UNIVERSIDADE FEDERAL DO PARÁ
INSTITUTO DE TECNOLOGIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA

A Modular Framework for AI/ML Applied to B5G V2X Networks Co-Simulations

Felipe Henrique Bastos e Bastos

DM: 04/03

UFPA / ITEC / PPGEE
Campus Universitário do Guamá
Belém-Pará-Brasil
2023

UNIVERSIDADE FEDERAL DO PARÁ
INSTITUTO DE TECNOLOGIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA

Felipe Henrique Bastos e Bastos

A Modular Framework for AI/ML Applied to B5G V2X Networks Co-Simulations

DM: 04/03

UFPA / ITEC / PPGEE

Campus Universitário do Guamá

Belém-Pará-Brasil

2023

UNIVERSIDADE FEDERAL DO PARÁ
INSTITUTO DE TECNOLOGIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA

Felipe Henrique Bastos e Bastos

A Modular Framework for AI/ML Applied to B5G V2X Networks Co-Simulations

A dissertation submitted to the examination committee in the graduate department of Electrical Engineering at the Federal University of Pará in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering with emphasis in Applied Computing.

UFPA / ITEC / PPGEE
Campus Universitário do Guamá
Belém-Pará-Brasil
2023

Dados Internacionais de Catalogação na Publicação (CIP) de acordo com ISBD
Sistema de Bibliotecas da Universidade Federal do Pará
Gerada automaticamente pelo módulo Ficat, mediante os dados fornecidos pelo(a) autor(a)

B327m Bastos, Felipe Henrique Bastos E.
A Modular Framework for AI/ML Applied to B5G V2X Networks Co-Simulations / Felipe Henrique Bastos E Bastos. — 2023.
59 f. : il. color.

Orientador(a): Prof. Dr. Aldebaro Barreto da Rocha Klautau Júnior
Dissertação (Mestrado) - Universidade Federal do Pará, Instituto de Tecnologia, Programa de Pós-Graduação em Engenharia Elétrica, Belém, 2023.

1. 5G. 2. V2X. 3. UAV. 4. AI/ML. 5. co-simulações. I. Título.

CDD 006.3

UNIVERSIDADE FEDERAL DO PARÁ
INSTITUTO DE TECNOLOGIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA

"A MODULAR FRAMEWORK FOR AI/ML IN DIGITAL WORLDS APPLIED TO B5G V2X NETWORKS"

AUTOR: **FELIPE HENRIQUE BASTOS E BASTOS**

DISSERTAÇÃO DE MESTRADO SUBMETIDA À BANCA EXAMINADORA APROVADA PELO COLEGIADO DO PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA, SENDO JULGADA ADEQUADA PARA A OBTENÇÃO DO GRAU DE MESTRE EM ENGENHARIA ELÉTRICA NA ÁREA DE COMPUTAÇÃO APLICADA.

APROVADA EM: 10/03/2023

BANCA EXAMINADORA:

Prof. Dr. Aldebaro Barreto da Rocha Klautau Júnior
(Orientador – PPGEE/UFPA)

Prof. Dr. Eduardo Coelho Cerqueira
(Avaliador Interno – PPGEE/UFPA)

Prof. Dr. Antônio Jorge Gomes Abelém
(Avaliador Externo ao Programa – PPGCC/UFPA)

Prof. Dr. Ilan Sousa Correa
(Avaliador Externo ao Programa – FCT/UFPA)

VISTO:

Prof. Dr. Carlos Tavares da Costa Júnior

(Coordenador do PPGEE/ITEC/UFPA)

Acknowledgments

I would like to express my deepest gratitude to Professor Aldebaro Klautau for his invaluable contributions throughout my academic journey, and also for the friendship.

I'm extremely grateful to all members of my defense committee, Professor Eduardo Cerqueira, Professor Antônio Abelém, and Professor Ilan Correa. This last one also made great contributions to this research.

This work would not have been possible without the generous support from The Brazilian National Council for Scientific and Technological Development (CNPq), and Ericsson Research, who financed this research.

I am also thankful to all my LASSE mates, for all their support and friendship. I would like to address special thanks to João Broges, Ailton Oliveira, and Daniel Takashi, the ones who worked directly with me since the beginning of CAVIAR project. Thanks should also go to PPGEE and UFPA staff, that maintain the entire operation of this program.

Lastly, I would be remiss in not mentioning the ones that supported this work being sources of force and inspiration. First I thank God, for the forces to overcome all difficulties. I thank my family, especially my mother Odinéa, my brothers and sisters for all their love that always motivated and supported me, especially in these last difficult years. All my gratitude to Shirley, who was always with me throughout this journey.

Felipe Bastos

March 2023

Somewhere, something incredible is waiting to be known

Carl Sagan

List of Acronyms

3GPP 3rd Generation Partnership Project

5G fifth-generation of mobile telecommunications technology

ABS agent-based simulation

AI artificial intelligence

AIIL AI-in-the-loop

API application programming interface

B5G beyond 5G

BCI brain–computer interface

BS base station

CAVIAR Simulation of Communication Networks, Artificial Intelligence and Computer Vision with 3D Computer-generated Imagery

CSV comma-separated value

CTS continuous time simulation

DES discret event simulation

gNB next generation nodeB

HIL hardware-in-the-loop

HITL human-in-the-loop

ITU International Telecommunication Union

KPI key performance indicator

LIDAR light detection and ranging

MIMO multiple-input multiple-output

ML machine learning

NR new radio

ns-3 Network Simulator 3

OS operating syste

PIR packet inter-reception delay

PRR packet reception ratio

RL reinforcement learning

SAR search and rescue

SIL software-in-the-loop

SU simulation unit

UAV unmanned aerial vehicle

UE user equipment

UE4 Unreal Engine 4

V2X vehicle-to-everything

VIIL virtual-images-in-the-loop

WcT wall-clock time

YOLO You Only Look Once

List of Figures

List of Tables

Contents

Abstract

The use of AI/Ml is a key feature for the new generations of mobile communications as the actual generations are becoming more complex in order to provide a faster connection for a large number of users, but in general, it requires large datasets in order to produce high-quality AI/ML models. Due to the costs of collecting real measurements, especially in vehicular and aerial scenarios, this dissertation proposes a modular methodology that enables the combination of different simulators in order to produce realistic datasets for V2X and aerial cellular communications. The methodology also brings the possibility to train AI/ML models in-loop with the simulations. Furthermore, this dissertation details benchmarks for CPU and simulation time in different simulation scenarios and also the results of a use case showing the data that can be extracted from the combinations of the used simulators, where it is possible to observe that the use of parallel computing can reduce the simulation time by approximately five times.

Keywords — 5G, V2X, UAV, AI/ML, co-simulation

Resumo

O uso de inteligência artificial é um recurso chave para as novas gerações de comunicações móveis, já que com a evolução das gerações os sistemas vem ficando cada vez mais complexos para conectar cada vez mais usuários com taxas mais altas de transmissão, porém isto normalmente requer grandes bancos de dados para o treinamento de modelos inteligência artificial de alta qualidade. Devido aos custos para coletar medições reais, especialmente em cenários veiculares e aéreos, esta dissertação propõe uma metodologia modular onde é possível combinar diferentes simuladores para produzir banco de dados realistas para V2X e comunicações aéreas celulares. A metodologia também traz a possibilidade de treinar modelos de inteligência artificial integrados com as simulações. Além disso, este trabalho detalha análises para o uso de CPU e para o tempo de simulação em diferentes cenários, os resultados de um caso de uso mostrando os dados que podem ser extraídos das combinações dos simuladores utilizados também é discutido, mostrando que o com o uso de técnicas de computação paralela o tempo necessário para executar as simulação pode ser reduzido em aproximadamente cinco vezes.

Palavras-chave — 5G, V2X, UAV, AI/ML, co-simulações

Chapter 1

Introduction

This chapter introduces the developed research for this dissertation. First, it describes the motivations and the relevance of this work (Section 1.1), followed by a brief review of the state-of-the-art (Section 1.2). In a second moment the aims (Section 1.3) and the research contributions (Section 1.4) are presented. An outline of the dissertation is also provided in Section 1.5.

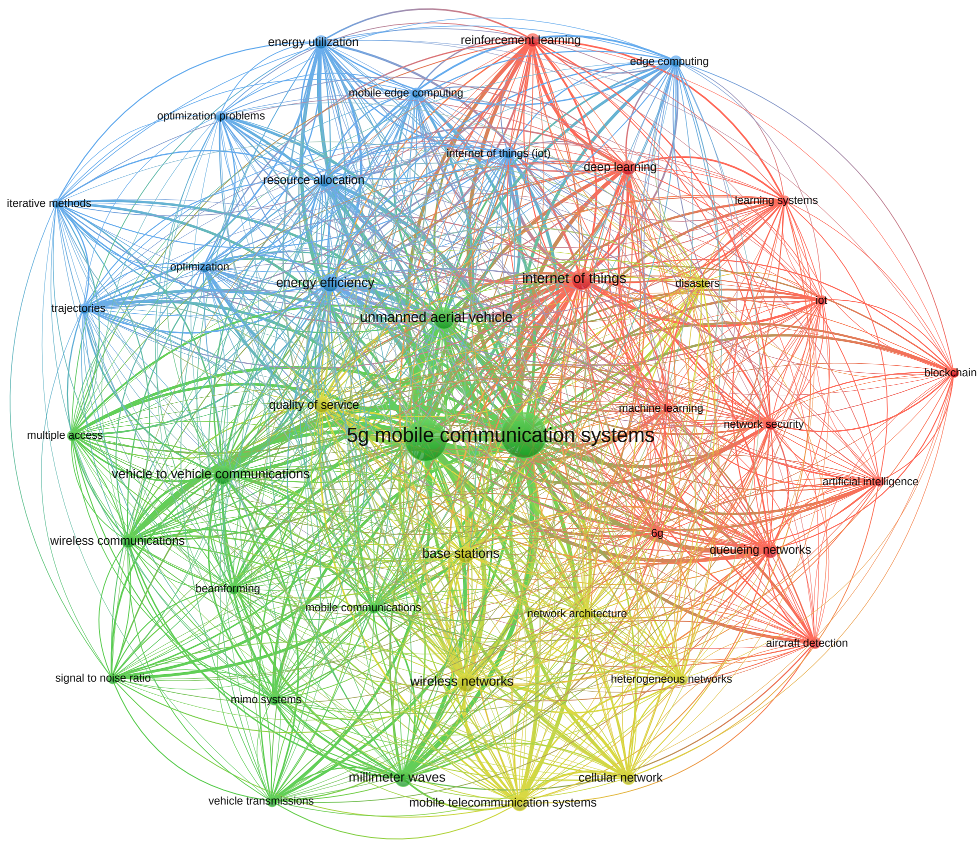
1.1 Motivation and Relevance

Wireless communications systems have become a crucial aspect of contemporary societies, and the most diverse types of essential services depend at some level on mobile communications networks. The fifth-generation of mobile telecommunications technology (5G) networks are ascending as the foundation for innovative solutions in various sectors, such as in the industry, agriculture, security, and so forth. These innovative solutions are emerging, due to some features brought by 5G networks that promise to provide reliable communications with low latency at ultra-high speeds (DOGRA et al., 2021).

Two emerging applications that will largely benefit from the next generations of mobile telecommunications technologies are autonomous and semi-autonomous driving and unmanned aerial vehicles (UAVs). Due to the relevance of wireless communications for vehicles, the 3rd Generation Partnership Project (3GPP) in its Release 16 has established the standards for vehicle-to-everything (V2X) communications based on the 5G new radio (NR) (3GPP, 2019). The 5G NR V2X introduced the concept of sidelinks, which refers to direct communications between the user equipments (UEs) without data going through a base station (BS) (GARCIA et al., 2021).

Figure 1.1 shows the relations among the keywords of papers that involve 5G networks and UAVs. The figure was produced from data collected at the Scopus platform, the metadata from all DOI-indexed research papers that mentioned 5G and UAV in the last 10 years was used to show how the keywords of these documents are related, only the 40 more recurrent keywords were used to produce the figure. Each line represents the connection between the keywords among the analyzed papers.

Figure 1.1: Relation between the keywords of papers involving 5G and UAVs



Source: Author (2023)

Regarding Figure 1.1 it can be noticed that there is a large number of publications that focuses on the physical layer of the wireless networks. The most recurring themes are beamforming and multiple-input multiple-output (MIMO) systems. Another recurrent research topic is the use of artificial intelligence (AI)/machine learning (ML) models alongside 5Gbeyond 5G (B5G) network functions in order to optimize different aspects of these networks for vehicle communications.

The use AI/ML is interesting for complex problems, especially when the solution requires the tunning of various parameters or problems that do not have a solution yet. In the new generations of mobile communications systems AI/ML techniques can be used in all layers and functions to improve the overall reliability. As wireless networks operate in stochastic environments, the use of reinforcement learning (RL) is one of the most interesting approaches, and has been widely used to solve Markov decision processes (MOROCHO-CAYAMCELA et al., 2019).

The training of AI/ML models, in particular when using deep learning and RL requires large datasets, which can become a problem for the applications in mobile networks, in special when it comes to the physical layer. A solution can be the use of synthetically generated data to train the AI/ML models for the communications systems (KLAUTAU et al., 2018). In this context, this dissertation will present the so-called Simulation of Communication Networks, Artificial Intelligence and Computer Vision with 3D Computer-generated Imagery (CAVIAR), a hybrid co-simulation methodology focused on the use of AI/ML in 5G/B5G networks.

1.2 Related Works

Table 1.1: Summary of related works

References	Communications	AI	3D	Supported UEs	Modularity
AirSimN	ns-3	PyTorch	-	UAVs,cars	-
Veneris	OMNeT++	-	Unity3D	Cars	-
Raymobtime	Wireless InSitee	TensorFlow	Blender	Cars	-
FlynetSim	ns-3	-	-	UAVs	-
CORNET	ns-3	-	-	UAVs	-
This work	ns-3+5G-LENA	PyTorch	UE4	UAVs, cars	✓

Source: Author (2023)

Table 1.1, summarizes the most relevant features of related works, that propose simulation environments for the use of AI/ML in communications. The AirSim^{N} (TANG et al., 2021), Veneris (EGEA-LOPEZ et al., 2019), and Raymobtime (KLAUTAU et al., 2018) are dependent on specific simulation softwares, which does not guarantee modularity in the system, limiting the use cases. Other projects such as FlynetSim (BAIDYA et al., 2018), and CORNET (ACHARYA et al., 2020) do not provide a realistic simulation of the simulation scenarios, such as providing virtual images of the 3D environment, which also limits the use cases.

1.3 Aims and objectives

All innovations that can be achieved based on the new generations of mobile communications systems require the development of integrated solutions that are capable to adapt the networks to the needs of the users in different aspects. This requires environments where it will be possible to simulate with realism different aspects of the real world. This work seeks the development of a hybrid co-simulation environment where each real-world aspect can directly or indirectly affect the performance and reliability of wireless communications systems. The research will focus on an architecture that would allow high flexibility, in order to ensure the maximum level of realism for each simulation scenario.

The most relevant objectives of this research can be summarized as:

- Develop a hybrid co-simulation system involving 5G/B5G networks, AI/ML models, and virtual worlds.
- Generate realistic simulations using standard computers.
- Enable the training and testing of AI/ML models inside the co-simulation sytem.
- Run fully automated co-simulations, where each part of the system can impact the future steps of the overall system.

1.4 Research Contributions

The simulation methodology generated during the development of this research can be used in different investigations, especially the ones involving AI/ML applied in mobile networks. Examples of how new wireless network research can benefit from hybrid co-simulation environments can be found in the results of the 2021 International Telecommunication Union (ITU) AI/ML in 5G Challenge[1], where an initial version of this work was used as the basis.

The most relevant contributions of this dissertation are:

- The development of a co-simulation environment for training and testing AI/ML models for communications networks.
- The integration of AI/ML models as co-simulation units of complex, where these models can directly impact the next steps of a co-simulation.
- The integration of different units in order to provide the most diverse scenarios considering mobility, 3D images, and communications networks.
- The use of parallel computing to reduce the simulation time.
- The use 3D virtual imagery for applications in communications networks.

1.4.1 Publications

During the development of this work, some research papers were published providing details of each development phase of the project. Initially, in 2021 an extended abstract was published showing how UAVs simulators can be used to provide more realism to mobile communications simulations. Latter in 2021 a conference and a journal paper were published describing an initial version of CAVIAR that was used in the 2021 ITU AI/ML in 5G Challenge. After the challenge, another journal paper was published in 2022 with all participants showing the results obtained using the CAVIAR co-simulations. Some parts of this work were also published in a book chapter published in 2023.

Book Chapters:

1. Aldebaro Klautau, Ilan Correa, **Felipe Bastos**, Ingrid Nascimento, João Borges, Ailton Oliveira, Pedro Batista, Silvia Lins. *Integrated simulation of deep learning, computer vision and physical layer of UAV and ground vehicle networks*. Deep Learning and Its Applications for Vehicle Networks, 2023.

[1] ITU-ML5G-PS-006: <https://challenge.aiforgood.itu.int/match/matchitem/39>.

Journal Papers:

1. Ilan Correa, Ailton Oliveira, Bojian Du, Cleverson Nahum, Daisuke Kobuchi, **Felipe Bastos**, Hirofumi Ohzeki, João Borges, Mohit Mehta, Pedro Batista, Ryoma Kondo, Sundesh Gupta, Vimal Bhatia, and Aldebaro Klautau. *Simulation of Machine Learning-Based 6G Systems in Virtual Worlds*. ITU Journal on Future and Evolving Technologies, 2022.

2. Ailton Oliveira, **Felipe Bastos**, Isabela Trindade, Walter Frazão, Arthur Nascimento, Diego Gomes, Francisco Müller and Aldebaro Klautau. *Simultaneous beam selection and users scheduling evaluation in a virtual world with reinforcement learning*. ITU Journal on Future and Evolving Technologies, 2021.

Conference Papers:

1. João Borges, Ailton Oliveira, **Felipe Bastos**, Daniel Suzuki, Emerson Oliveira, Lucas Bezerra, Cleverson Nahum, Pedro Batista, and Aldebaro Klautau. *Reinforcement Learning for Scheduling and Mimo beam Selection using Caviar Simulations*. ITU Kaleidoscope: Connecting Physical and Virtual Worlds, 2021.

Extended Abstracts:

1. Carlos Vinagre, Ailton Oliveira, **Felipe Bastos**, Emerson Oliveira, and Aldebaro Klautau. *Autonomous UAV Simulator for Research and Development Applied to 5G Networks*. Computer on the Beach, 2021.

1.5 Dissertation outline

This work consists of 5 chapters, and the following summarizes the organization:

- **Chapter 1:** Contains the introduction of this work, including its aims and Contributions.

- **Chapter 2:** Introduces important concepts related to co-simulations architecture and describes with detail the architecture of the proposed methodology.

- **Chapter 3:** Describes the implementation details of a simulation embodiment for disaster situations using CAVIAR methodology.
- **Chapter 4:** Presents different experiments that evaluate the performance and the usability of the proposed methodology. It also includes discussions about the obtained results.
- **Chapter 5:** Completes this dissertation by providing general conclusions and suggestions for future works.

Chapter 2

CAVIAR Architecture

This chapter describes the architecture of the modular simulation methodology entitled CAVIAR. In Section 2.1, important concepts related to hybrid co-simulations will be explained. In Section 2.2 the overall CAVIAR methodology will be explained, including some new concepts.

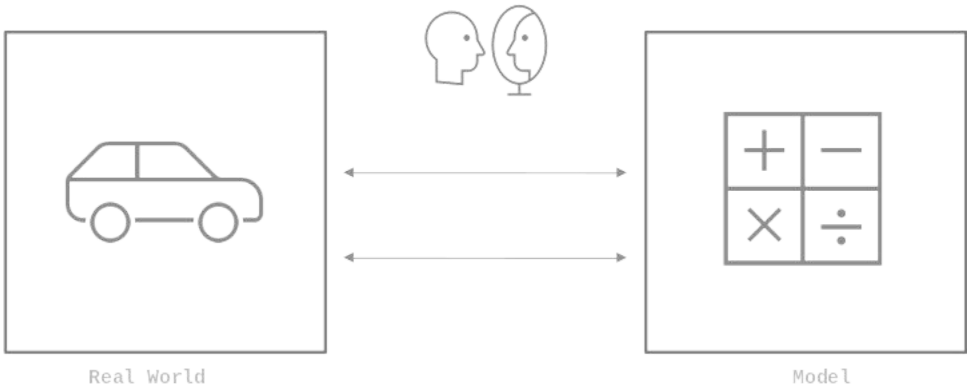
2.1 Co-Simulation Enviroments

In this section, important concepts related to simulations/co-simulations are defined. The first important thing we need to define is dynamical systems (Figure 2.1), which is a mathematical model of physical or computer systems, it is important to notice that these models are normally of real systems, but it is also possible to define models for systems that do not exist yet. During its existence, a dynamical system can change between diverse states and also produce different outputs, the sequence of states followed by the dynamical system's states and outputs are called, behavior traces (GOMES et al., 2018).

It is also important to define the time variables, that are used in the simulation environments. The simulated time $t \epsilon T$, defined over a time base T is different from the time that passes in the real-world, that is called wall-clock time (WcT) and defined as $\tau \epsilon WcT$. To compute the behavior trace for a dynamical system during a simulation time interval $[0, t]$ it needs τ units of WcT, than the simulated time t and the WcT τ are directly related variables. In real-time simulations, t tends to be equal τ (GOMES et al., 2018; FUJIMOTO, 2001).

The algorithms that are used to compute the approximated behavior traces of dy-

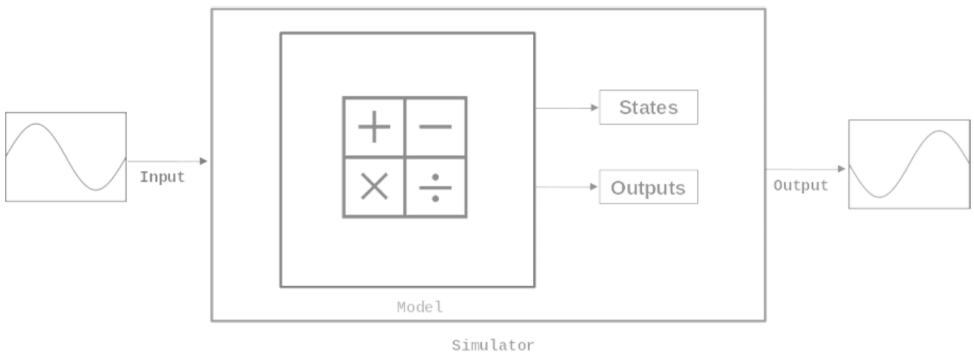
Figure 2.1: Dynamical System Diagram



Source: Author (2023)

namical systems are defined as simulators (Figure 2.2). A simulator always needs a dynamical system and input sequence of states to compute the behavior traces. All simulators have an associated error and the accuracy of a simulator can be defined by thresholds for the errors, which varies depending on the dynamical system (GOMES et al., 2018; CELLIER; KOFMAN, 2006).

Figure 2.2: Simulator Diagram



Source: Author (2023)

Another important term that needs to be defined, is the concept of simulation unit (SU). A SU can be defined as a black box that produces a behavior trace when inputs are provided. It can be a dynamic system or an entity in the real-world (GOMES et al., 2018), the different types of SU will be more detailed later. And finally, the behavior trace produced by a SU can be defined as a simulation.

According to Brailsford et al. (2019) a SU can be classified considering different simulation approaches, where the three most used are:

- **Discret event simulations (DESs)**, are based on queuing theory, where the models are decomposed in different events that are assigned to a specific timestamp. The time flow of DESs should be well-defined, allowing the processes to progress through time, and each event comprises a change in the system's state in a specific timestamp.

- **Continuous time simulations (CTSs)**, are systems where the state is continuously tracked, for that reason, they are often modeled by differential equations. The outputs of these dynamical systems are the integration of differential equations, and when ran in computers the outputs are approximated values, discretization is normally used.

- **Agent-based simulations (ABSs)**, are composed of different agents, that are independent entities with attributes and behaviors. Each agent autonomously makes decisions based on their state and the states of other agents that are around. In ABSs the outputs depend on the agents and the relationship between them (BONABEAU, 2002).

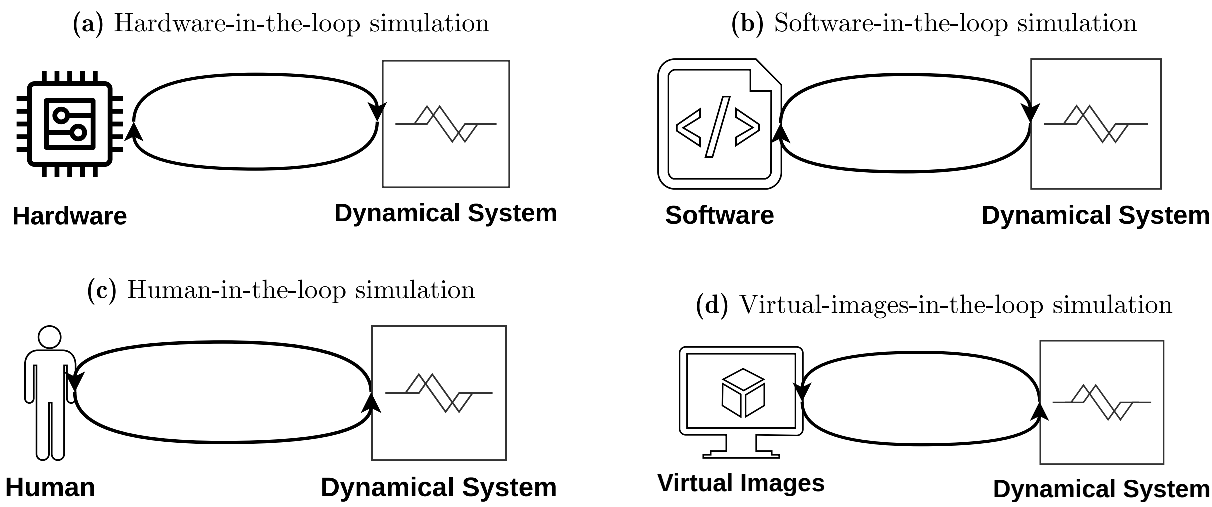
There are diverse techniques to couple distinct simulation systems, providing a single global simulation, these techniques are defined as co-simulation techniques. In co-simulations, each simulator is considered a SU, which receives inputs and produces behaviors (GOMES et al., 2018).

In co-simulations, it is also possible to have other entities besides dynamical systems. Real devices and even human beings can be considered parts of a co-simulation system. Despite being real devices or software, all parts of a co-simulation are considered SUs. When coupling other entities apart from mathematical models in a co-simulation, there is a specific nomination, the most common in the literature are illustrated in Figure 2.3 and can be defined as:

- **Hardware-in-the-loop (HIL)**, is a type of simulation where real physical devices are connected with other SUs, and the inputs of the real hardware will be fed with realistic virtual signals. The use of HIL is normally expensive and not flexible (KWON; CHOI, 1999).

- **Software-in-the-loop (SIL)**, is the integration of production source codes and other SU, that are normally mathematical models. SIL can be an less expensive alternative to HIL, it is also possible to use SIL to compare production software with pure simulation options (KWON; CHOI, 1999).
- **Human-in-the-loop (HITL)** simulations, consider human interactions as part of the co-simulation environment, and not as a simple input to a system. It is also possible to use HITL in brain–computer interface (BCI) simulations, or on other types of biological and medical simulations (ROTHROCK; NARAYANAN, 2011).
- **Virtual-images-in-the-loop (VIIL)**, consists of using synthetic data generated by 3D engines as an input to parts of a co-simulation system. This approach is normally used to simulate systems that require computer vision features (SCHOFIELD et al., 2023).

Figure 2.3: The different types of co-simulations models



Source: Author (2023)

The connection between the co-SUs that composes a co-simulation needs to ensure the accuracy of the final simulation, then an orchestrator becomes a critical part of these systems. The orchestrator is responsible to manage how the inputs and outputs of each SU will be connected in order to produce the correct behavior traces according to the simulation scenario, another crucial task of orchestrators is to control the simulation time flow in all SUs, ensuring that the timestamps will be precisely synchronized (GOMES et al., 2018).

When a co-simulation involves SUs from different simulation approaches, such as mixing CTS and ABS, the development of an orchestrator becomes considerably more complex, regarding the simulation time management. In CTSs SUs there is more flexibility in deciding the step size of the simulation, on the other hand, DESs SUs needs the inputs at precise timestamps. Simulations with SUs that use different approaches are called hybrid co-simulations, in Brailsford et al. (2019) the most common solutions for hybrid co-simulations orchestration are described as:

- **Sequential:** Where the SUs of each approach are executed in sequence. When a SU is running the simulation time is paused for the others SUs. In this work, this is the adopted solution.

- **Enriching:** Where the SUs uses a predominant approach, and the other types of SU are used only for special cases. When it occurs, the orchestrator needs to ensure synchronization for these special events.

- **Interaction:** Where the orchestrator can dynamically define the execution order of each SU at runtime.

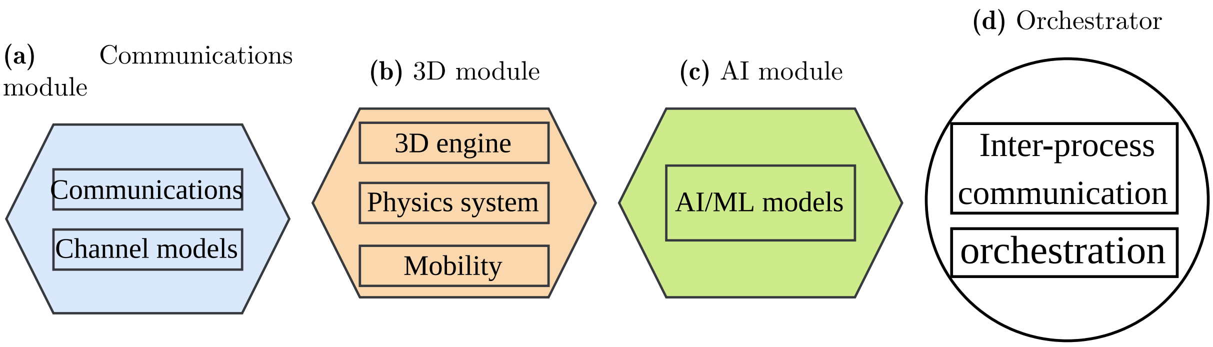
- **Integration:** Where the orchestrator precisely defines the moment where one approach ends and another begins. Globally the different simulation approaches are seamless.

The orchestrator can be classified according to its integration mode, the coordination of the simulations can be fully automated, can use intermediate files, or can be manual in simpler cases (BRAILSFORD et al., 2019).

2.2 Caviar Methodology

CAVIAR is a hybrid co-simulation methodology, that focuses on 5G/B5G realist scenarios, and how AI/ML models can impact these systems. One of the most important aspects of CAVIAR is that it tries to bring a high level of realism, creating an environment that simulates the most diverse facets of a real-world situation. In order to create realistic simulation scenarios, each CAVIAR simulation should include SUs that are categorized into three different modules; the communications module, the 3D module, and the AI modules.

Figure 2.4: CAVIAR's modules structure

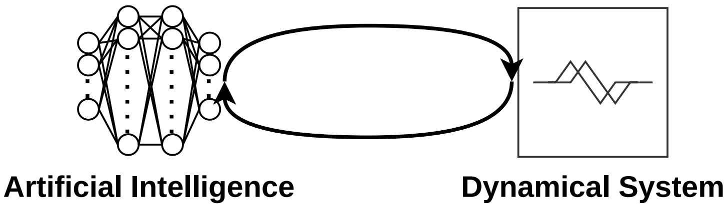


Source: Author (2023)

As illustrated in Figure 2.4 the CAVIAR's modules should be composed by SUs that are crucial to simulations involving the most diverse factors that impacts the performance of wireless communications systems. The communications module (Figure 2.4a) is responsible for all SUs related to data transmission, which includes all layers of a communications network. The 3D module (Figure 2.4b) is responsible for the creation of realistic virtual scenes, which include the vehicle's mobility and also the rendering of virtual 3D images. The AI module is fundamental to investigate how AI/ML agents will impact different parts of a wireless communications network. A smart orchestrator (Figure 2.4d) is indispensable to coordinate the various SUs that can compose each CAVIAR's module.

All inputs and outputs of each CAVIAR's SU can be shared with the AI module, which is composed of algorithms responsible to train and test AI/ML models. These models can be trained with large datasets composed by the traces of CAVIAR's simulations or they can be trained during the simulation process, which introduces the concept of AI-in-the-loop (AIIL) simulation (Figure 2.5), being this the integration of AI with the other SUs in a co-simulation system.

Figure 2.5: AI-in-the-loop simulation



Source: Author (2023)

The 3D module is also very important because the rendering of 3D scenes can enable meaningful strategies for the use of computer vision to improve the quality of service of 5G/B5G wireless communications, for example, it is possible to place a camera in a BS to detect the movement of vehicles and train an AI model to decide the best antenna positioning. The physical system provided by 3D engines also enables the use of sensors such as light detection and rangings (LIDARs), barometers, etc.

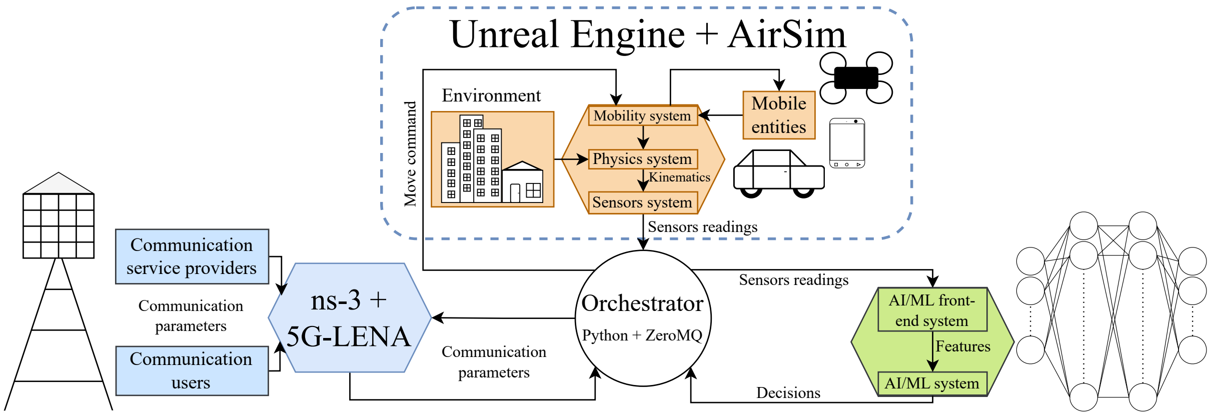
As each CAVIAR's module can be composed for distinct SUs that can be developed based on different simulation approaches (CTS or DESs), an orchestrator that is prepared to deal with hybrid co-simulation is necessary. A set of Python scripts along with an interprocess communications protocol are used to determine the execution schedule and also how the inputs and outputs will be shared between the SUs.

Figure 2.6 shows how the CAVIAR's modules can be connected in a search and rescue (SAR) simulation scenario. In the presented embodiment the Network Simulator 3 (ns-3) is used to simulate a V2X sidelink network for a swarm of virtual UAVs that are being simulated by AirSim simulator inside the 3D scenario provided by Unreal Engine 4 (UE4). The simulated UAVs used AI methods for real-time object detection in 3D scenes. More details about this implementation will be given in Chapter 3.

2.2.1 Automation of CAVIAR co-simulations

Regarding the level of automation of CAVIAR, the simulations can be orchestrated using diverse topologies, that are classified into two main categories, completely in-loop simulations, and out-loop simulations. The completely in-loop simulations (Figure 2.7a) is the main target of this work. In this topology, all CAVIAR's modules have its SUs

Figure 2.6: Embodiment of the CAVIAR method for a SAR use-case



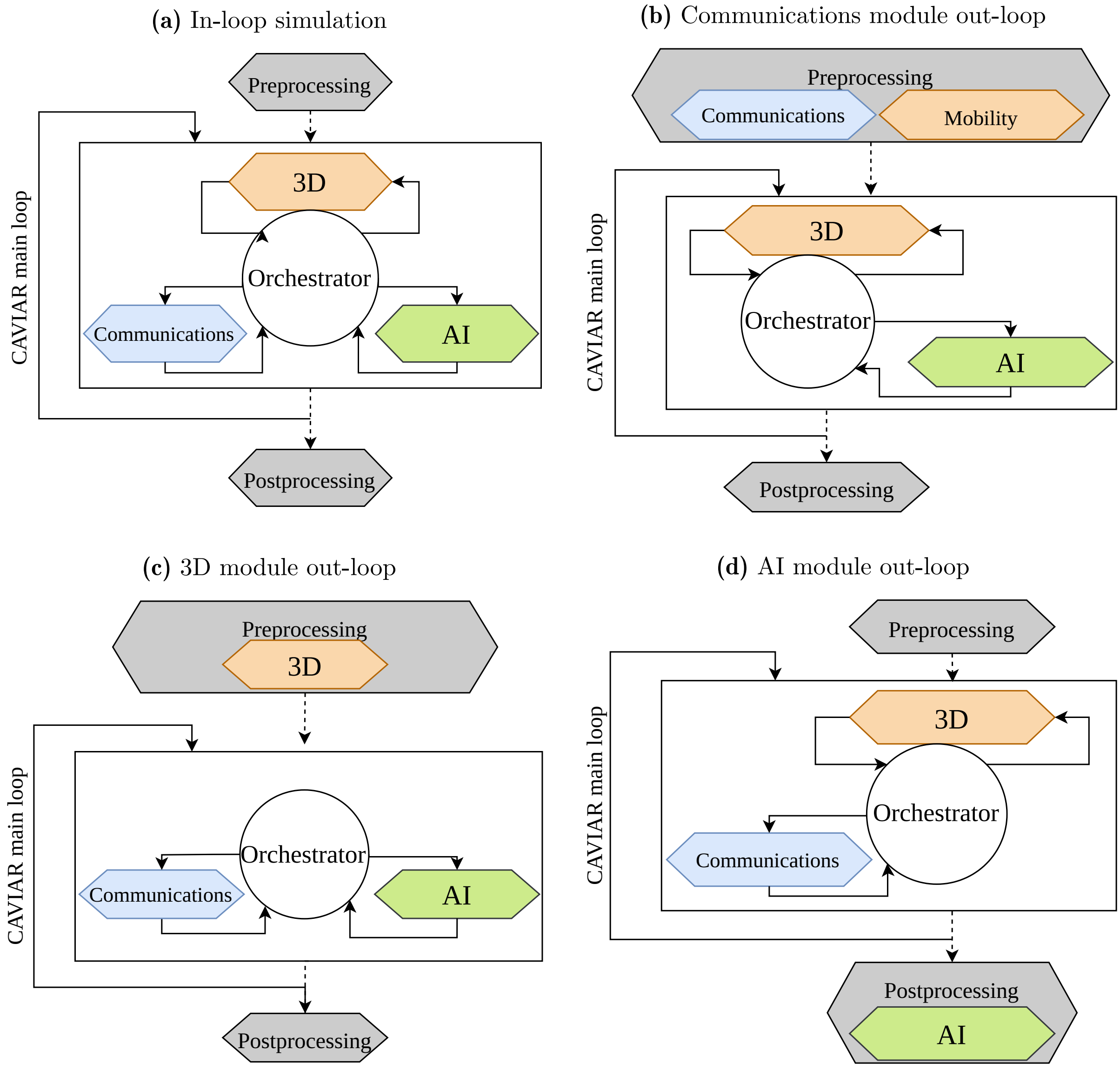
Source: Author (2023)

integrated in a completely automated way, using a sequential approach. The simulation steps advance synchronously between the SUs, which allows the outputs of one SU to influence the behavior trace of the other SUs in the next step. This type of simulation is an excellent option to measure the impacts of AI/ML models in communications systems.

Sometimes it is interesting to execute CAVIAR's modules or parts of a module in different moments, using a semi-automated routine, these topologies are classified as out-loop simulations. For example, in works developed in Klautau et al. (2018), Dias et al. (2019), Suzuki et al. (2022) all wireless communications channels are generated in a preprocessing moment and after virtual images are generated to be used to train and test AI/ML models (Figure 2.7b). This was necessary due to the characteristics of the ray-tracing simulator used in that embodiment.

As simulations involving 3D engines normally demand a high CPU and GPU usage, it is preferable to run them separately in some specific situations. All works described in Oliveira et al. (2021), Borges et al. (2021), Correa et al. (2022) use sets of mobility traces that were previously generated by the CAVIAR 3D module, putting in the simulation loop just the communications and AI modules (Figure 2.7c). This kind of approach is interesting to test different AI/ML models in a faster way. It is also possible to compose large datasets from CAVIAR traces to be used for AI/ML training in a postprocessing moment, as illustrated in Figure 2.7d.

Figure 2.7: The modes for integrating CAVIAR's modules



Source: Author (2023)

Chapter 3

Implementation

This chapter discusses an implementation of the CAVIAR methodology in a SAR situation, where different UAVs are used to search for people in an urban scenario, as previously illustrated in Chapter 2. In Section 3.1 a brief introduction about SAR is presented, while Section 3.2 describes with details the simulation environment that was implemented.

3.1 SAR missions assisted by UAVs

In disaster situations, such as floods, wildfires, storms, earthquakes, or several other emergency, finding and rescuing the survivors without delay and ensuring the safety of rescue teams is crucial. The use of UAVs in these situations is important to reduce the operation time and to ensure more efficiency in the rescue process (ALOTAIBI et al., 2019).

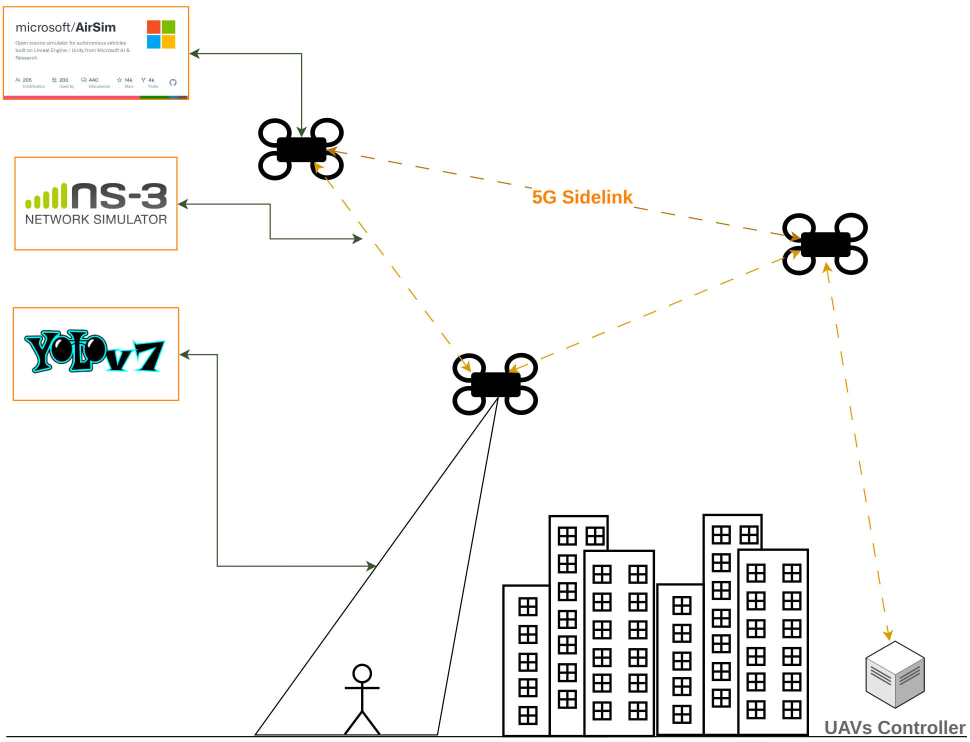
Due to the variety of sensors that a UAV can carry, it is possible to use UAVs to search for survivors via different methods, including computer vision, cellular localization, and sounds (LINS et al., 2021). The most used methods are based on computer vision, but Albanese et al. (2021) brings an important discussion about the use of cellular localization to search for survivors behind obstacles.

During a SAR mission it is possible to have UAVs controlled by a capacitated professional or fully autonomous vehicles. Alotaibi et al. (2019) reported that a swarm of autonomous UAVs is the more efficient manner to search for people in disaster situations, they also indicate that the number of UAVs is directly related to the number of rescued survivors.

When using a UAV swarm it is important to ensure that all vehicles involved in the mission are fully connected and also connected to a terrestrial controller in most cases. The connection between the UAVs can be done using different technologies. Cellular networks enable long-range communications which bring a great advantage to SAR missions. In cellular networks the UAVs can act as simple UE, in coverage areas, they can act as mobile BSs increasing the network coverage (ALSAEEDY; CHONG, 2020), and it is also possible to create a direct link using sidelinks in out-of-coverage scenarios (MISHRA et al., 2022).

3.2 Proposed simulation enviroment

Figure 3.1: Simulation Scenario

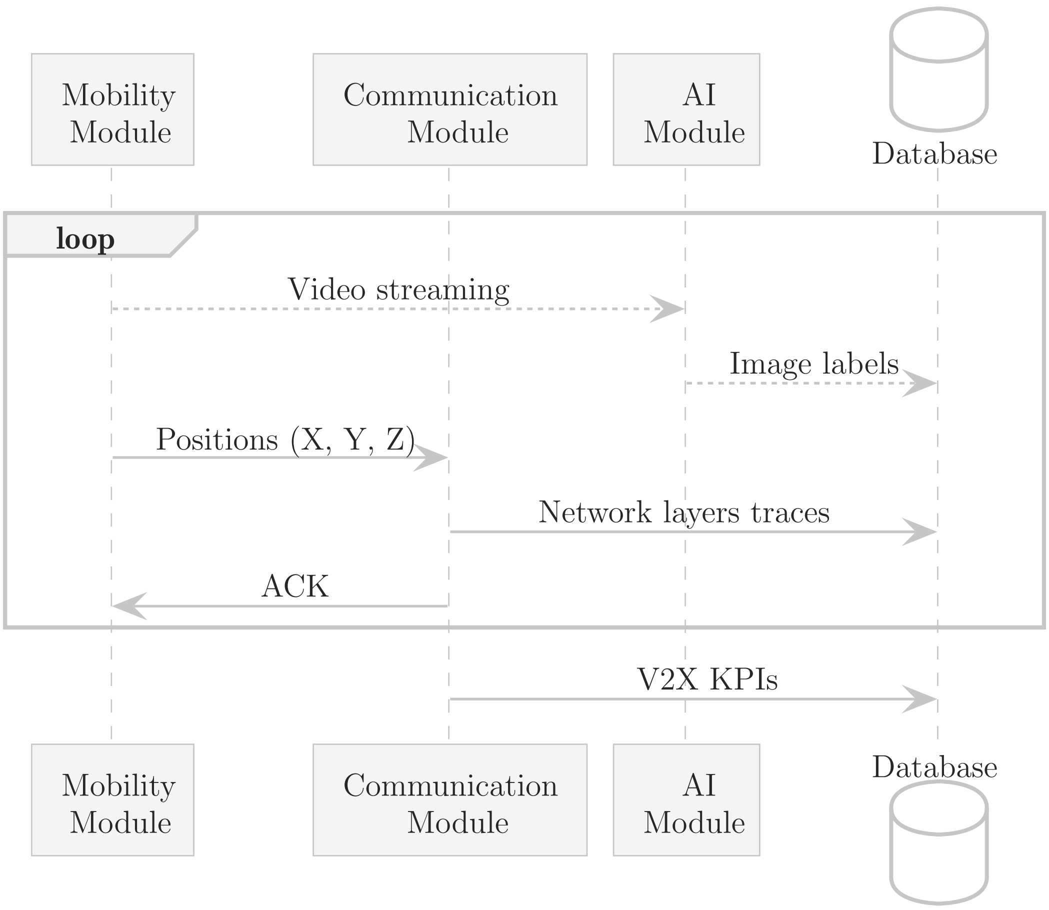


Source: Author (2023)

In order to validate the methodology described in Chapter 2, a simple simulation environment was developed considering the three essential modules of CAVIAR: mobility, communications, and AI. In this simulation, all modules work together using the in-loop paradigm.

The UE4 is used alongside the AirSim simulator to provide mobility for the simulation environment, with AirSim a swarm of UAVs is used to search for people in a possible SAR situation, and the UE4 also provides the mobility of cars and pedestrians. Taking advantage of the realistic graphics provided by UE4, a You Only Look Once (YOLO) deep neural network was implemented as the AI module, which is used to search for people to be rescued as illustrated in Figure 3.1.

Figure 3.2: Simulation Sequence Diagram



Source: Author (2023)

The communications module was deployed using the ns-3 with its module for 5G communications, the 5G-LENA. The communications network was inspired by the work of Mishra et al. (2022), considering 5G sidelinks channels.

As shown in Figure 3.2, the simulations start at the mobility module, which is responsible for the 3D images and also for the mobility of the users. The images captured by the UAVs are transmitted as a video streaming to the AI module, which is responsible to detect the pedestrians to be rescued. The mobility module also informs the position of each actor (UAVs, cars, and pedestrians) to the communications module, which simulates all layers of a 5G network.

After each simulation step, the mobility module saves the traces of all 5G network layers in a database, and the AI module also saves the labels for the detected pedestrians. It is important to notice that the AI module processes the images in parallel with the other modules, while the communications and mobility modules work in sequence. The mobility module only goes to the next step after the ACK from the communications module. At the end of the simulation, the communications module computes different key performance indicators (KPIs) related to the 5G network.

Table 3.1 shows that the number of users can vary from 2 to 45 in the described simulations, including different types of UEs. It also shows all parameters used for this simulation environment, each one of these parameters will be discussed in more detail in the following subsections.

Table 3.1: Parameters of the modules used in SAR use-case

ns-3 / 5G-LENA	
ns-3 version: : 3.36	**5G-LENA version:**: 0.2.y
Scenario: NR Sidelink Mode 4	**Channel model**: TR 37.885
Frequency: 5.9 GHz	**Bandwidth**: 40 MHz
Numerology: 0	**Transmission Power**: 23dBm
Antenna Element: Isotropic	**Antenna Array**: 1×2
YOLO	
Version: V7	**Model**: YOLOv7-tiny
ZMQ	
libzmq version: 4.3.4	**cppzmq version**: 4.11
pyzmq version: 23.2.1	
AirSim / Unreal Engine	
AirSim version: 1.3.0	**Unreal Engine version**: 4.27.2
Number of UAVs: 1-5	**Number of cars**: 0-2
Number of pedestrians: 0-36	**Number of UAV's controllers**: 0-2

Source: Author (2023)

3.2.1 The urban 3D scenario

Thinking about SAR mission involving UAVs, a good strategy is an urban or semi-urban environment, that offers a considerable number of obstacles, such as buildings, cars, trees, and other types of vegetation. In that kind of scenario, it is possible to simulate realistic situations for SAR and also for mobile communications networks.

Figure 3.3: Proposed Urban Scenario

Source: Author (2023)

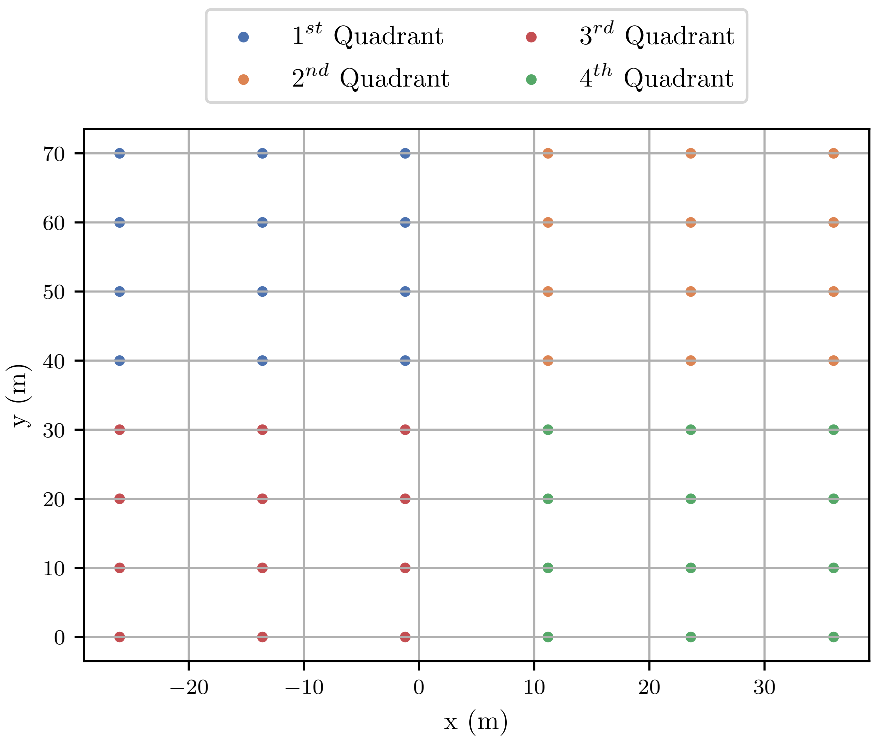
With the help of UE4 the 3D scenario of Figure 3.3 was developed seeking to achieve the maximum of realism, as techniques of computer vision will be used to detect possible survivors in the simulated disaster situation.

3.2.2 Mobility structure

The developed SAR simulation has different actors that are in constant movement: the cars, the pedestrians, and the UAVs. As previously described in Airsim Section, the AirSim is a complete UAV simulator, that provides an application programming interface (API) to control each vehicle, for this SAR mission five UAVs were configured to fly around the 3D scenario.

In this implementation, the simplest mode of AirSim is being used, where neither SIL nor HIL are considered. As this work does not focus on UAVs path planning, a script was developed to generate random trajectory for the UAVs. The square shown in Figure 3.3 was divided into 48 waypoints as illustrated in the graph of Figure 3.4, each UAV randomly selects four waypoints, one from each quadrant, and a land point to compose its trajectory. To avoid accidental crashes, all UAVs fly in different altitudes. The first UAV flys between 10m and 14m, the second one flys between 15m and 19m, and so on.

Figure 3.4: Waypoints Coordenates



Source: Author (2023)

The cars and the pedestrians do not have the same level of realism as the UAVs, they are just simple 3D objects that move around a predefined trajectory, not considering the air resistance or others physicals variables. The trajectories of the cars and pedestrians are shown in Figure 3.5. The cars are programmed to move in circles following the trajectory's lines, and the pedestrians have a more random comportment, but always follow the predefined lines, that are in the sidewalks. The simulations can also have one or two fixed UAVs controllers.

Figure 3.5: Cars and pedestrians trajectories, identified by the white lines

Source: Author (2023)

3.2.3 Network topology and patterns

As previously described in this chapter, the different actors of the simulation will use 5G NR sidelinks to communicate. The NR V2X sidelinks have two modes of operation considering the resource allocation (ALI et al., 2021):

- **Mode 1:** The next generation nodeB (gNB) schedules the resources for the UEs, and the UEs are only responsible for the data transmission.
- **Mode 2:** The UEs determines the transmission resources, normally with pre-configured instructions by the network. This mode is more used in out-of-coverage situations.

The NR V2X supports unicast, groupcast, and broadcast messages. For this SAR scenario all actors, including UAVs, cars, and pedestrians will be connected using the NR V2X and they will periodically send broadcast messages. Other parameters of the network, such as channel model, antenna configuration, frequency, etc. are described in Table 3.1.

At the end of the simulations, the network module also computes three KPIs in order to evaluate the V2X performance. These KPI are (ALI et al., 2021):

- The **packet inter-reception delay (PIR)**, that is the elapsed time between the reception of two packages transmitted by a specific UE. The average PIR is computed for each pair of UEs
- The **packet reception ratio (PRR)**, that is the ratio of neighbors that successfully received a package over the total number of neighbors. For this scenario, the PRR is computed for each transmitted package in a 200 m range.
- The **Throughput**, that is the total number of successfully received bytes during the simulation, and it is measured for each pair of UEs.

3.2.4 Real-time object detection

The images captured from the UAVs cameras are analyzed by an YOLO network to recognize the pedestrians to be rescued in the SAR mission. The use of AI in these scenarios can be done completely in the cloud, as the work developed by Surmann et al. (2019), the AI model can be partitioned between different actors inside a communications network, as suggested by Lins et al. (2021), or it can be done completely in the edge device (MCENROE et al., 2022).

Considering a SAR mission in an out-of-coverage scenario, the simplest way to perform AI image processing is using the AI models in the edge. Therefore in this simulation environment, all images will be processed directly on the UAVs. The YOLOv7 will be used considering its tiny mode, which is a model optimized for edge computing.

The YOLOv7-tiny model was completely optimized for edge AI applications, it uses a ReLU for the activation function, instead of the SiLU used by the others YOLOv7 models. Besides the activation function, the tiny version also reduces the number of parameters during the network training (WANG et al., 2022).

Table 3.2: Comparison of YOLO models for real-time object detection

Model	Nº of Parameters	Average Precision (validation)
YOLOX-S	9.0M	40.5%
YOLOX-M	25.3M	46.9%
YOLOX-L	54.2M	49.7%
YOLOX-X	99.1M	51.2%
YOLOv4	64.4M	54.8%
YOLOv4-CSP	52.9M	55.6%
YOLOv4-tiny	6.1M	28.4%
YOLOv4-tinyl3	8.7M	31.9%
YOLOv5-N	1.9M	28%
YOLOv5-S	7.2M	37.4%
YOLOv5-M	21.2M	45.4%
YOLOv5-L	46.5M	49.0%
YOLOv5-X	86.7%	50.7%
YOLOv7-tiny	6.2M	38.0%
YOLOv7-tiny-SiLU	6.2M	42.4%
YOLOv7	36.9M	55.5%
YOLOv7-E6E	151.7M	60.5%

Source: Wang et al. (2022)

Table 3.2, shows the performance of different versions of YOLO networks using the Microsoft COCO dataset (LIN et al., 2014). It is possible to note that the YOLOv7-tiny is 10% more accurate than the YOLOv5-N, which uses a larger number of parameters, and it is more than 25% faster than the YOLOv6-N (WANG et al., 2022).

3.2.5 Interprocess communications

As in this simulation, only two CAVIAR's modules will use the ZMQ protocol to exchange messages, the most basic ZMQ pattern will be used, the client/server mode.

Using the ZMQ client/server architecture, two sockets are open between the two simulators: the request socket and the response socket. A request socket can be connected and send requests to different ZMQ servers, but the socket will be blocked until it has received a reply. The ZMQ response socket will also be blocked if there are no requests. In summary, the client/server architecture of ZMQ works with pair of messages and the client can not send a new request before receiving the server response (HINTJENS, 2013).

The communication between the mobility module and the AI module is done by video streaming and does not pass through ZMQ, as illustrated in Figure 3.6. This simplest architecture is used because for this scenario the results of the AI module do not need to be feedbacked to the other modules.

Figure 3.6: Illustration of the messages exchanged between the CAVIAR modules

Source: Author (2023)

Chapter 4

Results and Discussion

This chapter presents the results of the simulations performed in the CAVIAR simulation embodiment described in Chapter 3. The discussions will be focused on the computer benchmarks discussed in Section 4.1. Results considering the KPIs related to the implemented communications network are presented in Section 4.2, and results about the AI/ML for real-time object detection are presented in Section 4.3.

4.1 Benchmarks

The computer performance and the WcT are key factors related to co-simulations environments involving a large number of complex SU, especially when it uses AI/ML models. To evaluate the performance of the CAVIAR methodology in completely in-loop simulation, three experiments were executed. In the first one various simulations were executed increasing the number of UEs from 5 to 40, to evaluate the stress that this would cause in the system. In this first experiment, just one UAV was used. In the second experiment, five UAVs were used, and the number of UEs was also increasing from 5 to 40. A third experiment was executed using the same parameters as the second experiment, but distributing the CAVIAR modules into two distinct computers.

The experiments were performed using modern personal computers, without any special configurations. Information concerning the hardware specifications of the two used computers is in Table 4.1. Computer 01 was using as operating syste (OS) the PopOS version 22.04, and Computer 02, the Ubuntu version 20.04.4, both are Debian-based Linux systems. The two computers were interconnected using a local network.

Table 4.1: Simulation hardware specifications

Computer 01	
CPU model: Intel® Core™ i7-8700	**Nº of CPU cores**: 6
CPU base frequency: 3.20 GHz	**GPU model**: NVIDIA® GeForce RTX™ 2060
RAM type: DDR4	**RAM capacity**: 16GB
RAM frequency: 2400 MHz	**VRAM**: 6GB
Storage type: SSD	**Storage speed**: 510MB/s
Computer 02	
CPU model: Intel® Core™ i7-10700F	**Nº of CPU cores**: 8
CPU base frequency: 3.20 GHz	**GPU model**: NVIDIA® GeForce RTX™ 3060
RAM type: DDR4	**RAM capacity**: 64GB
RAM frequency: 2400 MHz	**VRAM**: 12GB
Storage type: HDD	**Storage speed**: 245MB/s

Source: Author (2023)

Each SU of the implemented co-simulation environment was individually analyzed in terms of computational costs. The PSrecord[1] software was used to carry out all computational analyses. The PSrecord is a software that registers in comma-separated values (CSVs) files, all computational resources used by a process and its child process. It is important to notice in the CPU load analyses, that besides the process directly related to the simulations, the analyses software and the OS were also using parts of the computational available resources.

4.1.1 Results considering one UAV

In the first experiment, eight simulations were performed increasing the number of users from five to a total of 40 users. Among these, one UE was a UAV searching for survivors using computer vision, one UE was the UAV controller, two UEs were cars, and all the others were pedestrians walking in the scenario. These simulations were performed using only Computer 01.

Figure 4.1 shows the CPU load of each SU during the WcT. As the number of UAVs was fixed to just one UAV, the CPU load of almost all SUs does not change when the number of UE increases.

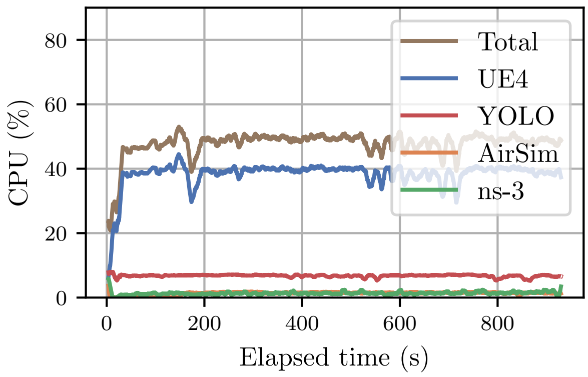
Only the processes related to the communications module (ns-3) are demanding more

[1]PSrecord: <https://github.com/astrofrog/psrecord>.

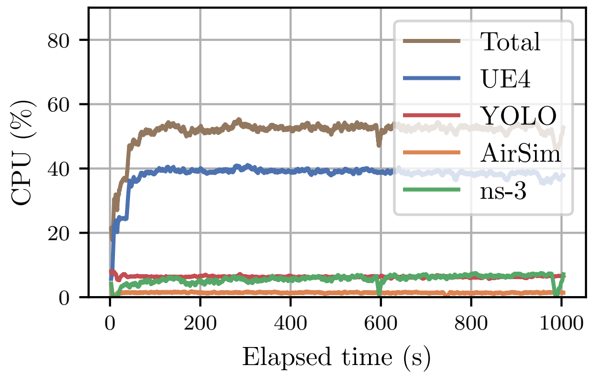
computational power with the increase in the number of users. But as shown in Figure 4.1c and Figure 4.1d, the CPU load for the communications modules does not increase after the simulation with 30 users, this happens because along with other processes, the simulations made the CPU reach its limit. Arriving at this boundary load, the CPU does not allow the ns-3 process to continue rising the CPU load.

Figure 4.1: CPU usage for a simulation considering one UAV

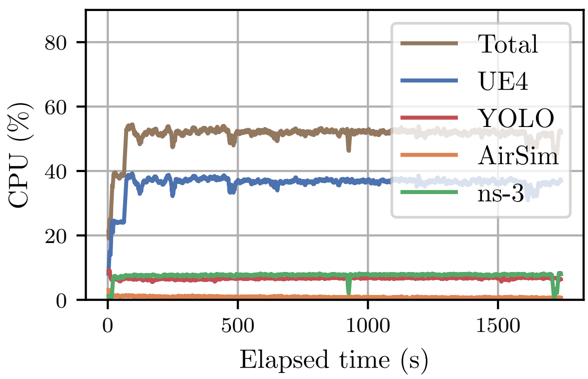
(a) CPU usage with 10 users



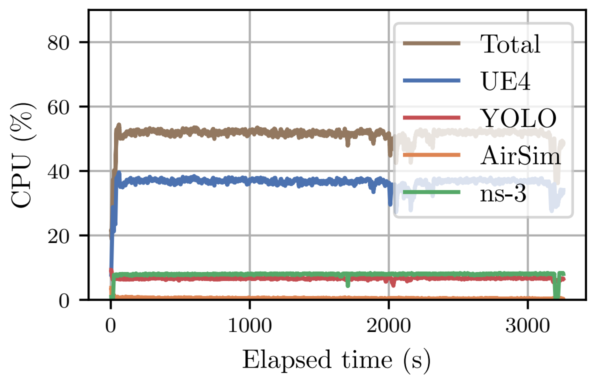
(b) CPU usage with 20 users



(c) CPU usage with 30 users



(d) CPU usage with 40 users



Source: Author (2023)

It is important to notice that the AI module represented by the YOLO process in Figure 4.1 is using a low percentage of the CPU, however, it used 52% of the GPU load during all simulations. The processes of AirSim and UE4 are parts of the 3D module, where the AirSim process is only responsible for the UAV control, and the UE4 process is responsible for the 3D rendering and the physics simulation, including the sensors and actuators that are embedded on the UAV.

4.1.2 Results considering five UAVs

The simulations executed in this second experiment used similar parameters to the ones of the first experiment: it was a set of eight simulations with an increasing number of users from 5 to 40. Differently from the previous experiment, the number of UAVs was fixed to five, the number of UAVs controllers varied from 0 to 1, the number of cars varied from 0 to 2, and the others UEs were pedestrians. As previously, all simulations were executed using only Computer 01.

In this experiment, it is possible to notice that the CPU load used by the UE4 process is greater than the percentage used previously and it also presents more variations during the time, as notable in Figure 4.2. This occurs because the UE4 is responsible for simulating all the physical parameters that are inside the 3D virtual scenario, including the wind speed, magnetic field, etc. When the number of UAVs is incremented it becomes more costly to simulate the stimulus that will be inputted in the dynamical system responsible for the UAVs control. It does not occur when other types of users are incremented because the cars and pedestrian models are much simpler and do not consider all the physical variables used in the UAVs controller.

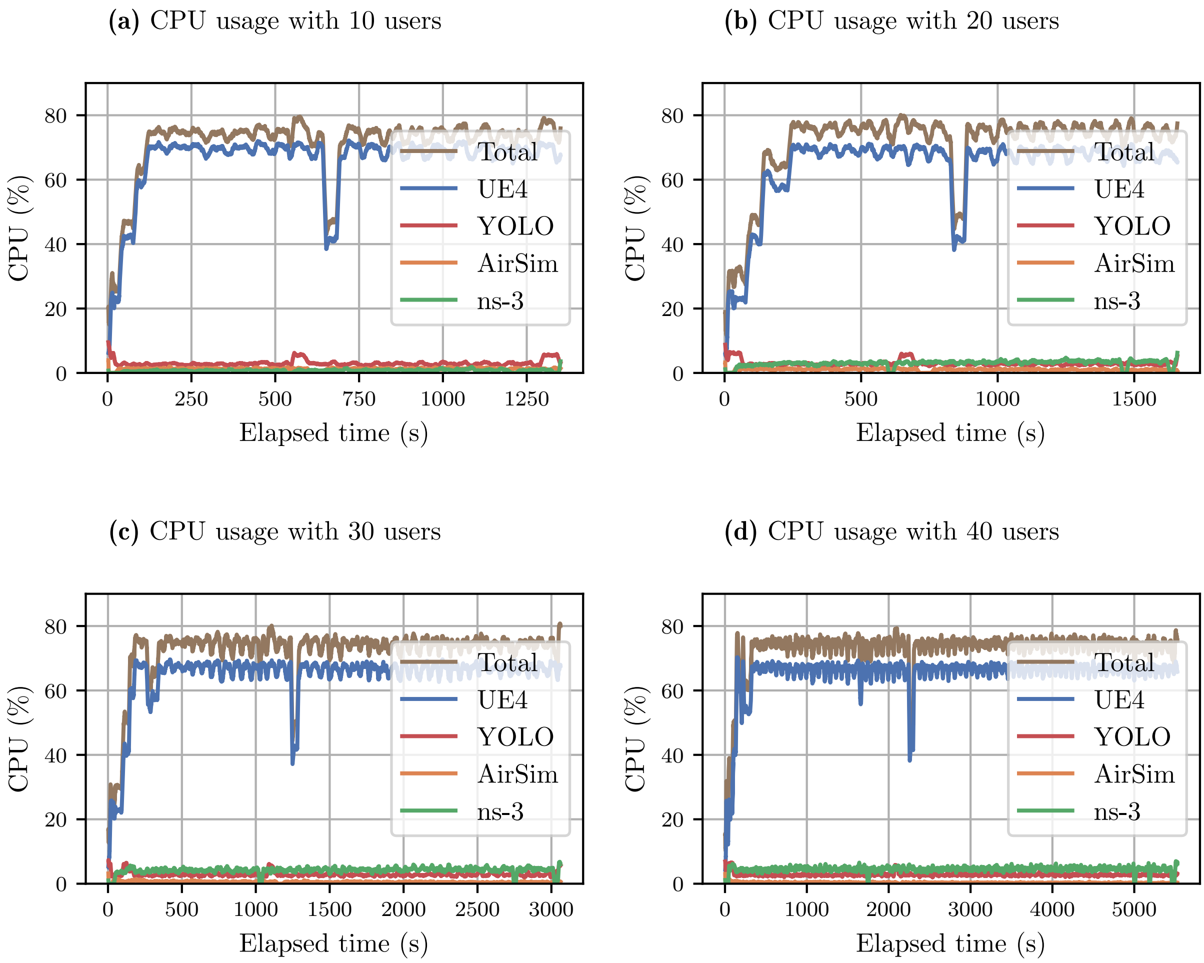
Similar to the first experiment it is noticeable that the growth of CPU load allocated for the ns-3 tends to stagnate after a certain number of users, as shown in Figure 4.2c and Figure 4.2d, but at this case, the maximum percentage of CPU load achieved by the communications module is much smaller. The CPU load allocated to the UE4 process also becomes stagnate in this second experiment, this is also related to the maximum capacity of the CPU.

The CPU load associated with the AI module remains low and static with a higher number of UAV because even having five UAVs in the simulation, only the images of one UAV are being used as input to the YOLO network.

4.1.3 Results for distributed simulation considering five UAVs

In this third experiment, the distribution of the users in the simulations was identical to the second experiment, with eight simulations with several UEs varying from 5 to 40.

Figure 4.2: CPU usage for a simulation considering five UAVs

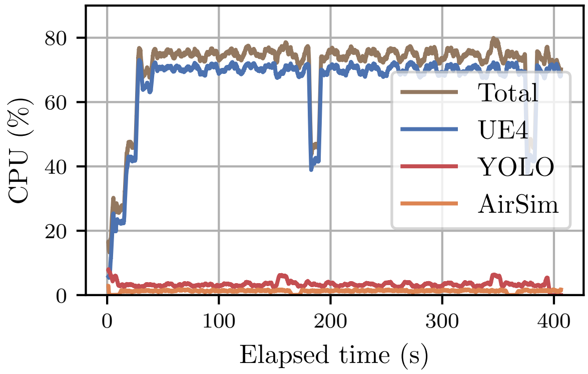


Source: Author (2023)

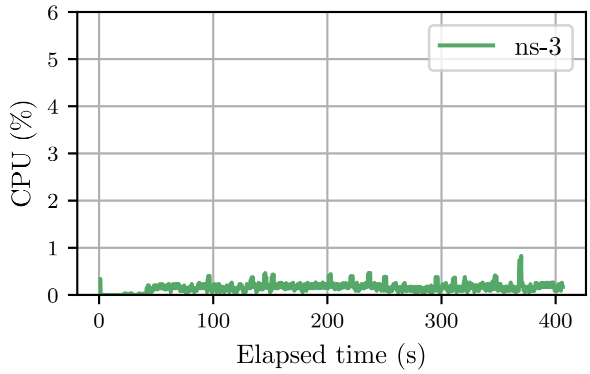
The difference is that the CAVIAR simulation modules were distributed: the 3D and the AI modules were executed in Computer 01, and the communications module was executed in Computer 02.

Figure 4.3: CPU usage for a simulation considering five UAVs using a distributed topology

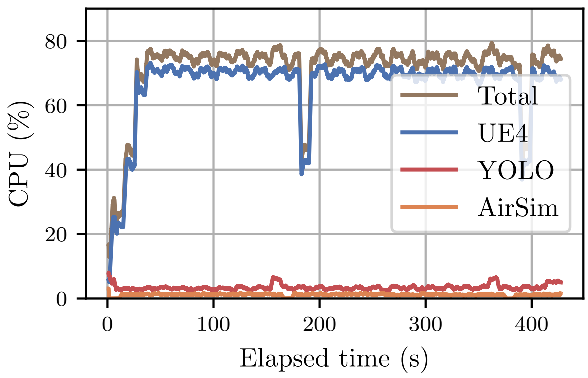
(a) CPU usage with 10 users at Computer 01



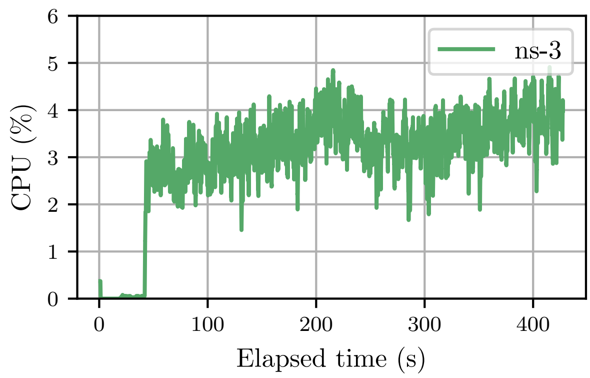
(b) CPU usage with 10 users at Computer 02



(c) CPU usage with 40 users at Computer 01



(d) CPU usage with 40 users at Computer 02



Source: Author (2023)

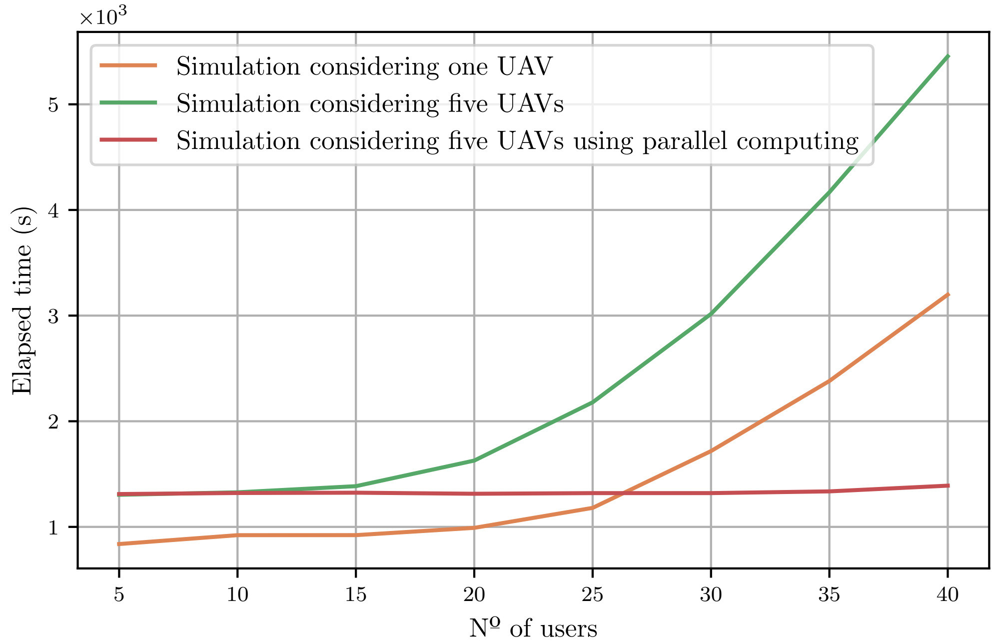
In Figure 4.3a and Figure 4.3c the total percentage of the CPU load used by the co-simulations remains at the same level as in the second experiment, what reinforces the CPU load limit due the high demands from the 3D module. On the other hand, Figure 4.3b and Figure 4.3d shows that the communications module has used less than five percent of the CPU load in the most stressful case. It is also noticeable that when executed in a separated computer the ns-3 process has more freedom to demand more

CPU resources when the number of UEs increases.

4.1.4 Simulation time

Figure 4.4 shows the elapsed WcT to execute each one of the simulations executed in the three previously discussed experiments. All simulations were executed within 2 minutes considering the simulation time. For the first experiment where just one UAV was used, time WcT starts to increase more strongly when the number of users overcomes the threshold of 25 users. This is the point where the communications module archived the maximum percentage of CPU usage, which causes an increase in processing time. For the experiment with five UAVs, the WcT starts increasing when the number of users reaches the number of 20 users because in this situation the CPU is more stressed by the 3D module.

Figure 4.4: Simulation time



Source: Author (2023)

When the co-simulation processing is split into two computers in the third experiment, the elapsed WcT remains almost constant along all the simulations, because in these cases the combined resources of the two computers are sufficient to process the demands from all the CAVIAR's modules. The WcT used in the distributed scenario is higher than the WcT used at the smallest simulation from the first experiment. This occurs because in the distributed topology the network delay needs to be considered, and the simulations trace storage in Compute 02 is done using an HDD, which has a limited writing speed.

4.2 Communications module results

To better evaluate the results produced from the implemented 5G V2X network, two more experiments were performed. For both experiments, five UAVs were used to search for people in a possible SAR situation, but only the UAVs were connected to the communications network, all UEs were sending broadcast messages with a fixed data rate in V2X sidelink mode 02 structure. All network parameters were set according to Table 3.1, and the only changed parameter was the bandwidth, in the first simulation a 40 MHz bandwidth was used, differently from the 10 MHz bandwidth used in the second simulation.

Table 4.2: PRR values for a simulation with 5 UEs and 40 MHz of bandwidth

UE ID	Range	Nº of receivers	Average PRR
1	200.0m	5	0.6926
2	200.0m	5	0.6685
3	200.0m	5	0.6955
4	200.0m	5	0.7031
5	200.0m	5	0.7043

Source: Author (2023)

Among the different computed KPIs, this section will focus on the PRR. As previously described, the PRR is related to the number of successfully received packages in a certain radius, being directly related to the reliability of the system. Table 4.2 shows that all UE have a PRR around 0.7, thus from all packages transmitted from all UEs 70% are arriving correctly to all the receivers.

Some simulations were performed to detect how the simulation parameters affect the PRR. First, the transmission power has been reduced by half, but it did not produce any significant change in the results, because the simulation 3D scenario has a limited area, where the maximum distance between the UAVs is around 14 m. After a new simulation was performed, at this time reducing the bandwidth to only 10 MHz, which causes a reduction to the PRRs to a value around 0.55, reducing the network reliability.

Table 4.3: PRR values for a simulation with 5 UEs and 10 MHz of bandwidth

UE ID	Range	Nº of receivers	Average PRR
1	200.0	5	0.5258
2	200.0	5	0.5163
3	200.0	5	0.6004
4	200.0	5	0.6033
5	200.0	5	0.5413

Source: Author (2023)

These results can be used as an example of how wireless communications networks can benefit from simulations using the CAVIAR methodology. For example, an AI/ML model can use data from the sensors that are embedded in the UAVs to choose the better parameters to configurations the communications network if the receiver UE is near the transmission UE it is possible to reduce the transmission power ensuring the reliability of the communications system, and at the same, the UAVs can benefit of it to reduce the power consumption.

4.3 AI module results

Figure 4.5 shows one single video frame that was transmitted from the CAVIAR's 3D module to the AI module. At the AI module the images were processed by an YOLOv7 network using the parameters described in Chapter 3. The pedestrians inside the simulation were correctly labeled with a mean average precision of 70%.

It is important to notice that the used AI model of trained with a dataset composed of real images of different objects, and when it was tested in the simulation environment with virtually generated images, the network classified correctly the objects inside the 3D scene, and with a mean average precision that was higher than the precision computed when the model was analyzed using real images. This demonstrates the efficiency of using VIIL in co-simulation environments.

Figure 4.5: Object detection result generated by the AI module

Source: Author (2023)

Chapter 5

Conclusion and Future Works

This chapter provides general conclusions and suggestions for future works.

5.1 Conclusion

This dissertation aimed to develop a hybrid co-simulation system for investigations involving AI/ML and the future generations of mobile communications networks. Based on the analysis of benchmark results and the outputs generated by the co-simulation environment, it can be concluded that it is possible to perform simulations with high levels of realism using different aspects of the real world in simple distributed or single computer topology.

The use of fully automated approaches (in-loop simulations), and the introduction of the AIIL concept brings to CAVIAR the possibility to easily integrate AI/ML in its simulations, including the use of RL agents in the mobile communications systems. Therefore, this work does not use any output of the AI module to improve the communications network, but further research can benefit from the implemented methodology to test how the wireless communications systems can interact with AI/ML in a realist simulation environment.

5.2 Future Works

As some concepts presented in this work are new and given the possible usage of CAVIAR methodology in a large range of situations, it leaves room for improvements and future works. Some suggestions for future investigations are provided as follows:

- The use of ray-tracing simulations, in order to provide more realistic wireless channels. The stochastic models that are being used do not benefit from all features that are provided by the 3D engines.

- The use of multiple mobility SUs. In the implemented embodiment the UAVs mobility was implemented with sophisticated models, but the cars and pedestrians are simple objects following a pre-defined trajectory. Other co-simulators can be implemented to ensure more realism for all the users.

- The study of interprocess communications protocols. The ZMQ was used to exchange messages between the SUs because it is one of the most used tools in the state-of-the-art, but other alternatives were not tested.

- The use of AI/ML as communications network functions. In the present implementation, the results of the AI do not impact the communications module. But an important research topic is how to use AI/ML to improve communications (for instance, in 6G), and CAVIAR enables such integrated simulations.

Bibliography

3GPP. *Architecture enhancements for 5G System (5GS) to support Vehicle-to-Everything (V2X) services*. [S.l.], 2019. Version 18.0.0. Available from Internet: <<https://portal.3gpp.org/desktopmodules/Release/ReleaseDetails.aspx?releaseId=191>>.

ACHARYA, S. et al. CORNET: A Co-Simulation Middleware for Robot Networks. In: *2020 International Conference on COMmunication Systems & NETworkS (COMSNETS)*. IEEE, 2020. Available from Internet: <https://doi.org/10.1109/comsnets48256.2020.9027459>.

ALBANESE, A.; SCIANCALEPORE, V.; COSTA-PÉREZ, X. First Responders Got Wings: UAVs to the Rescue of Localization Operations in Beyond 5G Systems. *IEEE Communications Magazine*, v. 59, n. 11, p. 28 – 34, 2021. Available from Internet: <https://doi.org/10.1109/MCOM.101.2100273>.

ALI, Z. et al. 3GPP NR V2X mode 2: overview, models and system-level evaluation. *IEEE Access*, IEEE, v. 9, p. 89554–89579, 2021. Available from Internet: <https://doi.org/10.1109/ACCESS.2021.3090855>.

ALOTAIBI, E. T.; ALQEFARI, S. S.; KOUBAA, A. LSAR: Multi-UAV Collaboration for Search and Rescue Missions. *IEEE Access*, v. 7, p. 55817–55832, 2019. Available from Internet: <https://doi.org/10.1109/ACCESS.2019.2912306>.

ALSAEEDY, A. A.; CHONG, E. K. 5G and UAVs for mission-critical communications: swift network recovery for search-and-rescue operations. *Mobile Networks and Applications*, Springer, v. 25, p. 2063–2081, 2020. Available from Internet: <https://doi.org/10.1007/s11036-020-01542-2>.

BAIDYA, S.; SHAIKH, Z.; LEVORATO, M. FlyNetSim. In: *Proceedings of the 21st ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems*. ACM, 2018. Available from Internet: <https://doi.org/10.1145/3242102.3242118>.

BONABEAU, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences*, National Acad Sciences, v. 99, n. suppl_3, p. 7280–7287, 2002. Available from Internet: <https://doi.org/10.1073/pnas.082080899>.

BORGES, J. P. T. et al. Reinforcement learning for scheduling and mimo beam selection using caviar simulations. In: *2021 ITU Kaleidoscope: Connecting Physical and Virtual Worlds (ITU K)*. IEEE, 2021. Available from Internet: <https://doi.org/10.23919/ituk53220.2021.9662100>.

BRAILSFORD, S. C. et al. Hybrid simulation modelling in operational research: A state-of-the-art review. *European Journal of Operational Research*, Elsevier, v. 278, n. 3, p. 721–737, 2019. Available from Internet: <https://doi.org/10.1016/j.ejor.2018.10.025>.

CELLIER, F. E.; KOFMAN, E. *Continuous system simulation*. [S.l.]: Springer Science & Business Media, 2006.

CORREA, I. et al. Simultaneous beam selection and users scheduling evaluation in a virtual world with reinforcement learning. *ITU Journal on Future and Evolving Technologies*, International Telecommunication Union, v. 3, n. 2, p. 202–213, set. 2022. Available from Internet: <https://doi.org/10.52953/chuz8770>.

DIAS, M. et al. Position and lidar-aided mmwave beam selection using deep learning. In: IEEE. *2019 IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*. 2019. p. 1–5. Available from Internet: <https://doi.org/10.1109/SPAWC.2019.8815569>.

DOGRA, A.; JHA, R. K.; JAIN, S. A Survey on Beyond 5G Network With the Advent of 6G: Architecture and Emerging Technologies. *IEEE Access*, Institute of Electrical and Electronics Engineers (IEEE), v. 9, p. 67512–67547, 2021. Available from Internet: <https://doi.org/10.1109/access.2020.3031234>.

EGEA-LOPEZ, E. et al. Vehicular Networks Simulation With Realistic Physics. *IEEE Access*, Institute of Electrical and Electronics Engineers (IEEE), v. 7, p. 44021–44036, 2019. Available from Internet: <https://doi.org/10.1109/access.2019.2908651>.

FUJIMOTO, R. M. Parallel and distributed simulation systems. In: IEEE. *Proceeding of the 2001 Winter Simulation Conference (Cat. No. 01CH37304)*. 2001. v. 1, p. 147–157. Available from Internet: <https://doi.org/10.1109/WSC.2001.977259>.

GARCIA, M. H. C. et al. A Tutorial on 5G NR V2X Communications. *IEEE Communications Surveys & Tutorials*, Institute of Electrical and Electronics Engineers (IEEE), v. 23, n. 3, p. 1972–2026, 2021. Available from Internet: <https://doi.org/10.1109/comst.2021.3057017>.

GOMES, C. et al. Co-simulation: a survey. *ACM Computing Surveys (CSUR)*, ACM New York, NY, USA, v. 51, n. 3, p. 1–33, 2018. Available from Internet: <https://doi.org/10.1145/3179993>.

HINTJENS, P. *ZeroMQ: messaging for many applications*. [S.l.]: " O'Reilly Media, Inc.", 2013.

KLAUTAU, A. et al. 5g mimo data for machine learning: Application to beam-selection using deep learning. In: IEEE. *2018 Information Theory and Applications Workshop (ITA)*. 2018. p. 1–9. Available from Internet: <https://doi.org/10.1109/ITA.2018.8503086>.

KWON, W. H.; CHOI, S.-G. Real-time distributed software-in-the-loop simulation for distributed control systems. In: IEEE. *Proceedings of the 1999 IEEE International Symposium on Computer Aided Control System Design (Cat. No. 99TH8404)*. 1999. p. 115–119. Available from Internet: <https://doi.org/10.1109/CACSD.1999.808634>.

LIN, T.-Y. et al. Microsoft coco: Common objects in context. In: SPRINGER. *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*. 2014. p. 740–755. Available from Internet: <https://doi.org/10.1007/978-3-319-10602-1_48>.

LINS, S. et al. Artificial Intelligence for Enhanced Mobility and 5G Connectivity in UAV-Based Critical Missions. *IEEE Access*, v. 9, p. 111792–111801, 2021. Available from Internet: <https://doi.org/10.1109/ACCESS.2021.3103041>.

MCENROE, P.; WANG, S.; LIYANAGE, M. A survey on the convergence of edge computing and AI for UAVs: Opportunities and challenges. *IEEE Internet of Things Journal*, IEEE, 2022. Available from Internet: <https://doi.org/10.1109/JIOT.2022.3176400>.

MISHRA, D. et al. Cooperative Cellular UAV-to-Everything (C-U2X) communication based on 5G sidelink for UAV swarms. *Computer Communications*, Elsevier, v. 192, p. 173–184, 2022. Available from Internet: <https://doi.org/10.1016/j.comcom.2022.06.001>.

MOROCHO-CAYAMCELA, M. E.; LEE, H.; LIM, W. Machine Learning for 5G/B5G Mobile and Wireless Communications: Potential, Limitations, and Future Directions. *IEEE Access*, Institute of Electrical and Electronics Engineers (IEEE), v. 7, p. 137184–137206, 2019. Available from Internet: <https://doi.org/10.1109/access.2019.2942390>.

OLIVEIRA, A. et al. Simulation of machine learning-based 6g systems in virtual worlds. *ITU Journal on Future and Evolving Technologies*, International Telecommunication Union, v. 2, n. 4, p. 113–123, ago. 2021. Available from Internet: <https://doi.org/10.52953/sjas4492>.

ROTHROCK, L.; NARAYANAN, S. book. *Human-in-the-loop simulations*. Springer, 2011. Available from Internet: <https://doi.org/10.1007/978-0-85729-883-6>.

SCHOFIELD, S.; BAINBRIDGE-SMITH, A.; GREEN, R. An improved semi-synthetic approach for creating visual-inertial odometry datasets. *Graphical Models*, Elsevier, v. 126, p. 101172, 2023. Available from Internet: <https://doi.org/10.1016/j.gmod.2023.101172>.

SURMANN, H. et al. Integration of uavs in urban search and rescue missions. In: *2019 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*. IEEE, 2019. p. 203–209. Available from Internet: <https://doi.org/10.1109/SSRR.2019.8848940>.

SUZUKI, D. et al. Ray-tracing mimo channel dataset for machine learning applied to v2v communication. In: IEEE. *2022 IEEE Latin-American Conference on Communications (LATINCOM)*. 2022. p. 1–6. Available from Internet: <https://doi.org/10.1109/LATINCOM56090.2022.10000783>.

TANG, S.-M. et al. An aerodynamic, computer vision, and network simulator for networked drone applications. In: *Proceedings of the 27th Annual International Conference on Mobile Computing and Networking*. ACM, 2021. Available from Internet: <https://doi.org/10.1145/3447993.3482862>.

WANG, C.-Y.; BOCHKOVSKIY, A.; LIAO, H.-Y. M. YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. *arXiv preprint arXiv:2207.02696*, 2022.