraAvailable \geq 1)AND(\#PcontrollerAvailable \geq 1)AND$ $(\#PmodemAvailable \geq 1)AND(\#PcloudServiceAvailable \geq 1)AND$ $(\#PstationBatteryAvailable \geq 1)AND(\#PsensorsAvailable \geq 6)\}) \times 8766$
Downtime with redundancy	$(1 - P\{(\#PcameraAvailable \geq 1)AND(\#PcontrollerAvailable \geq 1)AND$ $(\#PmodemAvailable \geq 1)AND(\#PcloudServiceAvailable \geq 1)AND$ $(\#PstationBatteryAvailable \geq 1)AND(\#PsensorsAvailable \geq 6)\}) \times 8766$

Table 5. Reliability metrics.

Metrics	Functions
Probability of failure without redundancy	$P\{(\#PcameraUnavailable \geq 1)OR(\#PcontrollerUnavailable \geq 1)OR$ $(\#PmodemUnavailable \geq 1)OR(\#PcloudServiceUnavailable \geq 1)OR$ $(\#PstationBatteryUnavailable \geq 1)OR(\#PsensorsUnavailable \geq 1)\}$
Probability of failure with redundancy	$P\{(\#PcameraUnavailable \geq 2)OR(\#PcontrollerUnavailable \geq 2)OR$ $(\#PmodemUnavailable \geq 2)OR(\#PcloudServiceUnavailable \geq 2)OR$ $(\#PstationBatteryUnavailable \geq 2)OR(\#PsensorsUnavailable \geq 7)\}$

The availability and reliability of a weather monitoring system can be compromised by equipment failures and connectivity issues, such as internet outages. These disruptions can degrade the system's performance, leading to loss of data or delayed updates on weather conditions. Therefore, assessing these metrics and implementing measures to mitigate such risks are crucial for maintaining operational continuity and ensuring the efficient monitoring of the weather station and its components.

Initially, the results related to the availability of the adopted model are analyzed. The SPN models presented in Figures 2 and 3, along with the expressions and metrics detailed in Tables 1, 2, and 4, were used as the basis for the evaluation. For this analysis, two distinct scenarios were considered: a non-redundant model, consisting of a battery for the weather station, a camera, a control board, six sensors, a modem, and a cloud server; and a redundant model, in which the number of each component was doubled. Thus, the number of sensors increased from six to twelve, and this same logic was applied to the other system elements.

The results obtained for both models are detailed in Table 6. The non-redundant model exhibited the lowest availability level (0.9569), which corresponds to a downtime of approximately 377.70 hours per year. On the other hand, the redundant model had a significantly lower downtime, estimated at 0.71 hours per year. In other words, the introduction of redundancy allowed for an increase of 376.99 hours per year in the operational availability of the monitoring system. In summary, the analysis revealed that implementing redundancy can significantly improve system availability compared to the non-redundant model, making the operation more robust and resilient to failures.

Table 6. Results related to availability and downtime.

Description	Availability (h)	Downtime (hrs per year)
Without Redundancy	0.9569130430135321	377.70026494337594
With Redundancy	0.9999187862132178	0.7119200549319917

Next, the results regarding the probability of failure for the reliability models are presented. The SPN models shown in Figures 5 and 4, along with the parameters and metrics outlined in Tables 1 and 5, were used to calculate the reliability metrics. The redundancy mechanisms were derived from the availability models presented earlier, and thus share similar characteristics. Figure 6 illustrates the impact of failures with respect to the adoption of redundancy in the system configuration over time. For this analysis, the two scenarios defined earlier were considered: one without redundancy and one with redundancy. The X-axis represents the average operational time of the infrastructure, varying from 0 to 43,830 hours, while the Y-axis shows the probability of failure (%) of the system's resources in both scenarios.

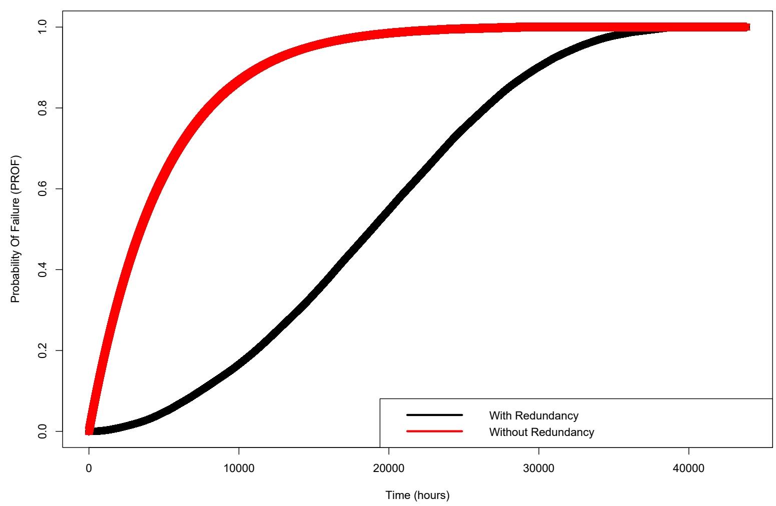

Figure 6. Failure curve.

When analyzing the reliability in terms of the probability of failure for the non-redundant model, it is observed that it surpasses a 90% failure rate after 20000 hours of infrastructure operation. In contrast, the redundant model reaches approximately 60% failure over the same period. This comparison highlights that the implementation of redundancy has the potential to reduce the infrastructure failure rate by approximately 50% per year compared to the non-redundant model. These results are crucial for supporting strategic decisions and investments in technologies that enhance the reliability and operational efficiency of the climate monitoring system, ensuring greater robustness.

The analyses presented here represent only a portion of the possible evaluations that can be conducted. It is important to recognize that additional studies can be carried out depending on the specific needs of each climate monitoring system. Each station may have different configurations, and the proposed models can be easily adapted to include new components and consider other critical factors. This flexibility allows for adjustments to meet a wide range of scenarios and specific requirements, particularly in mitigating disasters caused by intense precipitation.

5.1. Threats to the Validity of the Study

This study is subject to validity threats that must be carefully considered. The main threats include:

- **Generalization of Results:** The findings are specific to the weather monitoring system analyzed in this study. Different environmental contexts, hardware configurations, or geographical locations may lead to variations in system dependability, which could limit the generalizability of the conclusions to other monitoring systems. However, the models presented in this work can be adapted to different weather stations and monitoring configurations.
- **Limitations of Modeling and Simulation:** The SPN approach employed in this study may not fully capture all the complexities of real-world weather monitoring systems. For instance, certain unpredictable factors, such as extreme weather conditions or sudden component failures, may not be represented in the model, potentially influencing the accuracy of the results. However, the models presented remain valuable, as they provide important insights into system behavior and help identify key factors influencing availability and reliability.
- **Assumption of Exponential Transitions:** While modeling all transitions as exponential may not fully capture real-world variations in failure and repair times, it allows for a clearer and more practical analysis of both availability and reliability. This approach ensures the model remains manageable while still providing valuable insights into the impact of redundancy strategies on system dependability.
- **Performance vs. Redundancy:** While redundancy significantly improves fault tolerance and system resilience, it also introduces additional operational costs, including hardware, maintenance, and energy consumption. This trade-off must be carefully evaluated to ensure an efficient and cost-effective system. Depending on the operational requirements of the weather monitoring system, a non-redundant configuration may suffice to achieve acceptable availability, thus providing a balance between performance, reliability, and cost.

6. Conclusion

This study presented the modeling and analysis of a climate monitoring system using Stochastic Petri Nets to assess the impact of redundancy on the system's availability and reliability. Two distinct models were developed: one without redundancy and one with redundancy, enabling a comprehensive comparison of the results in terms of availability, downtime, and probability of failure.

The results showed that redundancy significantly enhances system availability by reducing the impact of failures in critical components. The non-redundant model exhibited longer downtimes and a higher probability of system failure, while the redundant model demonstrated greater resilience, ensuring continuous operation even under adverse conditions. These findings show the importance of implementing redundancy in critical systems, such as climate monitoring, where failures can have serious consequences, particularly in emergency situations. Redundancy not only contributes to maintaining system operations but also provides an efficient strategy for resource allocation among components.

As part of future work, we intend to explore additional factors that influence system availability, such as the costs associated with redundancy implementation, the variability in failure and repair times, and the effects of different redundancy configurations in operational scenarios. Furthermore, we plan to investigate how optimizing the transfer of information between system components can enhance the reliability of the processed and transmitted data.

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