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Analytical Evaluation of VANETs Routing Strategies

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Abstract

Vehicular ad hoc networks (VANETs) have emerged as a critical enabler of intelligent transportation systems, particularly when integrated with 5G infrastructure to achieve high-throughput, low-latency vehicle-to-everything (V2X) communication. Nevertheless, optimizing message routing in such environments remains a significant challenge, as the operational complexity and prohibitive cost of large-scale physical deployments severely limit empirical evaluation of alternative transmission strategies. This paper presents a stochastic Petri nets (SPNs) model for evaluating routing configurations in 5G-enabled vehicular ad hoc networks (5G-VANETs). The proposed model evaluates mean response time, drop probability, utilization, and throughput, enabling the identification of communication bottlenecks without requiring physical deployment. By abstracting the system's stochastic behavior through SPN formalism, the model supports both steady-state analysis and sensitivity evaluation under varying traffic workloads. Results demonstrate that Route 1, with direct RSU connection, achieves the lowest mean response time and highest throughput, while Route 3, which relays messages through a rear vehicle and an auxiliary RSU, yields the lowest drop probability. A sensitivity analysis based on Design of Experiments reveals that cloud capacity and cloud service time are the dominant factors affecting mean response time. The SPN model thus enables system architects to compare routing configurations, identify performance bottlenecks, and size infrastructure components without requiring physical deployment.

Keywords: VANET, 5G, Performance evaluation, Sensitivity Analysis, Stochastic Modeling, Stochastic Petri Nets, Routing Strategies

1 Introduction

Vehicular Ad Hoc Networks (VANETs) are wireless communication systems dynamically established among vehicles equipped with communication capabilities, enabling the exchange of information such as position, speed, and traffic conditions through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications Gupta and Patel [2016]; Anwer and Guy [2014]. Unlike traditional mobile ad hoc networks, VANETs operate under highly dynamic topologies, characterized by high node mobility and intermittent connectivity. These characteristics make VANETs a key enabling technology for Intelligent Transportation Systems (ITS), supporting applications aimed at improving road safety, traffic efficiency, and driving experience.

The evolution of fifth-generation (5G) mobile networks has significantly expanded the capabilities of VANETs, leading to the emergence of 5G-enabled VANETs (5G-VANETs). By incorporating Vehicle-to-Everything (V2X) communications, vehicles can interact not only with other vehicles and roadside infrastructure but also with pedestrians, cloud services, and intelligent transportation platforms. Combined with features such as ultra-low latency, high data rates, massive connectivity, network slicing, and edge computing, 5G-VANETs provide the communication foundation required by advanced applications, including cooperative collision avoidance, autonomous driving, distributed sensing, and dynamic route planning Balen *et al.* [2022].

The 5G-VANET system must demonstrate efficacy and make efficient use of available resources to ensure minimum packet loss, latency, and response time, making performance evaluation essential. However, such assessments are frequently complicated by the lack of infrastructure and the heterogeneity of 5G-VANET components, including RSUs, 5G base stations, and cloud-based virtualized computing resources. Furthermore, real-world deployments are both expensive and technically demanding, requiring specialized equipment and continuous monitoring capabilities. The dynamic nature of vehicular traffic also makes reproducible experimentation difficult. Misconfigured systems and varying conditions can lead to higher drop rates, increased packet delays, and inefficient resource consumption, all of which degrade the quality of service perceived by end users.

Several studies have investigated VANET performance using simulation and measurement-based approaches. Although these techniques provide valuable insights, they often require substantial computational resources, specialized infrastructure, or extensive experimental campaigns. In contrast, analytical modeling offers a cost-effective alternative for evaluating system behavior, exploring different configurations, and identifying performance bottlenecks before implementation. Nevertheless, the use of analytical models for evaluating routing alternatives in 5G-VANET environments remains relatively limited, particularly when combined with sensitivity analysis techniques capable of identifying the most influential system parameters.

To address this gap, this paper proposes a performance evaluation model based on Stochastic Petri Nets (SPNs), a formalism widely used for modeling and quantitatively analyzing concurrent and distributed systems. The proposed SPN model captures the stochastic behavior of a 5G-VANET architecture and enables the evaluation of key performance metrics, including Mean Response Time (MRT), Drop Probability (DP), Throughput (TP), and Cloud Utilization (UC). In addition, a Design of Experiments (DoE)-based sensitivity analysis is performed to investigate the impact of infrastructure and communication parameters on system performance.

The main contributions of this work are:

- The development of an SPN-based analytical model for evaluating routing strategies in 5G-VANET environments;
- A comparative performance analysis of three routing alternatives considering communication efficiency, reliability, and resource utilization;
- A sensitivity analysis based on Design of Experiments (DoE), identifying the parameters that most significantly affect system performance;
- Insights into routing trade-offs and infrastructure provisioning that support the design and optimization of future 5G-VANET deployments.

This paper is organized as follows: Section 2 presents the fundamental concepts for understanding the work. Section 3 reviews related work. Section 4 describes the base architecture used in the development of the model. Section 5 details the proposed model. Section 6 presents the sensitivity analysis and its results. Section 7 discusses the results obtained. Finally, Section 8 presents the conclusions and directions for future work.

2 Background

This section presents the fundamental concepts underlying the modeling and evaluation techniques used in this work. Figure 1 shows the standard components of a SPN, including places, transitions, tokens, directed arcs, and inhibitory arcs, which together enable the visual development of complex models and facilitate the analytical evaluation and analysis of system dynamics. By extending conventional Petri Nets, SPNs incorporate stochastic behavior into the system representation, assigning probabilistic characteristics to transitions and enabling the modeling of delays and random behavior inherent in real-world systems.

In its generic form, Petri Nets are very helpful for modeling systems where resource sharing, synchronization, and concurrency are crucial. These features are pertinent to vehicular communication systems, since many data flows can occur simultaneously and decisions rely on the interaction of autonomous components. An SPN can be depicted as a bipartite graph in which nodes alternate between places (represented as circles) and transitions (represented as rectangles or bars), connected by directed arcs. Input arcs flow from places to transitions, while output arcs flow from transitions to places, defining the preconditions and postconditions that must be satisfied for system events to occur.

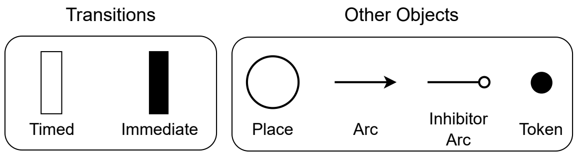


Figure 1. SPN components.

Based on their triggering characteristics, transitions in SPNs are divided into two types. Timed transitions are associated with a probabilistic triggering delay, typically modeled by exponential or other probability distributions, representing time-consuming processes such as transmission, processing, or propagation delays. Immediate transitions, in turn, are fired without delay as soon as they are enabled, being used to represent instantaneous decisions or control logic. A transition is enabled when its input places contain the required number of tokens. Once fired, it consumes tokens from the input places and produces tokens at the output places, updating the system state Nguyen *et al.* [2021]. Tokens are abstract entities, depicted as small black dots, that represent the availability of a resource, the presence of a message, or the progress of a system process.

In addition to ordinary arcs, SPNs support inhibitory arcs for modeling conditional logic. Represented by a small circle at their endpoint, these arcs prevent a transition from firing when a specified number of tokens is present at a given place, making them useful for modeling mutual exclusion, capacity constraints, and blocking behavior. By adopting SPNs, this work benefits from a formal and flexible framework capable of capturing the concurrent and stochastic behavior of vehicular communication networks. This model is used in the following sections to evaluate performance metrics relevant to 5G-VANETs and analyze the impact of different configurations and routing strategies on system behavior.

3 Related Works

This section presents related works identified in the literature that have a similar context or approach to this work. Specific criteria for the works were defined. The papers were selected based on five main criteria: evaluation method, metrics used, sensitivity analysis, analysis of routes with different distances between RSUs, and study focus. Table 1 shows the contributions of the works related to this study, followed by their selection criteria.

Three main evaluation techniques are identified in the analyzed studies: modeling, measurement, and simulation. Simulation is the most widely adopted approach, as observed in

Table 1. Comparative Table of Related Works

Work	Evaluation Method	Metrics	Sensitivity Analysis	Route Analysis with RSU Distances	Focus
[Hota *et al*., 2022]	Simulation	Throughput, Delay, PDR, Drop Probability, Transmission Rate	×	×	Routing protocols, propagation model
[Kushwaha and Jain, 2023]	Measurement	Drop Probability, Throughput, Overhead	×	×	Intelligent decision routing
[Mahdi *et al*., 2021]	Simulation	Throughput, PDR, Delay	×	×	Routing protocols
[Khan *et al*., 2024]	Simulation	Discovery Time, Reliability, PDR, End-to-End Delay, Throughput	×	×	Routing protocols
[Araújo *et al*., 2021]	Modeling	Availability, Reliability	✓	×	Vehicular cloud computing
[Gupta and Kapoor, 2022]	Simulation	Throughput, Delay, Drop Probability	×	×	Multicast strategy
[Pratama *et al*., 2020]	Simulation	Throughput, Received Packets, Goodput	×	×	Routing protocols
[Zhao *et al*., 2021]	Modeling	Throughput, PDR	×	✓	Route optimization
[Malik *et al*., 2020]	Simulation	Throughput, Latency	×	×	Routing protocols
[Waseem *et al*., 2022]	Simulation	Throughput, Delay, PDR	×	×	Routing protocols
[Plotnikov *et al*., 2023]	Measurement	Drop Probability, Utilization	×	×	Element interaction in VANETs
[Avvaru *et al*., 2024]	Simulation	Delay, Throughput, Routing Load	×	×	Routing protocols
[Kassir *et al*., 2020]	Modeling	Throughput, Connection Reliability, Connection Probability	×	×	Routing protocols
[Sakoguchi *et al*., 2018]	Simulation	Throughput, PDR, Mean Response Time	×	✓	Route optimization
[Smiri, 2020]	Simulation	Latency, PDR, Overhead, Energy, Throughput	×	×	Routing protocols
This Work	Modeling	MRT, Drop Probability, Throughput, Utilization	✓	✓	Comparative performance evaluation of routing alternatives

Hota *et al*. [2022], Mahdi *et al*. [2021], Khan *et al*. [2024], Gupta and Kapoor [2022], and Pratama *et al*. [2020], due to its flexibility in evaluating complex systems without requiring physical implementation. However, simulation results may not always capture all real-world variables. In contrast, modeling, as employed in this work and in studies such as Araújo *et al*. [2021], Zhao *et al*. [2021], and Kassir *et al*. [2020], provides a rigorous mathematical framework for analyzing system behavior under controlled conditions and exploring the effects of different parameters. Measurement-based approaches, although less common Kushwaha and Jain [2023]; Plotnikov *et al*. [2023], provide real data but are often limited by the complexity and cost of large-scale experiments.

Performance evaluation commonly relies on metrics such as utilization, packet delivery ratio, throughput, delay, and drop probability. Throughput is widely adopted because it directly reflects transmission efficiency, as demonstrated in Hota *et al*. [2022], Mahdi *et al*. [2021], and Khan *et al*. [2024]. Delay is particularly relevant for real-time communication systems Hota *et al*. [2022]; Gupta and Kapoor [2022], while drop probability is essential for assessing routing efficiency in highly dynamic vehicular environments.

Sensitivity analysis is an important tool for understanding how input parameter changes affect system performance. However, it is rarely employed in the reviewed works, with only Araújo *et al*. [2021] and the present study include this analysis, which represents a relevant gap in the existing literature. This work addresses that gap by providing a detailed sensitivity analysis showing how small variations in factors such as RSU distance or packet transmission rate can significantly affect system behavior.

This capability supports the design of more resilient communication systems adapted to different operating conditions. Another distinguishing aspect of this work is the analysis of routes with different distances between RSUs, a topic only marginally explored in studies such as Zhao *et al*. [2021] and Sakoguchi *et al*. [2018]. Since RSU spacing directly influences response time, coverage, and communication quality, evaluating different distance configurations provides valuable insights for optimizing vehicular network deployments, particularly in high-mobility scenarios.

This study focuses on the comparative performance evaluation of routing alternatives using a modeling approach that has received little attention in the reviewed literature. While the majority of works concentrate on routing protocols and propagation models with little attention to route comparison, this study investigates how different routing configurations perform in vehicular communication scenarios, in line with works such as Zhao *et al*. [2021] and Sakoguchi *et al*. [2018].

This work contributes to the understanding of communication challenges in dynamic vehicular environments and provides system designers with insights into the behavior and performance of alternative routing configurations.

4 Architecture

This section presents the architecture adopted for the work. Figure 2 presents the vehicle-to-vehicle (V2X) communication architecture. This architecture was based on the proposal by Luo *et al*. [2018]. Its objective is to improve traffic flow and safety by enabling communication between cars, road infrastructure, and cloud computing. Low-latency connections between cars and the cloud are enabled by the solution's 5G architecture. Vehicles can receive traffic information and safety alerts more easily thanks to Roadside Units (RSUs), which are placed along the roads. An On-Board Unit (OBU) and sensors are installed in every vehicle to gather information about its position, speed, and direction. After being processed and sent to the RSUs by the OBUs, the data is then sent to the cloud via 5 G. Due to the processing limitations of the OBUs Al-shareeda *et al*. [2021], the cloud takes over the most complex processing, expanding the analysis capacity of the vehicles.

The proposed architecture defines three fixed routing alternatives for message transmission between vehicles and the cloud, which are evaluated comparatively in terms of performance. In the first, RSU2 receives data straight from a central car (C2), transmits it to the 5G tower, and finally sends it to the cloud. In the second, data is sent by vehicle C2 to the vehicle ahead (C3), which then sends it back to RSU2 in the same manner. In the third, C2 transmits information to the vehicle behind (C1), which reroutes it to RSU1 and then to RSU2. The redundancy of data transfer is increased by these several connection channels with RSU2. Real-time data processing in the cloud produces alerts that are transmitted back to cars and RSUs. For instance, the cloud notifies the cars to brake when it detects an animal on the road, such as a dog, enabling them to adjust their behavior and prevent collisions. In this case, the cloud warns C1 and C3, lowering the possibility of chain crashes, while vehicle C2 slows when it senses the dog.

Among the many benefits this technology provides is improved road safety, with real-time notifications that help prevent accidents and improve traffic flow. It also encourages autonomous driving, which makes traffic safer and smoother, less crowded, and provides a better driving experience by enabling cars to make decisions based on their environment. This work is subject to the following restrictions:

- *Car-RSU Distance:* Assuming that the data transmission time is the same for every vehicle, we do not take into account the precise distance between the automobile and the RSU.
- *Focus on Communication with the Cloud:* This work focuses on communication with the cloud to determine the best route without addressing scenarios in which vehicles communicate directly with each other, excluding the need for interaction with the cloud.
- *Absence of Specific Protocols:* Specific communication protocols between vehicles and the infrastructure, which can impact network performance and efficiency Kumar *et al*. [2019], were not included in the analysis.

A number of simplifications were made to the model to make it more realistic and focus on the main elements affecting system performance. By excluding factors such as direct communication between vehicles, variations in vehicle spacing, and specific network protocols, we can reduce unnecessary complications that could skew the analysis. By focusing on the primary factors that directly affect traffic efficiency and safety, this method streamlines the identification of changes. Reducing the study's scope also allows us to provide more objective, transparent data, which is essential for validating the model and assessing its practicality. This method ensures that the most crucial features are covered in detail and speeds up the modeling process, which improves our understanding of the system.

To maintain analytical tractability, the proposed model abstracts several aspects of real VANET deployments, including vehicle mobility patterns, variations in vehicle-to-RSU distance, wireless propagation effects, interference, fading, handovers, and protocol-specific communication procedures. These effects are indirectly represented through the service and transmission times associated with the SPN transitions. Although such abstractions simplify the analysis and allow a clearer investigation of routing behavior, they may lead to performance estimates that differ from those observed in operational environments. In particular, real-world factors such as signal degradation, network congestion, and mobility-induced disruptions can increase latency and message loss rates. Therefore, the results presented in this work should be interpreted as comparative performance indicators among routing alternatives rather than exact predictions of real-world 5G-VANET deployments.

An additional limitation of this study is the absence of external validation against network simulators or real-world vehicular datasets. The primary objective of the proposed SPN model is to provide an analytical framework for comparative performance evaluation of routing alternatives in 5G-VANET environments. Therefore, the focus is on understanding system behavior and identifying performance trade-offs rather than reproducing a specific deployment scenario. Future work will compare the analytical results obtained with the proposed model against simulation platforms such as NS-3 and SUMO, as well as real vehicular communication datasets, in order to further assess the accuracy and applicability of the model under realistic operating conditions.

The effects of mobility, communication delays, and infrastructure interactions are represented in the model through the service and transmission times associated with the SPN transitions. These abstractions allow the proposed approach to focus on the comparative evaluation of routing alternatives while preserving the essential communication behavior of the analyzed 5G-VANET architecture.

5 SPN Model

In this section, the SPN model for the proposed architecture is described. SPN is an effective technique for modeling and analyzing distributed and parallel systems, enabling a formal representation and detailed analysis of system behavior Balbo [2000]. The model was built and numerically evaluated using the Mercury tool, which computes the steady-state solution of the underlying stochastic process Maciel *et al*. [2017]. Four separate layers make up the SPN model, as shown in Figure

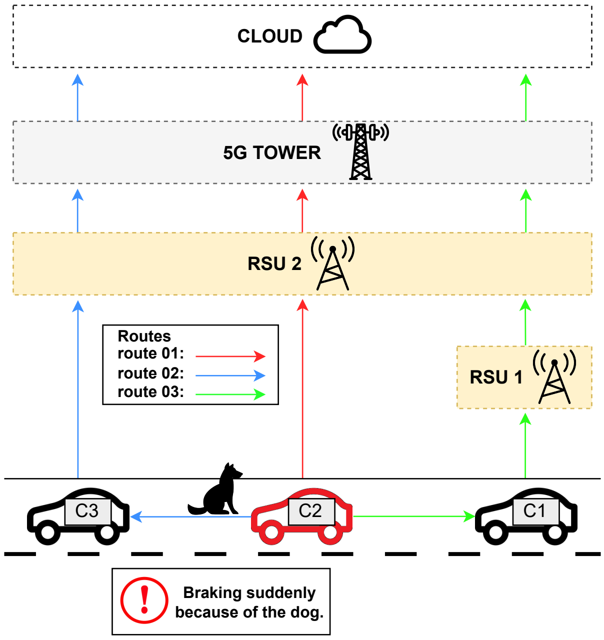


Figure 2. 5G-VANET architecture showing communication between vehicles (V2V) and infrastructure (V2I), with cloud integration and RSU coordination.

3: the admission layer, where data is generated; the routing layer, which shows potential routes for data transmission; the data transmission layer; and, lastly, the cloud layer, where data processing will take place. The component descriptions are shown in Table 2. The SPN model presented illustrates the architecture discussed, consisting of four main layers: admission, routes, transmission, and cloud. This model aims to represent the flow of messages in a distributed system, where vehicles and communication units (RSUs and towers) transmit data in different scenarios. Tokens represent the state of messages in the system and the progress of their transmission between components. All places that have the prefix "CAP" represent the capacity for processing or transmitting data.

Data admission is represented by Arrival Delay (AD). When there is a token in `Pad`, it means that the car has a message to be sent. When the `Tsad` transition is triggered, the token is consumed and moved to the `Padt` place, indicating that the message is ready to be sent via one of the routes. `Tsad` represents the service time of the car. When the AD transition is triggered, a new token is generated. Each token in the `Pmrt` place represents a message present in the system. When the cloud processes this message, the corresponding token is consumed. `Pmrt` simplifies the calculation of the system's MRT by representing all messages within the system.

Messages follow three distinct transmission routes, and the chosen path depends on guard conditions defined in the immediate transitions ([Eg-01], [Eg-02], [Eg-03]), which indicate the route to be used.

- Route 1: The message is sent directly to the central RSU. When a token is present at `Ptr1`, it indicates that the message is ready to be transmitted directly to the central RSU, bypassing intermediaries. The transition `Ts1` represents the time of sending the message.
- Route 2: In this route, a vehicle in front of you relays the message. The vehicle ahead has received the message and is prepared to transmit it, according to the token at `Pr2`. The message is then prepared for transmission to the central RSU once the token is used and passed to `Ptr2`. The time of transmission to the central RSU is indicated by `Ts2`, whereas the transition `Tsr2` indicates the service time of the vehicle relaying the message.
- Route 3: A trailing vehicle relays the message to an auxiliary RSU prior to it reaching the primary RSU. The token at `Pr3` indicates that the trailing vehicle has received the message and is ready to send it to the auxiliary RSU. The transition `Tsr3`, the transmission time to the auxiliary RSU `Ts3`, and the retransmission time from the auxiliary RSU to the central RSU `Ts4` all indicate the car's service time.

The transmission layer comprises the central RSU and the transmission tower. Both play essential roles in sending messages. The central RSU receives messages sent directly through one of the routes or an auxiliary RSU and then retransmits them to the tower. The processing and transmission time at the central RSU is represented by `Tsrsu`. When the transition is triggered, the token in place, `Prsu`, is consumed. The transmission tower, on receiving the message from the central RSU, forwards it to the cloud. The processing time at the tower is represented by `Tstow`. When a token is in `Ptow`, it indicates that the tower is transmitting the message to the cloud.

The last layer of the model is the cloud, where the data is processed. When a token is in `Pcl`, it indicates that the message has reached the cloud and is awaiting processing. The processing time is represented by `Tsc`. The cloud is composed of several VMs, and the number of available VMs is indicated by `Cap_C`.

Timed Transitions include several specific times that govern the behavior of the system, such as the time between message arrivals, the times for sending data along the routes (`Ts1`, `Ts2`, `Ts3`), and the service times in the different components of the architecture, such as the cars during relay (`Tsr2`, `Tsr3`), the central RSU (`Tsrsu`), the transmission

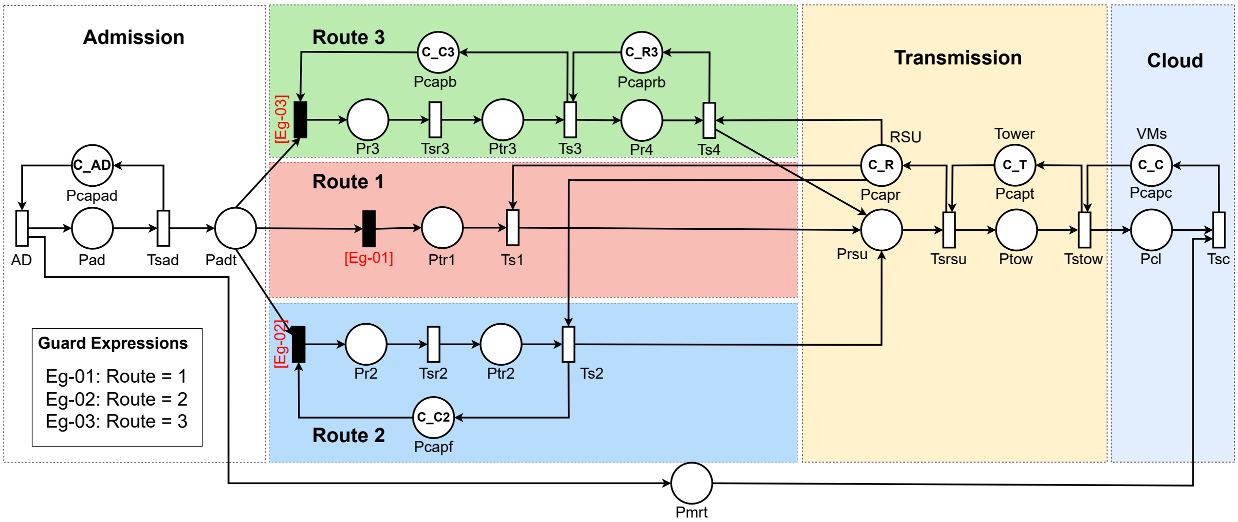


Figure 3. SPN model designed to analyze communication and mobility in VANET architectures.

Table 2. Description of the main model components.

Type	Component	Description
Timed Transitions	AD	Time between data arrival
	Ts1, Ts2, Ts3	Data sending time
	Tsad	Car service time
	Tsr2, Tsr3	Time service of the route cars
	Ts4	Time of data sending of the auxiliary RSU
	Tsrsu	Time of service of the central RSU
	Tstow	Time of service of the Tower
	Tsc	Time of service of the Cloud
Place Marking	CAP_C3, CAP_R3, CAP_C2, CAP_R, CAP_T, CAP_C	Processing or transmission capacity
	Pad	Place of origin of the message
	Padt	Place where the message is ready to be sent by one of the routes
	Ptr1	Place where the message is ready to be transmitted directly to the central RSU (Route 1)
	Pr2, Ptr2	Place of message transmission by the front car (Route 2)
	Pr3, Ptr3	Place of message transmission by the rear car to the auxiliary RSU (Route 3)
	Prsu	Place of message transmission by the central RSU
	Ptow	Place of message transmission by the Tower
	Pcl	Place of message processing and storage in the cloud
	Pmrt	Place representing the presence of messages in the system
Immediate Transitions	Eg-01, Eg-02, Eg-03	Guard conditions for route selection

tower (`Tstow`), and the cloud (`Tsc`). These times are crucial for calculating the system's performance at each transmission layer. Place Marking refers to the data processing or transmission capabilities of the different system components (`CAP_R3`, `CAP_C2`, `CAP_R`, `CAP_T`, `CAP_C`) and the specific places where messages are originated, transmitted, and processed. For example, the place `Pad` represents the point of origin of the message (car generating data), `Padt` indicates that the message is ready to be sent, while `Prsu` and `Ptow` indicate the transmission of messages by the central RSU and the tower, respectively. In addition, `Pcl` refers to the processing and storage of messages in the cloud, and `Pmrt` represents the number of messages present in the system at a given time.

Immediate Transitions involve the guard conditions that determine the message transmission route. These conditions are represented by the transitions Eg-01, Eg-02, and Eg-03, which define the route to be used according to the system state and the adopted transmission strategy. Timed transitions refer to the waiting times between events, such as data arrival, transmission, and processing. For example, data arrival time (AD) is fast, while cloud processing time (`Tsc`) is slower, reflecting the latency and performance characteristics of each component. Placeholders indicate the processing and storage capacity of various system components, including routes and the cloud. Components such as the cloud have greater capacity, whereas routes have less.

Although the current SPN model is implemented with only three predefined routes, it is fully parametrizable and can be extended to support n routing alternatives. This flexibility is inherent to the model's modular design, which allows additional routes to be incorporated by replicating the relevant subcomponents, such as service transitions, buffers, and routing paths, and updating the corresponding guard conditions that determine route selection. The three-route configuration presented in this paper serves as a proof of concept, demonstrating the feasibility of modeling routing diversity in 5G-enabled VANET systems. We retain tractability for analysis and validation and guarantee a better understanding of system behavior by restricting the number of pathways. Even so, the fundamental SPN structure remains flexible enough to be used in more complex scenarios in the future, such as multi-hop communication, adaptive routing, or large-scale analytical evaluation with dynamic vehicle participation.

5.1 Metrics

This section presents the key metrics obtained from the model solution. Specifically, we calculated mean response time (MRT), cloud processing utilization percentage (UC), data communication errors by drop probability (DP), and system throughput (TP). Next, we describe how we obtained each metric with the SPN model. Equation 1 shows how the Throughput of the model system is calculated. TP is a quantitative measure of the number of messages successfully processed by the system within a given period. The TP metric is crucial for assessing the system's processing capacity and efficiency in handling data and transferring information. In the model, Throughput is calculated as the expected number of tokens in the queue representing processing and storage, divided by the time it takes for those tokens to leave that place.

$$TP = \frac{\text{Esp}(P_{cl})}{T_{sc}} \tag{1}$$

Equation 2 shows how MRT is obtained. Little's Law, one of the most widely used theorems in queueing theory, relates the average number of tasks in a system to the average time spent in the system. According to Little's Law: "Average number of tasks in the system = arrival rate × mean response time" Little [1961]. The MRT indicates the average time required for the system to process and respond to a message. This metric enables us to assess the system's efficiency in mean response time, from the moment a message leaves a vehicle until it is processed in the cloud —thereby contributing to agile, effective decision-making. The MRT is calculated by dividing the token expectations in Place `Pmrt` by the system throughput. Replacing the arrival rate with TP is justified because TP reflects the system's true processing capacity, whereas the arrival rate may be higher due to congestion.

$$MRT = \frac{\text{Esp}(P_{mrt})}{TP} \tag{2}$$

The DP is derived using the equation 3. DP shows the likelihood that the system may drop messages or data due to overload or inability to process them. The DP metric is crucial for evaluating the system's processing capacity to handle large volumes of data, thereby preventing the loss of information relevant to urban mobility. In the proposed system, we evaluate the message drop probability at the transmission layer, as the RSU serves as an intermediary that receives the messages. The DP is calculated as the probability P that there are no tokens at a given place. This study examines the likelihood of token absence in the central RSU queue. This absence indicates that the RSU can no longer receive data, resulting in message drops and overloading the entire downstream system. The drop rate is then calculated by multiplying the drop probability by 100.

$$DP = P\left((P_{rsu} > 0) \land (P_{capr} = 0)\right) \times 100 \tag{3}$$

The UC may be found using the equation 4. The percentage of time that available resources are actually used is called utilization. The utilization metric evaluates load balancing across layers and identifies potential bottlenecks or idle resources in the system. In the model, it is possible to identify uses in specific parts of the system, allowing for equipment configurations in the scenarios studied. In this work, we focus on the use of the *cloud* layer, the system's main layer. The calculation is based on the expectation of having tokens in the cloud processing queue divided by the cloud processing capacity. The result is multiplied by 100 to obtain the percentage.

$$UC = \frac{\text{Esp}(P_{cl})}{CAP\_C} \times 100 \tag{4}$$

6 Sensitivity Analysis

In this section, the SPN model is employed to investigate factors that may affect the system's performance. Factorial experimental design is a methodology that seeks to identify the impact of variations in parameter values on the desired metrics Rocha *et al.* [2019]. The objective of the analysis is to determine how changes in specific system components may impact its performance. The Mean Response Time (MRT) is the performance evaluation metric. Reaction time is important in the context of a VANET system, as long reaction times can cause communication delays between vehicles, increasing the risk of accidents. A sensitivity analysis must adhere to a specific framework that includes defining the independent variables to be varied during the experiments, as well as selecting and identifying the system components to be examined. This framework examines how specific adjustments affect the system's performance and provides practical configurations to maximize its functionality. Then, the results are discussed, analyzing the relationships identified between the system components and their impact on the MRT.

6.1 Design of Experiments-DoE

For sensitivity analysis, this study uses Design of Experiments (DoE) methodologies, as described by Antony [2023], Santos *et al.* [2021], and Montgomery [2017]... DoE is the process of organizing, creating, and evaluating experiments in order to quickly and effectively arrive at reliable and impartial conclusions. DoE can also be understood as a series of tests in which the researcher manipulates the set of input variables or factors to observe and identify the reasons behind the changes in the output response. In this study, a DoE analysis is performed based on graphical categories recommended in the literature. The factor effect graph uses bars in decreasing order to represent the impact of the factors on the analyzed measure. The higher the bar, the greater the influence of the corresponding factor. In addition, the factor effect graph identifies and prioritizes the most important factors to maximize their impact. On the other hand, interaction graphs use lines to show how components interact. There is no interaction between the factors if the graph's lines are parallel. On the other hand, there is interaction between the factors if the lines are not parallel.

The experiment was performed for the architecture considered. The sensitivity analysis explored the architecture's layers; however, only the interacting factors will be presented. The interaction is verified based on the MRT metric. The choice of MRT is due to its direct impact on the end user's perception. The factors adopted for this study are: (I) STC - Cloud service time, (II) CapC - Number of VMs in the cloud, (III) CapRSU - RSU capacity, (IV) STRSU - RSU service time, (V) STT - Tower service time. The factors have two levels, called low configuration and high configuration. Table 3 presents all the factors and levels analyzed.

Table 3. Experimental factors and levels

Factor name	Low Setting	High Setting
CapC	2.0	6.0
CapRSU	1.0	3.0
STRSU	2.5E-4	7.5E-4
STT	0.003	0.009
STC	0.1	0.3

The factors and their corresponding levels employed in the numerical evaluation are described in Table 3. While each factor represents a unique system variable, the levels display the range of values that these variables can have during the experiment. A low level of 2.0 and a high level of 6.0 are exhibited by the CapC component, for instance. Therefore, during the numerical evaluation, the parameter may vary between these values, enabling us to evaluate its effect on system performance in different scenarios. Similarly, the minimum and maximum values for the other elements in the table, including CapRSU, STRSU, STT, and STC, were established by varying +50% and -50% from the base value used in the model.

It is important to note that the results presented in this study are obtained from the numerical evaluation of an analytical SPN model. Therefore, the reported metrics correspond to steady-state expected values rather than estimates derived from repeated simulation runs. As a consequence, confidence intervals and variability measures commonly used in discrete-event simulation studies are not directly applicable. To assess the robustness of the conclusions, a DoE sensitivity analysis was performed, allowing the identification of the parameters that most strongly influence system performance and the evaluation of their interactions.

6.2 Results Analysis

Figure 4 presents the factor effect graph, which reveals the magnitude and importance of the factors related to the MRT metric. This graph identifies which factors significantly affect system performance. This graph provides a clear visualization of the absolute effects of each factor, highlighting the most influential ones in the system, but does not indicate whether these factors increase or decrease the mean response time.

The factors CapC and STC are the most significant and have the greatest effect on the system among those examined. This demonstrates that service time and the quantity of virtual machines (VMs) in the cloud are both essential for data processing efficiency. The relationship between the number of virtual machines (VMs) and their service time in the cloud is important for system performance, as evidenced by the significant interaction between these two factors (CapC x STC). Apart from these, the CapRSU factor also has a significant impact, albeit less than the others. On a smaller scale, interactions like CapRSU x STC and CapC x CapRSU also have an effect. Factors such as STRSU and its interactions, together with STT, have a significantly smaller effect on overall performance, indicating that these factors do not significantly influence mean response time.

Figure 5 presents interaction graphs, powerful visual representations that help us understand how different variables relate to and influence one another in a data analysis context. They enable us to identify complex patterns and interdependencies among variables, revealing how changes in one variable can affect the final result, while accounting for the presence of other variables.

Figure 5a shows the link between the CapC and STC components, indicating a significant interaction between them. In this analysis, 0.1 and 0.3 were considered service times for the STC factor, which varied with the number of VMs in the cloud. When adopting 0.3 as the service time, the optimal number of VMs is 6, resulting in a significant reduction in the Mean Response Time (MRT) to approximately 600 ms. Figure 5b shows the interaction between the CapRSU and STC factors. In this analysis, 1 and 3 were considered as the number of processing cores for the CapRSU factor, varying with the service times of 0.1 and 0.3 for the STC factor. The factors present a significant interaction. The interaction shows that although increasing CapRSU from 1 to 3 VMs increases MRT, the impact is more pronounced for STC = 0.1. However, when adopting STC = 0.3, the increase in MRT is relatively minor, suggesting that additional machine capacity in the RSU can partially mitigate the effects of longer service times.

7 Results

In this section, the results of the performance analysis of the proposed model are presented, considering different scenarios. Metrics such as cloud utilization, throughput, message drop probability, and mean response time were evaluated. The results obtained in each scenario are graphically represented, allowing comparison of variations in system parameters.

The evaluation procedure adopted in this work consists of modeling the VANETs architecture using SPN. The proposed

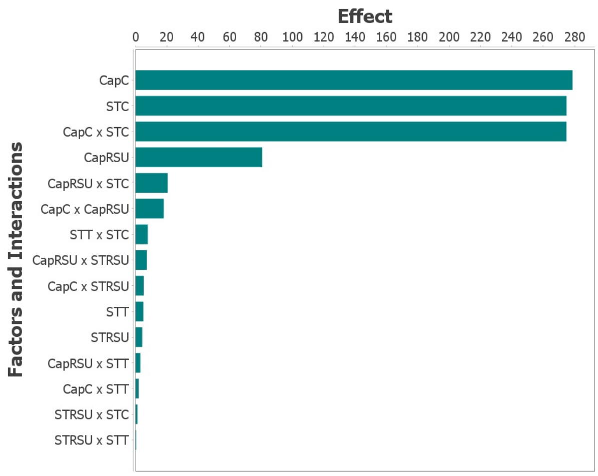
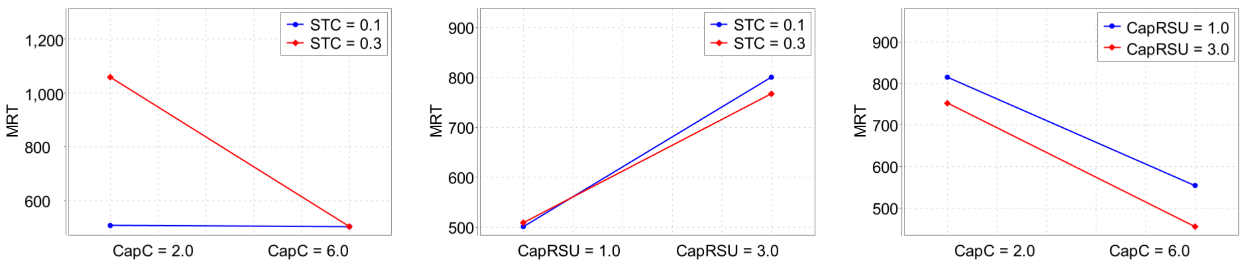


Figure 4. Impact of different factors on the MRT metric.



(a) Cloud Capacity * Cloud Service Time. **(b)** RSU Capacity * Cloud Service Time. **(c)** Cloud Capacity * RSU Capacity.

Figure 5. Interaction between factors in relation to the impact on the MRT metric.

SPN model was implemented on the Mercury platform and evaluated through the numerical solution of the underlying stochastic process. Mercury was used to calculate steady-state performance metrics. Therefore, the results obtained correspond to the numerical evaluation of an analytical model.

The values adopted for the model parameters were based on representative values reported in the literature on VANETs, 5G communication, and cloud-assisted vehicular systems. When necessary, these values were adjusted to reflect the assumptions of the proposed scenario while preserving realistic relationships among communication, processing, and transmission delays.

The selected parameters are consistent with previous studies, although differences are expected due to distinct architectures and modeling assumptions. The adopted cloud service time (`Tsc`=0.2s) is close to the cloud processing delays reported by Patil *et al*. [2021] (0.12–0.18 s), supporting the use of processing delays on the order of hundreds of milliseconds. Similarly, the relay service times (`Tsr2`=20 ms and `Tsr3`=40 ms) and the vehicle/tower transmission delays are consistent with the communication delays reported by Ilango *et al*. [2026], who observed authentication delays between 38 and 45 ms and message dissemination delays between 2 and 5 ms.

In contrast, Li *et al*. [2022] consider an ultra-low-latency SDN-based vehicular architecture, with RSU processing delays of 10 µs and an end-to-end latency target of 60 ms. Consequently, the RSU service time adopted in this work (`Tsrsu`=500 µs) is higher, reflecting the additional communication and processing overhead expected in conventional cloud-assisted VANET environments.

Table 4 presents the model's main parameters, divided into two categories: Timed Transitions and Place Markings. Each of these components has an associated value that defines the processing or transmission capacity within the modeled system.

Table 4. Model Parameters.

Type	Components	Value
	AD	0.005
	Tsad	0.002
	Ts1	0.07
	Ts2	0.04
	Ts3	0.035
Timed Transitions	Tsr2	0.02
	Tsr3	0.04
	Ts4	0.03
	Tsrsu	0.0005
	Tstow	0.006
	Tsc	0.2
	CAP_AD	1
	CAP_C3	1
	CAP_R3	2
Place Markings	CAP_C2	1
	CAP_R	2
	CAP_T	1
	CAP_C	4

7.1 Scenario I - Route Variation

This section presents the results of analyzing the impact of varying the different message-sending routes for urban mobility in the VANET architecture. Using an SPN model, metrics such as cloud utilization, throughput, drop probability, and MRT were examined. The graphs of the metrics are shown in Figure 6. It is important to note that the response-time values presented in this section follow the units adopted during the evaluation of the SPN model. For clarity, the corresponding units are explicitly indicated throughout the discussion whenever this metric is analyzed. The obtained latency values are discussed considering their impact on vehicular communication performance and the requirements of VANET applications.

The MRT results are shown in Figure 6a, illustrating how MRT behaves across the three routes in terms of arrival rate (AR). Route 1 consistently achieves the lowest MRT, indicating that direct transmission to the RSU is the most efficient path, followed by Routes 2 and 3, respectively. Although Route 3 yields the highest MRT, the results for Routes 1 and 2 are relatively close, particularly at lower arrival rates, suggesting that direct transmission or relay through the front vehicle are preferable in most conditions. Despite their higher MRT, Routes 2 and 3 provide important redundancy, ensuring message delivery even when a direct RSU connection is unavailable. This is particularly relevant in dense urban environments where buildings or other physical obstructions may block the direct signal. Therefore, while Route 1 is the most efficient, Routes 2 and 3 serve as viable alternatives under adverse conditions or higher traffic loads.

Regarding cloud utilization, shown in Figure 6b, Route 1 reaches nearly 90% utilization at an arrival rate of approximately 35.71 msg/s, while Route 2 stabilizes at around 80% and Route 3 at approximately 70%. All three routes reach near-maximum utilization at low arrival rates and stabilize thereafter, suggesting that the cloud infrastructure is adequately provisioned to handle the imposed traffic demands without overloading.

As shown in Figure 6c, Route 1 presents the highest drop probability, exceeding 20% at an arrival rate of approximately 35.71 msg/s, while Route 2 ranges around 10% and Route 3 remains the most stable, oscillating near 4%. The low drop probability of Route 3 can be attributed to its use of two RSUs and message relay through the rear vehicle, which distributes traffic more effectively and reduces the overhead per RSU, maintaining reliable communication even as the arrival rate increases.

Although Route 1 offers the lowest MRT and highest cloud utilization, its elevated drop probability limits its overall effectiveness in reliability-sensitive scenarios. Route 3, in contrast, proves to be the most reliable option in terms of communication integrity, making it preferable when message delivery guarantees are a priority. As shown in Figure 6d, Route 1 achieves the highest throughput, reaching approximately 18 msg/s at an arrival rate of 71.43 msg/s, followed by Route 2 at around 16 msg/s and Route 3 at approximately 12 msg/s.

This performance gap reflects the structural differences between routes: Route 1 benefits from a direct RSU link, while Routes 2 and 3 introduce additional relay hops, increasing delay and reducing throughput. Nevertheless, the optimal route selection depends on the balance between performance and reliability. In scenarios demanding greater robustness, Route 3 may be preferable despite its lower throughput, given its significantly lower drop rate.

These results reveal a clear trade-off between MRT and drop probability across the three routes. Route 1 minimizes latency and maximizes throughput, making it suitable for delay-sensitive applications such as collision avoidance. However, its higher drop probability, exceeding 20% at moderate arrival rates, limits its reliability in high-load scenarios. Route 3, despite its higher MRT and lower throughput, achieves the lowest drop probability (approximately 4%), making it more appropriate when message delivery reliability is critical, such as in cooperative driving or safety alert dissemination. Route 2 represents an intermediate trade-off, balancing latency and reliability without excelling in either dimension.

7.2 Scenario II - Cloud Layer Influence

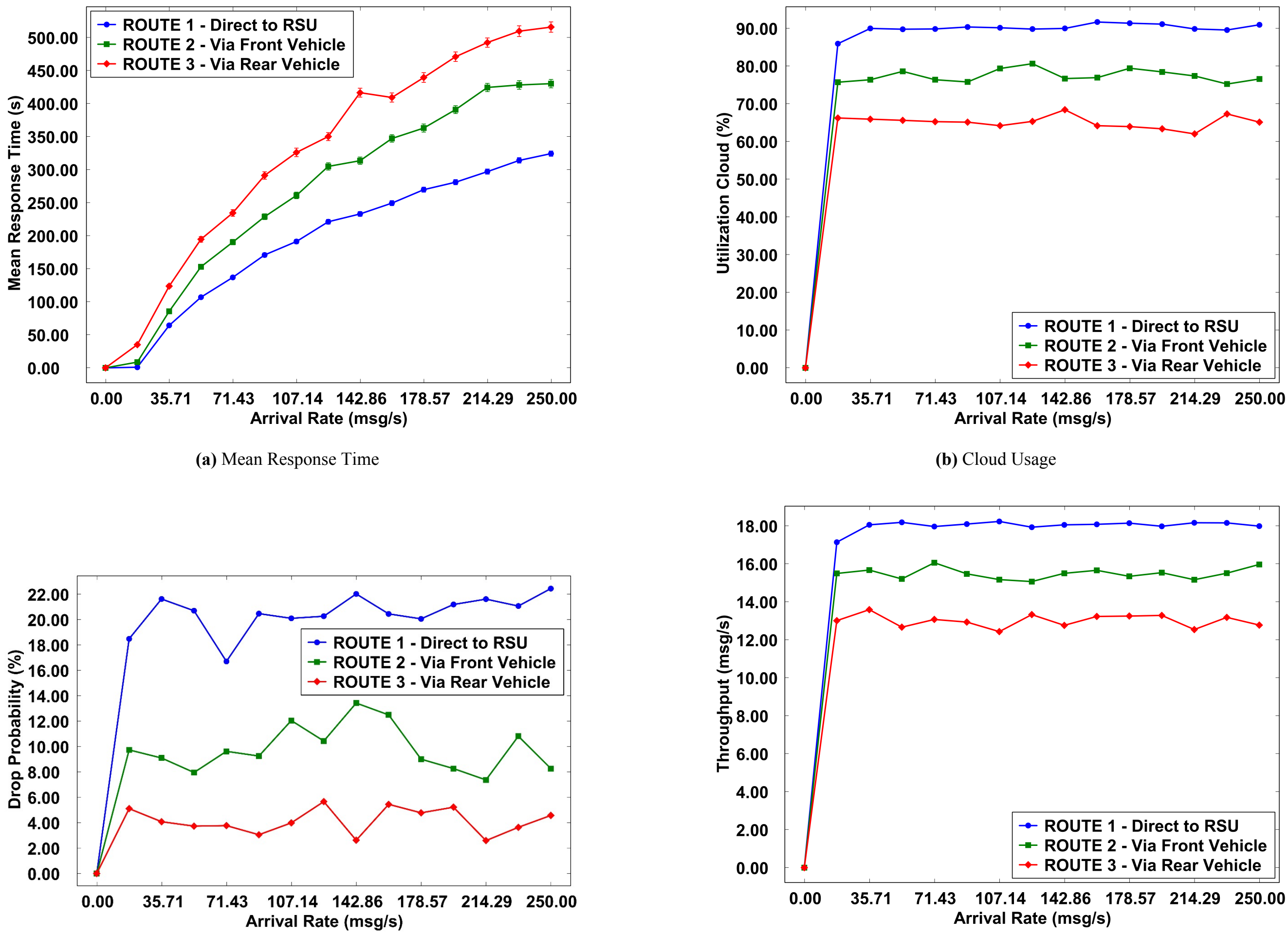
This section presents the impact of the variation in the number of VMs in the Cloud layer, considering Route 1, which offered the lowest MRT but the highest drop probability in Scenario 7.1. Thus, Figure 7 shows improvements in the *Cloud* utilization metrics across drop probability and MRT.

Figure 7a illustrates the MRT behavior across three cloud configurations with 4, 6, and 8 virtual machines as a function of arrival rate. The 8-VM configuration consistently achieves the lowest MRT across all arrival rates, followed by the 6-VM and 4-VM configurations, respectively, indicating that increasing the number of VMs leads to significant improvements in MRT. At lower arrival rates, the difference between the 6-VM and 8-VM configurations is less pronounced, suggesting that the benefit of additional VMs becomes more relevant as traffic load increases. Conversely, the 4-VM configuration exhibits a more pronounced MRT increase as the arrival rate grows, indicating higher sensitivity to workload and the need for adequate VM provisioning in high-traffic scenarios.

As shown in Figure 7b, cloud utilization is strongly influenced by the number of VMs. The 4-VM configuration approaches 90% utilization at an arrival rate of approximately 35.71 msg/s, while the 6-VM setup stabilizes at around 80% and the 8-VM configuration settles at roughly 70%. All configurations reach near-maximum utilization at low arrival rates and stabilize thereafter, suggesting that the cloud infrastructure is adequately provisioned to handle traffic demands without overloading. The lower utilization observed in the 8-VM configuration reflects more efficient load distribution across available resources.

As shown in Figure 7c, the 4-VM configuration presents the highest drop probability, exceeding 20% at an arrival rate of approximately 35.71 msg/s, while the 6-VM setup ranges around 10% and the 8-VM configuration remains the most stable, oscillating near 2%. The low drop probability of the 8-VM configuration can be attributed to its greater processing capacity and more effective load distribution, which reduce per-VM overhead and maintain reliable communication even as the arrival rate increases.

Although the 4-VM configuration makes intensive use of



(a) Mean Response Time **(b)** Cloud Usage

(c) Drop Probability **(d)** Throughput

Figure 6. Numerical analysis varying the arrival rate.

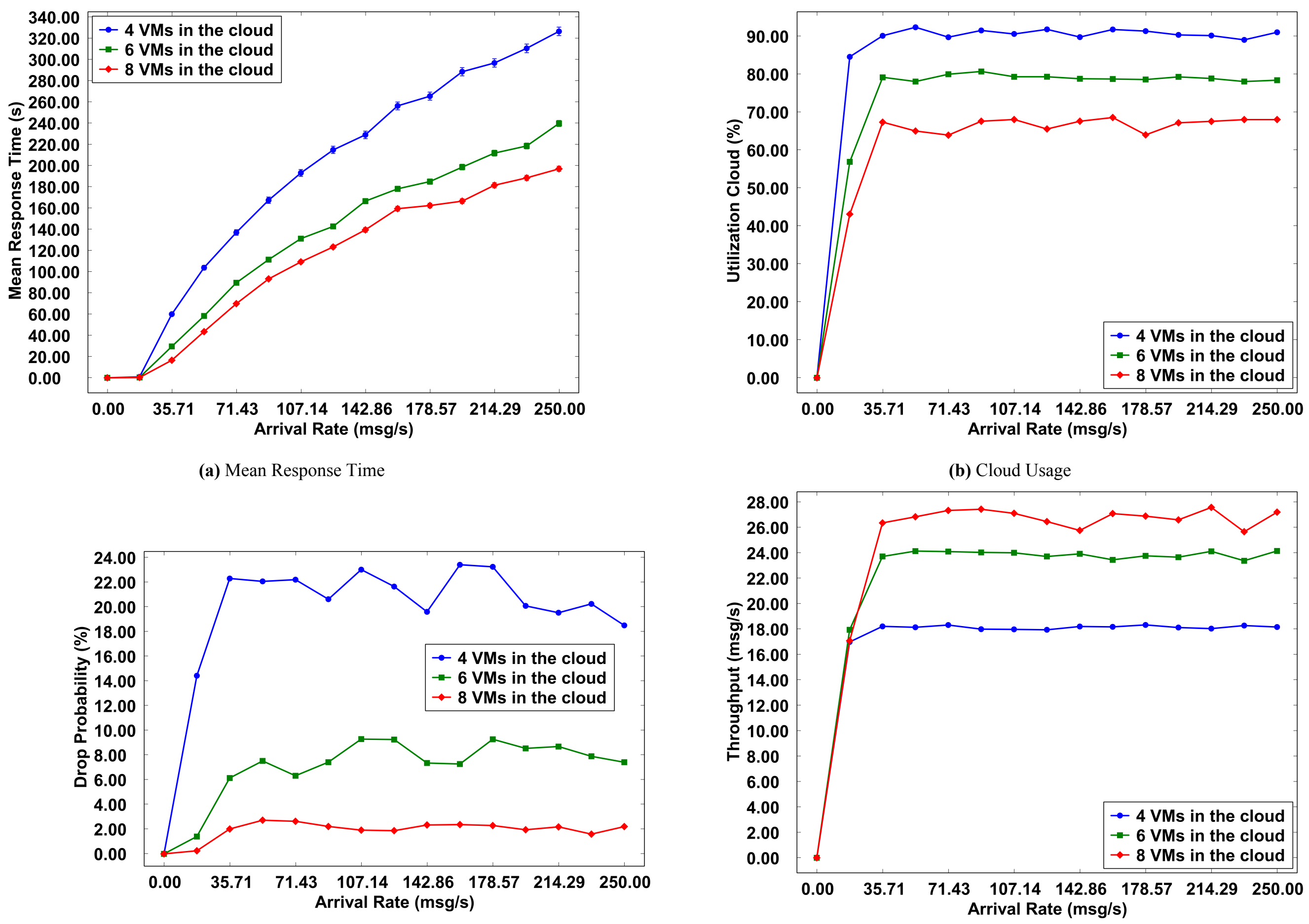
cloud resources, its elevated drop probability limits its overall effectiveness in reliability-sensitive scenarios. The 8-VM configuration, in contrast, proves to be the most reliable option, balancing workload efficiently and minimizing message loss even at high arrival rates. As shown in Figure 7d, the 8-VM configuration achieves the highest throughput, maintaining approximately 26 msg/s at an arrival rate of 71.43 msg/s, followed by the 6-VM configuration at around 24 msg/s and the 4-VM configuration at 18 msg/s.

This performance gap reflects the direct relationship between processing capacity and throughput: the 8-VM configuration can handle more concurrent messages, while the 4-VM configuration is more constrained, limiting its throughput under higher loads. The optimal configuration will depend on the balance between throughput requirements and operational costs. In scenarios where resource efficiency is prioritized, the 4-VM configuration may be acceptable, provided that minimum performance requirements are met.

These results highlight a trade-off between resource utilization and communication reliability. Configurations with fewer VMs achieve higher cloud utilization but at the cost of increased MRT and drop probability, which can compromise communication continuity in time-sensitive VANET applications. Conversely, the 8-VM configuration reduces drop probability to approximately 2% and increases throughput to 26 msg/s, at the expense of higher infrastructure investment. For latency-critical scenarios such as cooperative driving or emergency alerts, the 8-VM configuration is recommended. When operational cost is the primary constraint, the 6-VM configuration offers a balanced compromise between performance and resource consumption.

8 Conclusion

Stochastic Petri Nets are valuable tools for modeling and analyzing dynamic systems such as VANETs, providing insights into key performance metrics, including mean response time, throughput, resource utilization, and drop probability. The SPN model proposed in this work enables the evaluation of system behavior without requiring costly physical deployments, supporting the identification of bottlenecks, parameter tuning, sensitivity analysis, and comparing routing alternatives. The results demonstrated that different routing strategies present distinct trade-offs between response time, throughput, and communication reliability, while the DoE analysis identified the cloud-related parameters as the most influential factors affecting system performance. Overall, the combination of SPN modeling and DoE provides an effective framework for supporting the design and optimization of 5G-VANET systems. As future work, we intend to extend the proposed model by incorporating more realistic mobility and



(a) Mean Response Time

(b) Cloud Usage

(c) Drop Probability

(d) Throughput

Figure 7. Numerical analysis varying the number of VMs in the Cloud.

communication aspects, including wireless propagation effects, mobility variability, and protocol-specific behavior. In addition, external validation will be conducted through comparisons with established vehicular network simulators, such as NS-3 and SUMO, as well as available real-world datasets. These extensions will allow a more comprehensive assessment of the model's accuracy, scalability, and applicability to large-scale 5G-VANET deployments.

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