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Dependability Evaluation of a Smart Poultry Monitoring System with Disaster Recovery Mechanism

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Abstract The Internet of Things (IoT) has changed how poultry farming is carried out, offering various advantages to farmers. One notable benefit is the real-time monitoring of bird breeding tasks, ensuring the well-being of the animals. Farmers can enhance their operations through task automation by incorporating an edge server for local sensor data processing. Tasks automation enables farmers to make informed decisions, improving production efficiency, bird quality, and agribusiness profits. However, poultry farming faces challenges, with disaster recovery a critical concern. Potential events like fires, power outages, or equipment failures can significantly impact birds and production. Consequently, continuous monitoring of birds is vital, and any disruptions must be minimized to uphold system integrity. This study introduces Stochastic Petri Nets (SPN) models to evaluate the availability and reliability of an intelligent bird breeding system. The system integrates a disaster recovery solution for uninterrupted operations. Furthermore, a sensitivity analysis is conducted on the components of the smart poultry system to pinpoint the most relevant one to the system's availability in the proposed architecture. This analysis can aid system architects in developing distributed architectures, considering points of failure and recovery measures. The study results demonstrate the system's high availability and reliability, enabling farmers to make informed decisions and improve the overall productivity of their farms.

Keywords: Smart Poultry, Dependability, Edge Computing, Disaster Recovery, Stochastic Petri Net

1 Introduction

The IoT has been widely adopted in everyday life, encompassing public safety, industrial operations, education, healthcare, and agriculture, using sensor-based technologies [Mohammadian *et al.*, 2020; Santos *et al.*, 2021a]. The number of Internet of Things (IoT) devices worldwide is forecast to almost double from 15.9 billion in 2023 to more than 32.1 billion IoT devices in 2030. In 2033, the highest number of IoT devices will be found in China, with around 8 billion consumer devices Statista [2024]. IoT has emerged as an evolutionary business opportunity for the poultry industry, enabling its connectivity technologies for real-time data collection, remote monitoring, and process automation [Xu *et al.*, 2022].

Poultry farming is raising birds for the meat and egg production industry. In this context, the poultry industry plays a vital role due to its significant demand in the global market for animal-derived food products. By 2050, the global demand for poultry meat will double compared to 2005, while the demand for chicken eggs will increase by nearly 40% [Smith *et al.*, 2015]. In poultry farming, IoT has proven to be a fundamental tool for monitoring the well-being of birds, optimizing feeding, and controlling environmental conditions in breeding facilities [Astill *et al.*, 2020]. Large-scale poultry farming requires advanced management practices. Poultry houses are structures designed for bird rearing, providing a safe and suitable environment for the healthy development of the animals.

Facilities for birds are planned with considerations such as ventilation, lighting, climate control, and available space to ensure the well-being of the birds. Using advanced avian management systems becomes advantageous in optimizing production, reducing expenses, and resource consumption [Lashari *et al.*, 2018]. In a smart poultry farm scenario, producers can utilize sensors to assist decision-making, automatically adjusting environmental and feeding conditions. Connected sensors can be installed at various points within the poultry house, collecting real-time data on temperature, humidity, air quality, water, feed consumption, and bird behavior.

Implementing a smart poultry house faces the challenge of dealing with system availability for long periods of uninterrupted operation. As the number of components in a system increases, predicting its behavior becomes more complex [Silva *et al.*, 2024]. Any failure that directly affects an entire ecosystem's availability must be considered. In the context of a smart poultry house, maintaining monitoring services in constant operation is essential to ensure the quality of the final product. Otherwise, system interoperability issues can result in severe financial losses, resource wastage, and even the loss of bird lives. Therefore, such IoT systems must be designed using effective fault tolerance techniques. Disaster recovery represents making a system capable of withstanding unexpected events or exceptional adversities [Andrade and Nogueira, 2020].

In this context, this paper proposes SPN models to analyze the availability and reliability of a smart poultry house with a disaster recovery solution. Petri Nets (PNs) are mathematical models that allow the modeling of a system using states and transitions to represent its operation. PNs also enable the portrayal of various system behaviors not seen in other mathematical models, such as parallelism, concurrency, synchronization, and other aspects of systems. Therefore, the main contributions of this paper are:

- **Availability SPN Model:** A model capable of representing the behavior of the components in the architecture of a smart poultry system and representing the interaction with the edge server using disaster recovery techniques.
- **Reliability SPN Model:** A model capable of analyzing the reliability of a smart poultry system over time and allows analysis both with and without the application of disaster recovery.
- **Case Studies Demonstrating the Practical Application of the Proposed Models:** To demonstrate the practical utility of our approach, we present a series of case studies. These case studies emphasize our models' effectiveness and serve as valuable resources for other researchers, offering guidance and initial instructions. Furthermore, they provide various analytical possibilities that can be explored using our models.
- **Sensitivity Analysis:** A sensitivity analysis was conducted using the Design of Experiments (DoE) on both models with and without disaster recovery. This analysis helps identify cause-and-effect relationships between the factors and the response variable, providing a solid foundation for decision-making and implementing improvements in the proposed architecture.

The subsequent sections of this paper are organized as follows: Section 2 briefly explains the topics covered in this paper. Section 3 presents related works. Section 4 introduces the architecture employed in this work. Section 5 provides an overview of the SPN modeling based on the architecture. Section 6 elaborates on a case study exploring disaster recovery and availability. In Section 7, DoE is presented, along with its results. Finally, Section 8 concludes the study and suggests possible directions for future work.

2 Background

This section briefly overviews the fundamental concepts essential for understanding this work. Firstly, it covers the basic concepts of SPN, followed by explanations of disaster recovery and sensitivity analysis using DoE.

2.1 Stochastic Petri Nets

PNs are graphical and mathematical modeling tools used to represent different systems characterized by concurrency, asynchrony, distribution, parallelism, non-determinism, and stochastic processes [Chen and Ha, 2018]. Petri nets (PN), in their various shapes and sizes, have been used for the study of the qualitative properties of systems exhibiting concurrency and synchronization characteristics, Marsan [Marsan, 1990] and Petri [Petri, 1962] and Reising [Reisig, 1985] and Peterson [Peterson, 1981]. The Stochastics Petri nets allow you to model a real system, without the costs of real equipment for the system. PNs provide a set of formalisms to abstract complex systems. Furthermore, several software tools facilitate their modeling, analysis, and verification [Girault and Valk, 2013]. SPN is a special case of PN that adds timing to the PN formalism and can be used to model performance and reliability [Murata, 1989]. SPN modeling helps evaluate systems and identify relevant points for them. This way, it is possible to save costs when a designer or engineer implements a real system.

SPNs can be identified as a directed graph divided into two parts, populated by three types of objects. These objects are places, transitions, and directed arcs connecting places to transitions and transitions to places [Rodrigues *et al.*, 2020]. Timed transitions follow a stochastic behavior, following a probability distribution function [Murata, 1989]. Immediate transitions fire when activated without waiting for any specific period. White circles symbolize places. Arcs are used to connect places to transitions. Inhibitor arcs block or permit the passage of tokens from one place to another. Additionally, tokens are assigned to specific places [Brito *et al.*, 2021]. Figure 1 illustrates the components of an SPN model.

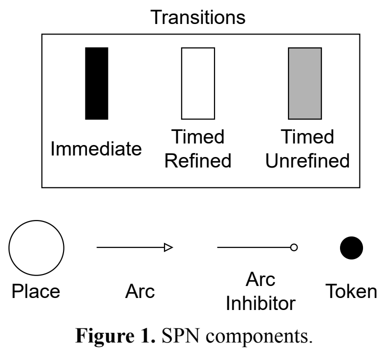

Figure 1. SPN components.

2.2 Recovery Disaster

Disaster recovery is a set of procedures and strategies to restore and recover systems, infrastructure, and data after a catastrophic event or a severe incident that causes disruption or partial or total destruction of an organization's resources. In today's business world, shutting down services for hours or even minutes for maintenance services such as tape backups [Rooney *et al.*, 2008] is no longer acceptable. The need for disaster recovery is evident in all sectors and organizations, regardless of size or complexity.

Modern computing systems must handle all failures or disasters to keep services running. The approach to disaster recovery involves creating solutions to help an organization deal with potential disasters. These solutions should be cost-effective yet efficient enough to provide high availability [Mendonça *et al.*, 2018]. Disasters can occur in various forms, such as hardware failures, human errors, cyberattacks, fires, floods, and earthquakes. DR solutions help systems withstand unexpected or extraordinary failures [Reese, 2009].

In modern farms, a centralized server automatically monitors real-time weather, soil, irrigation, and animal health data. In this context, disaster recovery is vital for uninterrupted agricultural operations. Strategies like continuous data replication to secure secondary servers are essential to maintain this continuity.

2.3 Sensitivity Analysis

The DoE corresponds to a set of statistical techniques that deepen the understanding of the product or process under study [Kleijnen, 1995]. DoE is a powerful technique used to explore new processes and gain deeper insights into existing processes, followed by optimizing these processes to achieve world-class performance [Antony, 2014]. It can also be defined as a series of tests where the researcher manipulates the set of variables or input factors to be observed and identifies the reasons for changes in the output response. Furthermore, proper experimental design allows for obtaining valuable insights with a minimal number of experiments, maximizing efficiency and reducing costs.

System designers often adopt sensitivity analyses to assess how "sensitive" a metric is to changes in the model [Santos *et al.*, 2021b]. Sensitivity analysis measures the impact of specific input data on the output data to identify weak links in computational systems. Subsequently, techniques are employed to enhance these systems in various scenarios [Campolongo *et al.*, 1999]. The Pareto chart allows us to identify which factor interaction has a more significant effect on the optimization process or design of the study, indicating where attention should be focused. Understanding the magnitude of interactions between factors enables the selection of the best combination of measures, identifying patterns of cumulative or degrading effects among the factors. The interaction between factors A and B can be calculated using Equation (1).

$$I_{A,B} = \frac{1}{2}(E_{A,B(+1)} - E_{A,B(-1)}) \tag{1}$$

The $E_{A,B(+1)}$ represents the effect of factor A at the high level of factor B, and $E_{A,B(-1)}$ represents the effect of factor A at the low level of factor B. If the lines on the interaction plot are parallel, there is no interaction between the process parameters. The different levels of factor B do not influence the variation in the average response of factor A. On the other hand, if the lines are not parallel, there is an interaction between the factors. The greater the deviation from parallelism, the more significant the interaction effect between these factors.

3 Related Works

This section presents related works with similar contexts or approaches to this work. The selection of works considered those that addressed evaluating availability and reliability in smart farming. The scientific literature reveals a notable gap, with a need for related works focusing on assessing reliability and availability in the context of smart farms. The selected papers present significant contributions, highlighting the need for further research and attention in smart farming. Table 1 displays the selected works in the literature and their respective comparison criteria.

The study by Oliveira *et al.* [2023] assesses the reliability of an automated system utilizing computer vision to estimate live poultry weight. The reliability analysis employs hierarchical models like Markov chains, Reliability Block Diagrams, and closed-form equations to represent the entire system. Metrics such as steady-state availability and annual downtime are calculated. Similarly, Kamyod [2019] evaluates the reliability of an IoT-based communication architecture system designed for small and medium-sized farms. Additionally, Catelani *et al.* [2021] investigate wireless sensor networks' (WSNs) reliability under adverse conditions and various design constraints, including limited processing capacity, reduced storage memory, restricted energy consumption, and fixed deployment.

The study by Montoya-Munoz *et al.* [2022] introduces an optimization model designed to enhance reliability and ensure uninterrupted service in smart farms. This model assists stakeholders in determining the optimal number of Fog Nodes necessary for deploying agricultural services. It considers factors such as variations in fog capabilities, resource demands, redundancy techniques, and reliability requirements. Similarly, Kamyod [2018] focuses on evaluating the end-to-end reliability of two IoT communication network architectures. They employ the OPNET tool to analyze the impact on reliability as the number of sensor nodes increases. Additionally, Londra *et al.* [2021] explores the sizing of rainwater harvesting systems for agricultural greenhouse irrigation. Their approach involves utilizing a daily water balance model to calculate the required size of rainwater tanks, considering factors such as daily precipitation and water needs. The study by Abdulhamid *et al.* [2024] propose to address the reliability of IoT systems in agriculture, with a specific focus on analyzing failures in Smart Irrigation Systems (SIS) using Fault Tree Analysis (FTA). The proposal includes introducing a Security-Based Model (MBSA) to model the behavior of failures in SIS, and using FTA to identify and understand the propagation of failures in system components. Additionally, Rahman *et al.* [2023] explores the use of Fault Tree Analysis (FTA) to identify and analyze potential failure causes in smart irrigation systems. It highlights the importance of understanding how component failures can contribute to overall system failure, aiming to enhance the reliability and security of these critical agricultural systems.

This work introduces SPN models to assess the availability and reliability of a smart poultry system employing disaster recovery techniques. The first model precisely depicts the behavior of smart poultry system components for availability assessment. It is worth noting that the studies addressed in

Table 1. Related works.

Work	Focus	Evaluation Method	Availability	Relaibility	Recovery Disaster
Oliveira *et al*. [2023]	Availability and reliability evaluation of a smart poultry.	Modeling	✓	✓	×
Kamyod [2019]	Reliability assessment of smart farm system.	Modeling	×	✓	×
Catelani *et al*. [2021]	Assessment of the reliability of Wireless Sensor Networks in precision agriculture.	Modeling	×	✓	×
Montoya-Munoz *et al*. [2022]	Reliability analysis in smart farms for service continuity with IoT-Fog-Cloud.	Modeling	×	✓	×
Kamyod [2018]	End-to-End Reliability Characteristics in Smart Agriculture.	Simulation	×	✓	×
Londra *et al*. [2021]	Reliability Analysis of Water Tanks for Irrigation in Greenhouse Agriculture.	Measurement	×	✓	×
Abdulhamid *et al*. [2024]	Reliability Analysis in Smart Irrigation Systems.	Modeling	×	✓	×
Rahman *et al*. [2023]	Reliability in smart agriculture systems for food security.	Modeling	×	✓	×
This work	Availability and Reliability Analysis in Smart Poultry with Disaster Recovery.	Modeling	✓	✓	✓

the literature almost do not cover availability, focusing more on reliability. The second model measures system reliability over time. Both models incorporate case studies examining scenarios with and without disaster recovery. Additionally, sensitivity analyses were performed using DoE to evaluate system behavior under varying failure times of specific components. Both disaster recoveries and sensitivity analysis with DoE are unique characteristics of this work compared to those mapped in the literature. Importantly, the model enables designers to customize input parameters without the necessity of an existing physical infrastructure.

4 Architecture

This section presents the underlying architecture used in this work. Figure 2 depicts the architecture of a smart poultry house for bird production on a farm. The smart poultry house consists of IoT devices that monitor light, water, gas, and temperature within the poultry house. Monitoring is carried out to ensure a healthy environment for the birds. Data is collected by a gateway and transmitted to the local edge server. The edge server is near the poultry house, resulting in low latency. Due to the nature of modeling, specific data, such as the exact amount of latency, are abstracted to ensure the validity of the model, as these data are generally obtained accurately only after the implementation of the real system.

The importance of bird monitoring justifies the choice of a local edge server, as an error could result in losses or ad-

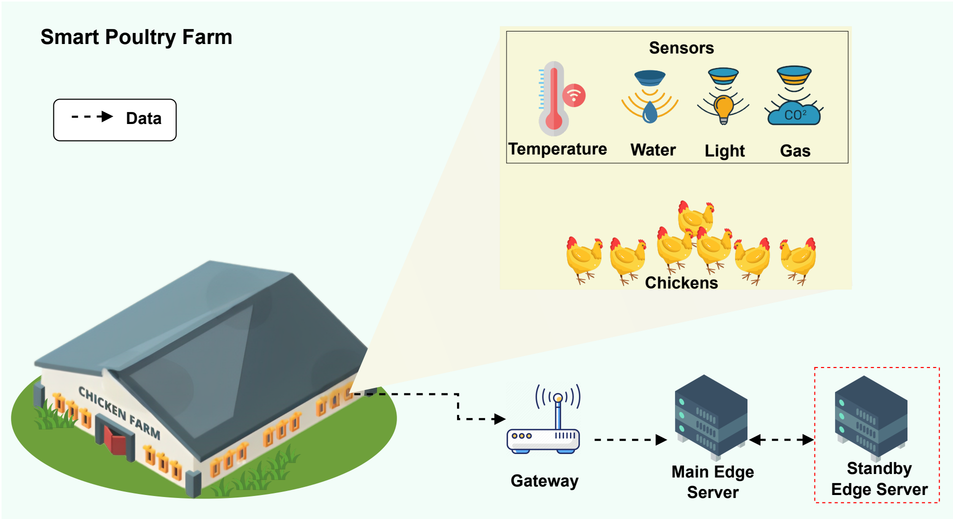

Figure 2. Evaluated architecture.

ditional expenses. Having the local server allows for more direct control over the data. To ensure that bird monitoring is not affected by any losses or disruptions, it is essential to have a well-planned disaster recovery solution in place. A secondary edge server would be on hot standby mode in the proposed setup, so if there are disasters or failures in the primary edge server, the secondary server would be immediately accessible, ensuring uninterrupted bird monitoring. The system is reactive, meaning that in the event of a failure of the first server, the second one may need access to historical data to maintain operations or make informed decisions. The frequency with which the second edge server receives information and whether it needs past information in case of failure in the first one depends on the specific design of the system. It is important to note that this data is usually obtained only after the implementation of the real system, and the developed models serve as a basis for initial planning, abstracting this step to avoid increasing complexity.

In this context, disasters refer to events that might happen in the edge server responsible for processing sensor data. It is crucial to emphasize that events such as floods and hurricanes are not considered in this analysis because they would have wider effects, impacting the entire aviary. Our main concern is guaranteeing the edge server's specific operational safety and continuity, which is vital for bird monitoring. As a result, we are excluding the analysis of natural phenomena that could have a broader impact on the location.

5 Models Overview

This section introduces the foundational model of the work based on the architecture mentioned in the previous section. The section also describes the disaster recovery solution's representative, availability, and reliability models. All modeling and simulations were performed using the Mercury Tool Maciel *et al*. [2017].

5.1 Availability Model

Figure 3 presents the SPN availability model for the smart poultry farm. Availability is the probability that the system is operational during a specific period or has been restored after a failure [SOUSA, 2015]. The model comprises sensors such as water (SW), temperature (ST), light (SL), and gas (SG). It also includes a gateway (GATEWAY) for transmitting data to the main server at the edge (Edge). Smart Poultry (SMART_POULTRY) represents the connection of all sensors responsible for generating data in the model. Each component has a timed transition representing the mean time to failure (MTTF) and mean time to repair (MTTR).

The Smart Poultry component represents the status of the poultry house system. The poultry house is active when all sensor components are active. The poultry house is inactive when all sensor components have tokens in the inactive state. Smart Poultry operates when there is a token in SMART_POULTRY_U. Smart Poultry is not operational when there is a token in SMART_POULTRY_D. The transition between the active and inactive states is triggered by transitions MTTR_SP and MTTF_SP, respectively. Thus, transition MTTF_SP is activated when all sensors are inactive, as expressed by the guard condition = ((#SW_D>0) AND (#ST_D>0) AND (#SL_D>0) AND(#SG_D>0)).

Transition MTTR_SP is activated when all sensors are active, as expressed by the guard condition = ((#SW_U>0) AND (#ST_U>0) AND (#SL_U>0) AND(#SG_U>0)). The Gateway is active when there is a token in GATEWAY_U and inactive when there is a token in GATEWAY_D. The edge server is active when there is a token in EDGE_U and inactive when there is a token in EDGE_D. The equation that calculates the availability of the proposed model is given by Equation (2), i.e., the probability that Smart Poultry, the Gateway, and the Edge are all operational simultaneously. P represents probability, and $\#$ represents the number of tokens in a specific place.

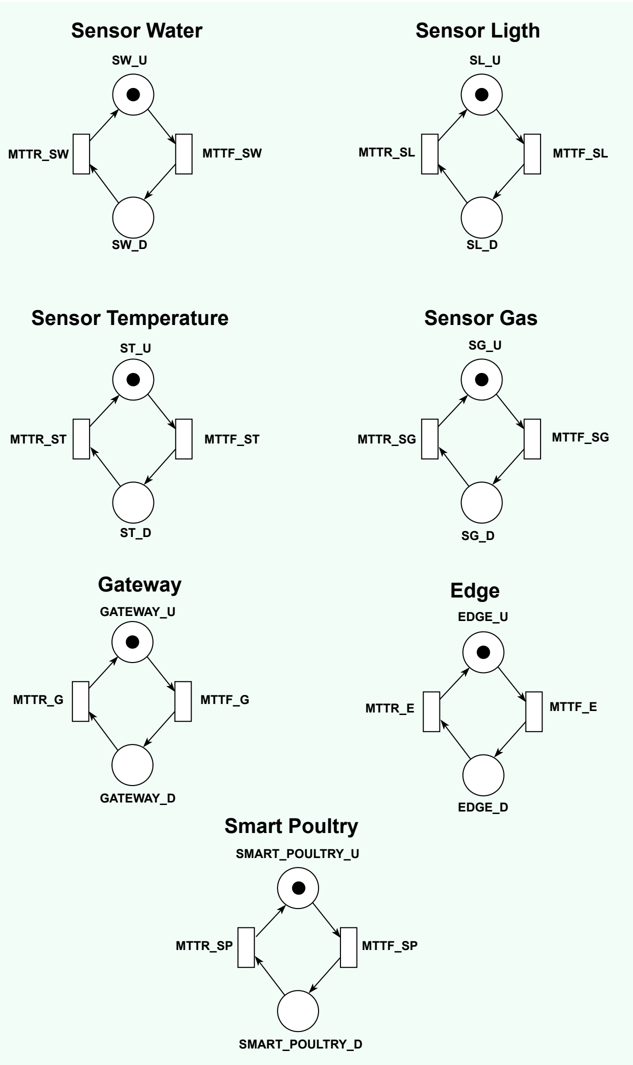

Figure 3. Availability SPN model.

$$A = P\{(\#Smart\_Poultry\_U > 0)AND \\ (\#Gateway\_U > 0)AND(\#Edge\_U > 0)\} \quad (2)$$

5.2 Reliability Model

Figure 4 presents the reliability SPN model for the smart poultry farm. Reliability is the conditional probability of a system remaining operational over time [0, t], considering that it was operational at t = 0 [Silva *et al.*, 2022]. Initially, the model operates similarly to the availability SPN model. In this model, the components do not have the MTTR transitions that allow for their recovery.

The reliability of the presented model can be calculated using Equation (3). Such metric is given by one minus unavailability, which is the probability that any system component fails. P calculates the probability that the system is unavailable. The equation can generate a curve showing how reliability decreases over time.

$$R = 1 - P\{(\#Smart\_Poultry\_D > 0)OR \\ (\#Gateway\_D > 0)OR(\#Edge\_D > 0)\} \quad (3)$$

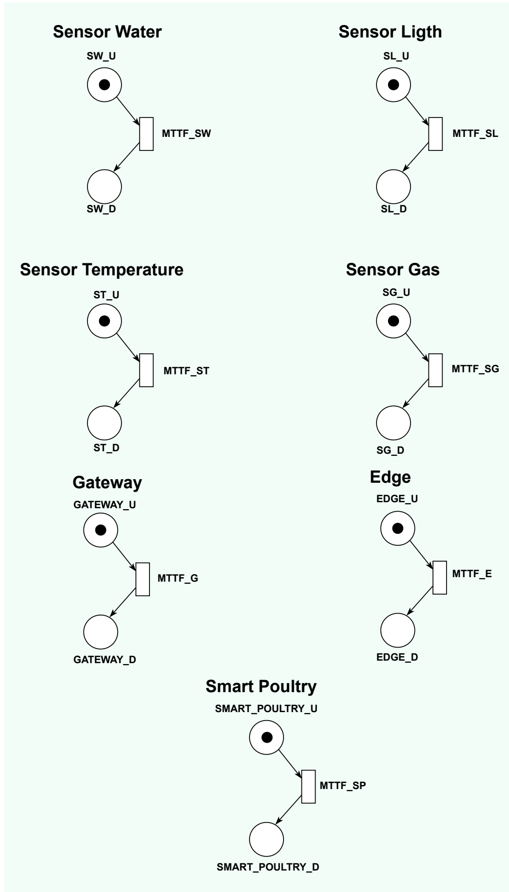

Figure 4. Reliability SPN model.

5.3 Recovery Disaster Model

Figure 5 presents the SPN model for disaster recovery in the edge server. In this model, a natural failure is considered a brief disruption in the main edge's operation, indicated by the location EDGE_D, caused by events like power outages. Conversely, a disaster, represented by the location EDGE_DD, involves more serious events, such as fires, leading to a complete server shutdown and substantial data loss. The standby edge consists of a place representing its hot standby state (EDGER_HOT), a timed transition MTFF_ER representing a failure in the standby edge when it is not in use, and a timed transition MTTR_ER representing the repair of the standby edge and placing it back in the hot standby state. Place EDGER_D represents the standby edge's inactive state.

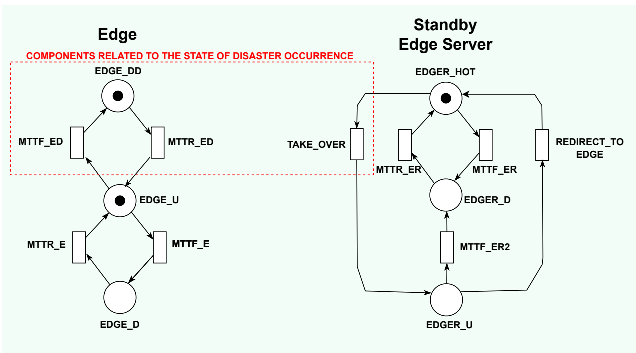

Figure 5. Disaster recovery SPN model.

The timed transition TAKEOVER represents the edge's failover time, i.e., the time it takes for the standby edge to take control in case of a disaster in the primary edge. Place EDGER_U indicates that the standby edge is active, meaning that the primary edge is inactive due to a disaster. Timed transition MTTF_ER2 represents the failure of the standby edge when it is active; in this case, both the primary and secondary edges would be inactive, constituting the worst-case scenario. Finally, timed transition REDIRECT_TO_EDGE redirects the data to the primary edge, indicating it is active again. The guard condition for the secondary edge to take over is given by (EDGE_DD>0) in TAKEOVER, and for the data to be redirected back to the primary edge is given by (EDGE_U>0) in REDIRECT_TO_EDGE.

The disaster recovery model is applied alongside the models shown in Figures 3 and 4. To integrate it into the model depicted in Figure 3, adjustments are made to the edge server component to accommodate the changes in this model, enabling disaster recovery implementation on the edge server. Regarding integration with the model in Figure 4, in addition to the modifications made in the Figure 3 model, components representing the MTTF are removed, ensuring the system's availability and reliability with the implemented disaster recovery.

6 Case Studies

This section presents the results obtained by analyzing the proposed models in this work. The following subsections analyze the availability and reliability with and without disaster recovery for all the presented models. Table 2 presents the values used for each system component. The values were extracted from other works in the literature [Oliveira *et al.*, 2023; Silva *et al.*, 2022; Andrade and Nogueira, 2020].

Table 2. Model Parameters

Component	MTTF (h)	MTTR (h)
Edge Servers	940.0	1.37
Gateway	480.77	8.0
Sensor Water	13140.0	2.0
Sensor Light	13140.0	2.0
Sensor Temperature	13140.0	2.0
Sensor Gas	13140.0	2.0

6.1 Availability and Disaster Recovery

In this section, we will present the results of the availability model. Figure 6 displays the results of this model. The availability was analyzed based on the edge failure time, allowing an assessment of the system with and without disaster recovery. When the edge does not have disaster recovery, the availability is approximately 2.33 nines. As the failure time increases, the availability also grows, reaching just over 2.63 nines when the MTTF is 4700 hours. On the other hand, availability with disaster recovery shows a significant increase as MTTF increases. When the edge has an MTTF of 4700 hours, availability reaches 3.53 nines. The results suggest disaster recovery significantly improves system availability, especially in situations with longer MTTF.

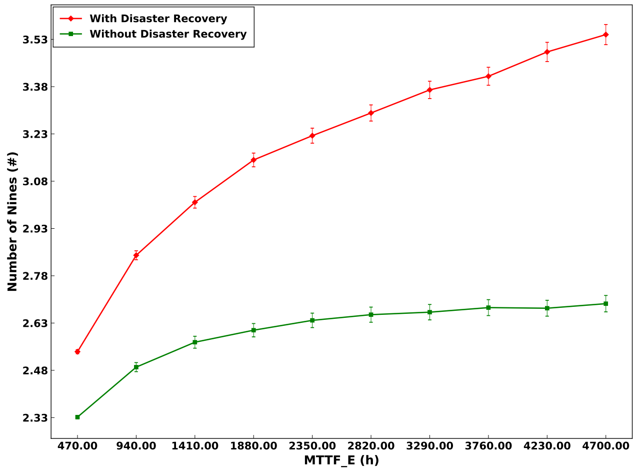

Figure 6. Availability.

6.2 Reliability and Disaster Recovery

Figure 7 presents the system's reliability over time. For reliability analysis, the system was assessed with and without disaster recovery. Initially, both reliability levels started with a high probability. As the system's operating time progresses, the reliability levels become distinct. The reliability line with disaster recovery shows higher values than reliability without disaster recovery. Both results decrease exponentially as the reliability of a system tends to decrease over time. Therefore, given a disaster scenario, implementing disaster recovery in the system allows it to operate longer and with fewer failures.

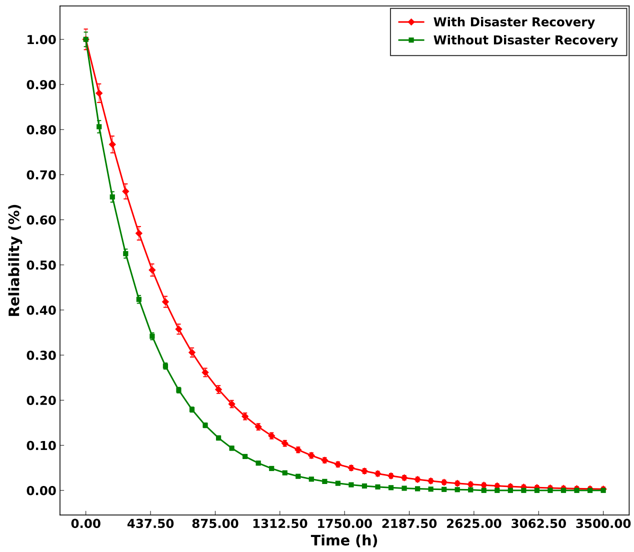

Figure 7. Reliability.

7 Design of Experiments

This section presents the sensitivity analysis results in the system using DoE. The analysis considered parameters from the models presented, both without and with disaster recovery. The results were obtained through simulations, aiming to comprehend how each factor influences the system's performance, identifying potential effects and interactions.

For the sensitivity analysis using DoE, we employed availability models, both with and without disaster recovery, on the edge server. Factors were selected based on their significance in the proposed architecture. As the number of components in DoE increased, creating combinations became more complex. Therefore, we limited the selection to 5 factors. Due to the importance of the edge, the edge with disaster recovery, and the gateway, only two sensors were chosen randomly, including temperature and water sensors.

The factors chosen for this study were: (i) MTTF_SW, (ii) MTTF_ST, (iii) MTTF_GW, (iv) MTTF_E, and (v) MTTF_ED. Each factor was investigated at two levels: low configuration and high configuration. Interactions were verified using the availability metric, as this metric directly impacts the end user's perception. Table 3 presents all the analyzed factors and levels. Additionally, Table 4 displays all possible combinations between the factors and their respective levels.

Table 3. Design table.

Factor name	Low Setting	High Setting
MTTF_SW	13140.0	19710.0
MTTF_ST	13140.0	19710.0
MTTF_GW	480.77	721.155
MTTF_E	980.0	1470.0
MTTF_ED	2350.0	3525.0

7.1 Case Without Disaster Recovery

Figure 8a presents the factor effect graph without disaster recovery. The graphical representation of factor effects uses bars arranged in descending order to illustrate the impact of factors on the analyzed measure. The higher the bar, the greater the influence of the corresponding factor on the variable in question. This visual representation allows for identifying factors with significant impact on the tests.

Among the factors analyzed in the system without disaster recovery, the failure time of the edge server has the most significant impact on the system's availability. Compared to others, the disparity in the height of the edge server failure bar indicates that for the system to achieve satisfactory performance, the edge server needs to function correctly. Factors representing sensor failure times also have significant relevance in the system.

Figure 8b illustrates the interaction between MTTF_GW and MTTF_E. Upon analyzing the figure, it is evident that there is a mutual influence between these two factors. When the gateway failure time is 480.77h, the combination that results in higher availability is when the edge failure time is 980h. However, as the gateway failure time increases, the best combination with the edge occurs at 1470h.

Figure 8c represents the interaction between MTTF_ST and MTTF_E. Regardless of the temperature sensor's failure time, any combination with the edge failure time is set at 1470h, resulting in higher system availability. The longer it takes for a failure to occur in this component, the better the system's processing, ensuring greater availability and operational efficiency.

Figure 8d represents the interaction between MTTF_SW and MTTF_E. In this interaction, we observe a pattern similar to the one shown in the previous figure. Regardless of the water sensor's failure time, the system maintains good availability in both situations where the edge failure time is 1470h. In other words, the system's availability is not significantly affected by variations in the water sensor's failure time as long as the edge failure time is maintained at specific levels.

7.2 Case With Disaster Recovery

Disaster recovery operations are extremely challenging and place significant demands on multiple resources, including local and international emergency response personnel, non-governmental organizations, and the military. In the immediate aftermath of a disaster, one of the most pressing requirements is situational awareness so that resources, including personnel and supplies, may be prioritized to have the most impact and help those in the most need. Disaster recovery mechanisms are very important in the context of not only cities but also in rural areas.

Figure 9a displays the factor effect graph with disaster recovery, emphasizing the importance of factors related to the availability metric. In this analysis, we identified that the two factors exerting the most significant influence on the system's availability are the edge disaster recovery server and the edge server itself. The gateway is also a relevant factor in ensuring the system's availability.

Figure 9b illustrates the interaction between MTTF_E and MTTF_ED. Both components significantly impact the system, and the system's behavior varies depending on the failure time of these components. When the edge failure time is low, the best availability is achieved with disaster recovery set at 2350h. However, when the edge failure time is high, the optimal combination is with the recovery time set at 3525h. This pattern emerges because disaster recovery maintains a stable outcome regardless of the edge failure time, providing a reliable solution to maintain system availability.

Figure 9c illustrates the interaction between MTTF_GW and MTTF_E. In general, regardless of the failure value of the gateway component, whether low or high, the edge server with a failure time of 1470h maintains stable performance and offers higher system availability. Combining the edge failure time at 980h with the low gateway failure time also yields satisfactory results. While different from the first combination mentioned, this option should be considered in certain scenarios.

Figure 9d illustrates the interaction between MTTF_GW and MTTF_ED. Upon analyzing this interaction, it is evident that the best combination occurs when the disaster recovery failure time is set to 2350 hours for both a gateway with low and high failure times. When the failure time in recovery is increased, the system's availability is lower than the previous interaction. The system already achieves satisfactory results with the standard failure time of disaster recovery, eliminating the need for investing capital to increase the failure time

Table 4. Combination of factors.

MTTF_SW	MTTF_ST	MTTF_GW	MTTF_E	MTTF_ED	DR and WDR (%)
13140.00	13140.00	480.76	980.00	2350.00	0.99
13140.00	13140.00	480.76	980.00	3525.00	0.99
13140.00	13140.00	480.76	1470.00	2350.00	0.99
13140.00	13140.00	480.76	1470.00	3525.00	0.99
13140.00	13140.00	721.15	980.00	2350.00	0.99
13140.00	13140.00	721.15	980.00	3525.00	0.99
13140.00	13140.00	721.15	1470.00	2350.00	0.99
13140.00	13140.00	721.15	1470.00	3525.00	0.99
13140.00	19710.00	480.76	980.00	2350.00	0.99
13140.00	19710.00	480.76	980.00	3525.00	0.99
13140.00	19710.00	480.76	1470.00	2350.00	0.99
13140.00	19710.00	480.76	1470.00	3525.00	0.99
13140.00	19710.00	721.15	980.00	2350.00	0.99
13140.00	19710.00	721.15	980.00	3525.00	0.99
13140.00	19710.00	721.15	1470.00	2350.00	0.99
13140.00	19710.00	721.15	1470.00	3525.00	0.99
19710.00	13140.00	480.76	980.00	2350.00	0.99
19710.00	13140.00	480.76	980.00	3525.00	0.99
19710.00	13140.00	480.76	1470.00	2350.00	0.99
19710.00	13140.00	480.76	1470.00	3525.00	0.99
19710.00	13140.00	721.15	980.00	2350.00	0.99
19710.00	13140.00	721.15	980.00	3525.00	0.99
19710.00	13140.00	721.15	1470.00	2350.00	0.99
19710.00	13140.00	721.15	1470.00	3525.00	0.99
19710.00	19710.00	480.76	980.00	2350.00	0.99
19710.00	19710.00	480.76	980.00	3525.00	0.99
19710.00	19710.00	480.76	1470.00	2350.00	0.99
19710.00	19710.00	480.76	1470.00	3525.00	0.99
19710.00	19710.00	721.15	980.00	2350.00	0.99
19710.00	19710.00	721.15	980.00	3525.00	0.99
19710.00	19710.00	721.15	1470.00	2350.00	0.99
19710.00	19710.00	721.15	1470.00	3525.00	0.99

of this component.

8 Conclusion

This paper proposed SPN models for the architecture of a smart poultry system using edge computing resources and including a disaster recovery solution. The models aim to assist system administrators in planning the architecture before deployment. The models take into account various factors that influence the final system availability. Availability and reliability metrics with disaster recovery were used to analyze each model. The analysis showed that when the edge does not have disaster recovery, availability reached approximately 2.33 nines, indicating a reasonable ability to keep the system operational. However, when considering disaster recovery, availability reached 3.53 nines, demonstrating a significant increase in system availability and reliability. The results show how each model behaves with varying parameters through sensitivity analyses, highlighting the interaction between the factors. The DoE analysis allowed for a meticulous examination of how changes between these factors influence system availability. In future work, we will analyze specific disaster recovery metrics, such as Recovery Point Objective (RPO) and Recovery Time Objective (RTO).

Declarations

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Authors' Contributions

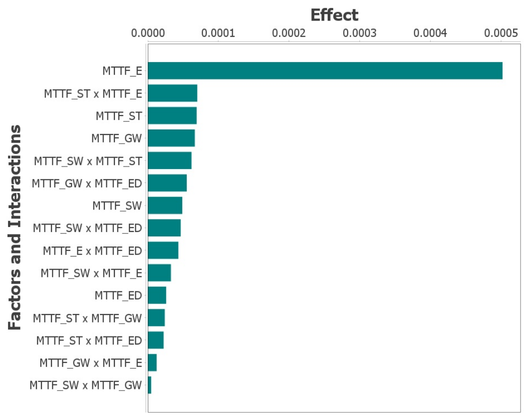
All authors contributed equally to the work.

Competing interests

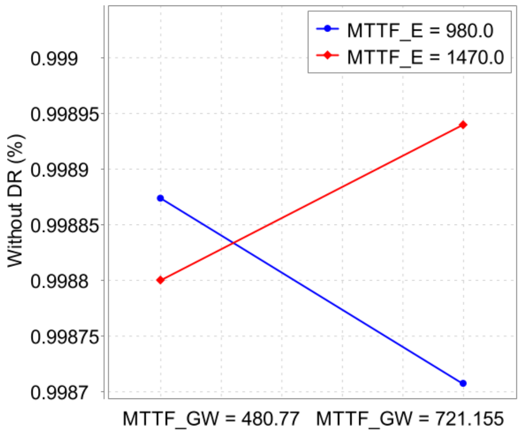
The authors declare that they have no competing interests

Availability of data and materials

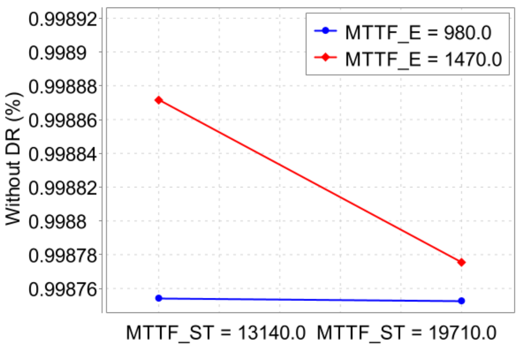
Data sharing is not applicable.



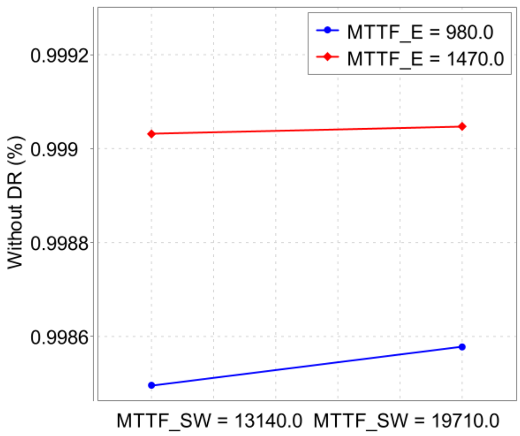
(a) Impact of different factors on the system without disaster recovery.



(b) MTTF_GW x MTTF_E.



(c) MTTF_ST x MTTF_E.



(d) MTTF_SW x MTTF_E.

Figure 8. Case without disaster recovery DoE results.

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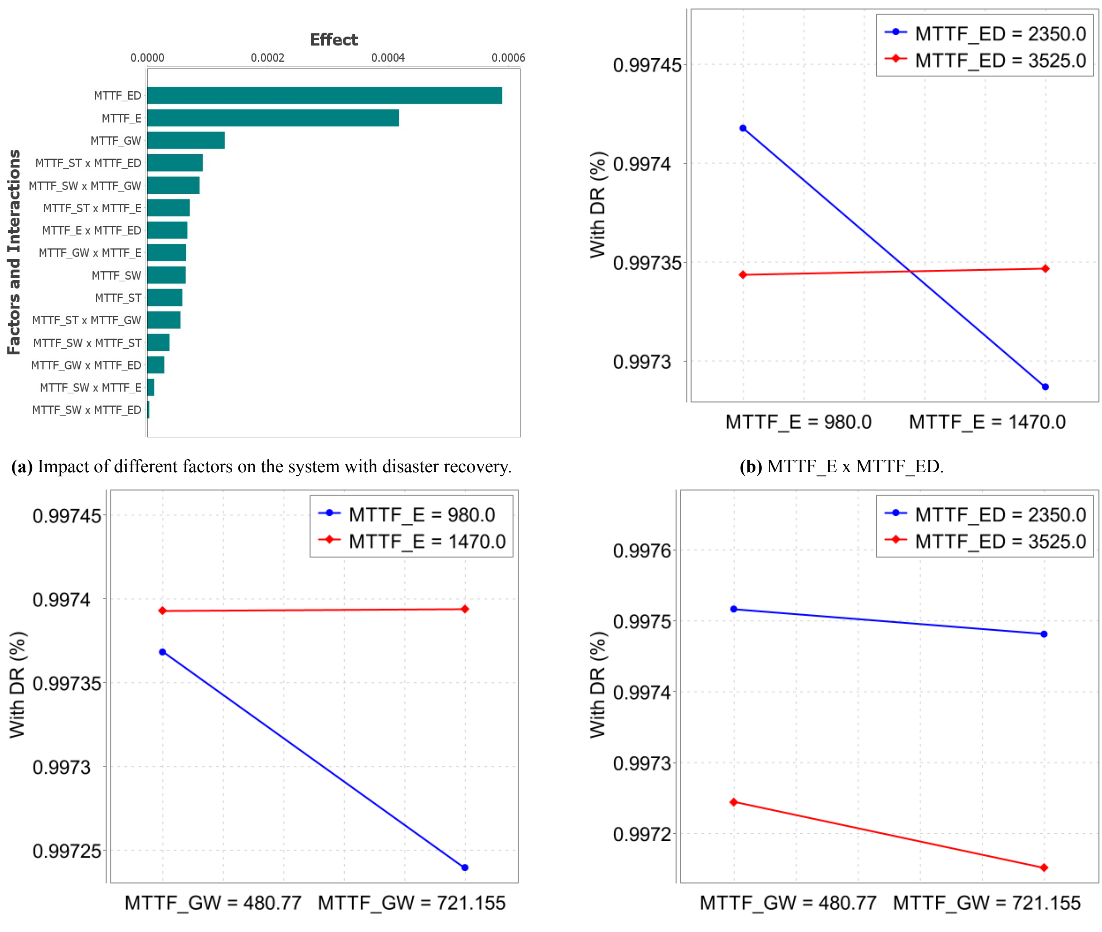

(a) Impact of different factors on the system with disaster recovery.

(b) MTTF_E x MTTF_ED.

(c) MTTF_GW x MTTF_E.

(d) MTTF_GW x MTTF_ED.

Figure 9. Case with disaster recovery DoE results.

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