Interoperability of Physical Simulation Models and Probabilistic Reliability Assessment Tool: A Case Study on Heating, Ventilation, and Air Conditioning Systems

Hassane CHRAIBI[a*], Richard QUATRAIN[a], Pascal BOREL[a], Youssef HAMMADI[a], Philippe CARER[a]
[a]EDF Lab Paris Saclay, Palaiseau, France

Abstract: Many industrial processes depend on specific temperature and humidity levels to operate effectively, highlighting the importance of Heating, Ventilation, and Air Conditioning (HVAC) systems. Therefore, HVAC systems must be designed with an appropriate level of dependability that matches their criticality, posing two main challenges: overcomplicating them in the pursuit of higher reliability, which can be costly, or oversimplifying them, risking unreliability. To address these challenges, it is necessary to conduct reliability assessments to determine the appropriate design that fulfills the required level of dependability.
Traditional reliability assessment methods may be insufficient as they might not consider all relevant information. Indeed, these methods cannot effectively leverage the information provided by physical models. In this article, we present a comprehensive reliability study that uses a simulation model created by coupling an HVAC system model (including a process control device to be cooled) with a model simulating the stochastic behavior of the entire system. The former refers to an existing physical model based on TAeZoSysPro, a MODELICA library of thermo-aeraulic component behaviors, while the latter is a PyCATSHOO model. We based this coupling on the Functional-Mockup Interface standard. Our study shows that traditional methods of reliability assessment can be overly cautious, which is beneficial for safety assessment but should not be overdone. We also found some cases where these methods were overly optimistic, and these issues must be addressed in a more specific manner.

Keywords: Dynamic PSA, PDMP, HVAC, PyCATSHOO, TAeZoSysPro

1. INTRODUCTION

This article presents research conducted by EDF R&D aimed at developing a probabilistic performance evaluation method for complex systems. The purpose sought by this method is to overcome the limitations of conventional approaches which are primarily exploratory and rely on fault trees and event trees. Unlike the latter, the method discussed in this article belongs to the category of methods referred to as Model-Based Safety Assessment (MBSA). The scope of application of this method goes beyond safety assessment, enabling other system performance criteria to be evaluated. It operates by simulating a model that captures both continuous deterministic behaviours and either stochastic or deterministic discrete behaviours. Stochastic discrete behaviours represent event such as failures and repairs, while deterministic discrete behaviours simulate the consequences of control actions. Additionally, deterministic continuous behaviours replicate the evolution of one or more physical phenomena interacting with the system's material support. The interactions between physical phenomena and system components are significant, as they mutually influence each other. In safety studies, it is imperative to account for these mutual influences, as they can potentially compromise safety barriers or accelerate equipment failures by contributing to an increase in their occurrence rate.

EDF R&D has developed a methodology to integrate various behaviours within a single model, enabling the formulation of physics equations governing deterministic continuous behaviours. The PyCATSHOO [1] simulation engine implements this method. It has been used to construct models for numerous safety-critical systems, predominantly in the hydraulic domain. These systems entail moderately complex physical phenomena, limited to material or heat balances, and material degradation laws. The modelling of such phenomena with PyCATSHOO has not necessitated substantial investment.

In more complex contexts, modelling intricate physical phenomena, while possible with PyCATSHOO, may prove difficult. Thus, when a validated numerical implementation of such models exists, it is advisable to refrain from creating new versions for use in safety evaluation models. Recent enhancements to PyCATSHOO [2] aim to improve its efficacy in such contexts by ensuring compliance with the Functional Mock-up Interface (FMI) standard [3]. FMI sets forth a communication protocol among simulation codes, simplifying the coupling of simulators developed by various parties, if they adhere to the FMI protocol.

This article presents the second validation study of implementing FMI in PyCATSHOO. This study, closer to the concerns of probabilistic performance assessment studies of complex systems operated by EDF, serves as a proof of concept (POC). It is supported by a simplified thermo-aeraulic model of buildings with typical industrial electronic rooms, including the HVAC system and an associated simplified instrumentation and control approach. The proposed model is inspired by a test platform, called ZEPHYR, developed in the laboratories of EDF's R&D.

The POC unfolded into two aspects, Firstly, a technical computing aspect aimed at verifying the feasibility of coupling between a PyCATSHOO model and a real simulator developed using the Modelica Dymola tool [4]. This simulator is encapsulated according to the FMI standard in what is referred to as a Functional Mock-up Unit (FMU). Secondly, a reliability aspect aimed to highlight the potential benefits of an assessment not solely based on a discrete behavioural model (failures/repairs) of the system components, as done by conventional reliability engineering methods. The approach implemented in this POC also utilizes a physical model to track the evolution of physical variables. These variables condition the occurrence of the undesired event and depend on the proper and improper functioning of the components of the studied system.

In Section 2, we introduce the ventilation system model. Section 3 outlines the objectives of the reliability study, along with the data and considered assumptions. Section 4 describes the coupling procedure and summarizes the principles of the FMI standard. Section 5 presents the results. Finally, we conclude the study and discuss prospects.

2. ZEPHYR MOCK-UP AND VENTILATION SYSTEM

A numerical physical model of a typical industrial electronic room is proposed as depicted on Figure 1. The model is based on the simple thermal package of the TAeZoSyPro library [5]. This package provides elementary components to model typical thermal dynamic response of buildings by modelling main inertial components such as the concrete structure of the building or the main components of the studied rooms.

Only the conservation equation energy is solved in a simple thermal model approach:

$$\rho \frac{\partial h}{\partial t} + \overrightarrow{\nabla} \bullet [\rho \overrightarrow{V} h] = -\overrightarrow{V} . \overrightarrow{\varphi_c} + \rho \dot{\omega} \tag{1}$$

Where h=$c_p T$ is the specific enthalpy, ρ the density, $\rho \overrightarrow{V}$ is the mass flux, $\overrightarrow{\varphi_c}$ is the thermal flux and $\dot{\omega}$ is a specific heat source. Thermal fluxes modelled are conductive and convective heat transfers, using Fourier and Newton law respectively. Radiant thermal fluxes are modelled using a Carroll Node [6], radiant absorbed energy is treated through the term $\dot{\omega}$. Equation (1) is then integrated on each elementary volume (room air node, wall concrete layer for example) to lead to a coupled system of equation to be solved to study the dynamic response.

In the present study, the room studied is an electronic room housing thermal sensitive components which can fail in case of too high room temperature. To model the room thermal behavior in case of HVAC failure, core of the model is the studied room made of 6 elementary walls (floor, ceiling and 4 verticals walls) as well as the electronics cabinet which are lumped into a single component. Electronics cabinets are modeled as a heat emitter housed in box, heat being transmitted to environment either by convection or by thermal radiation to the casing which then exchanges heat with the other elementary entities of the room.

Limit conditions of the studied room are imposed thanks to a globalized building model. This component is made of a global air node equivalent to the whole volume of the building that exchange heat with global equivalent buildings walls with global heat transfer modelling (globalization of convective and radiant transfers through a single heat exchange coefficient). Outside limit conditions are imposed through Cooling Load Temperature Difference Method. Building air conditioning chillers are modeled through a negative power injected in the building mixing box to ensure supplied air to room is at the wanted temperature given the HVAC recirculation rate of the building. A proportional integral regulator (PI) is used to model an equivalent quasi static behavior of the chiller.

Starting from a steady state with ventilation in operation, various HVAC failures can be simulated, and electronics room temperature rise can be studied. The HVAC failure accounted within this model are either failure of the chiller leading to supply outside air to the building without conditioning or the total loss of the HVAC fans leading to a loss of ventilation for the building.

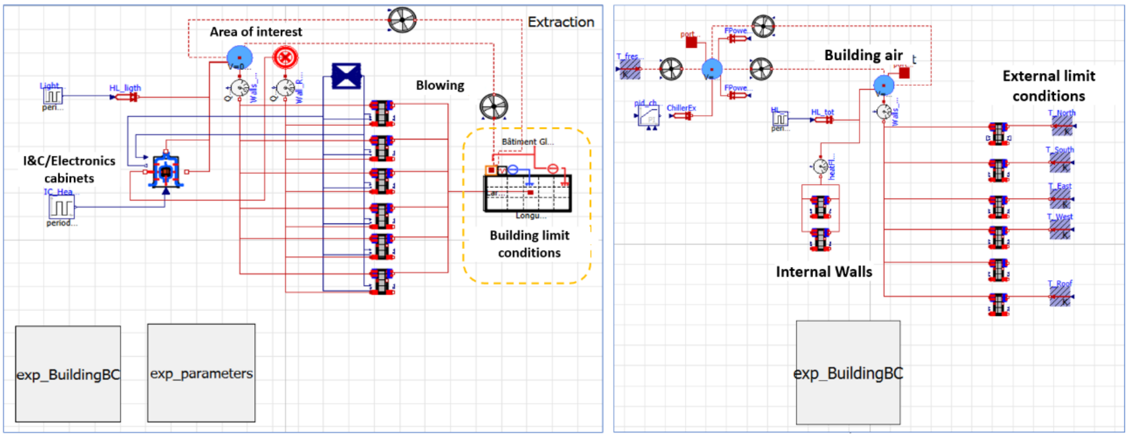

Figure 1. - left: TaeZoSysPro Physical model of typical electronic room housed in its building - right: details of the limit condition CLDT building

3. STUDY OBJECTIVES AND DATA

3.1. STUDY DATA

The system studied includes two identical and independent buildings. Our simulation model represents a single instance of them. This is an FMU generated by the Dymola software using the TAeZoSysPro library. Each of the two buildings houses an instrumentation and control system (I&C). Both I&Cs operate in active redundancy to control the same safety-critical process. Their simultaneous failure is then a necessary cause of loss of control of the process.

The loss of the I&C system in a building can occur due to two different reasons:

1. Exceeding a critical threshold of indoor air temperature.
2. Intrinsic failures following an exponential occurrence law, whose lambda parameter increases with the indoor air temperature according to the Arrhenius law [7]:

$$\lambda = \lambda_0 . e^{\left[\frac{-1.5}{8617E-5} . \left(\frac{1}{T+273} - \frac{1}{T_0+273}\right)\right]} \quad (2)$$

This equation illustrates the relationship between the failure rate and temperature. At $T=T_0=30°C$, the rate is λ_0 = 1.1E-5/h. The indoor temperature of a building may rise due to the operation of various electrical equipment, generating heat. This heat emission is an FMU parameter represented by a power density relative to the building's area. In our study, we considered three potential values for this density: 200, 300, and 400 $W.m^{-2}$.

The intrinsic failure of the I&C system is presumed to be reparable, with a repair rate of 1.1E-2/h.

To mitigate the rise in indoor air temperature, each building is equipped with an HVAC (Heating, Ventilation, and Air Conditioning) system. According to the FMU model, this HVAC system comprises two primary components: the chiller unit and the fan. Both components are susceptible to failures and repairs, with respective rates of λ= 1.1E-5/h and μ= 1.1E-1/h.

Since the two buildings are identical, both the chiller units and the fans are vulnerable to common cause failures. Assuming a component state check every 24 hours, we establish the probability of occurrence of these common cause failures at the start of the check period as P_{ccf} = 2.6E-5. Subsequently, we set the impact rate, which denotes the rate of conversion into actual material loss, to λ_{ccf} = 3E-2/h.

All this data is hypothetical and has been arbitrarily chosen. It is summarized in Tables 1 & 2, where rates are expressed in occurrences per hour. These figures have been appropriately adjusted by the PyCATSHOO model to match the calculation time step of the FMU, which is one second.

Table 1. I&C dependability data

	I&C dependability
Failure rate at 30°C	λ_0=1.1E-5/h
Repair rate	μ =1.1E-2/h

Table 2. Fans and chillers dependability data

	Chillers and Fans dependability data
Failure rate	λ=1.1E-5/h
Repair rate	μ =1.1E-1/h
Check period	24h
CCF probability	P_{ccf} = 2.6E-5
CCF impact rate	λ_{ccf} = 3E-2/h

3.2. Definition of indicators to be assessed

In addition to verifying the technical feasibility of coupling a physical model code encapsulated in an FMU with a PyCATSHOO model according to the FMI standard, this study aimed to highlight the benefits of the hybrid approach compared to a conventional approach. First, we assessed two key indicators.

1. System reliability assessed using the hybrid methodology supported by the PyCATSHOO simulation engine. In this method, the undesirable event is the loss of both instrumentation and control devices (I&C), either due to their intrinsic failures or after the temperature in the buildings housing them exceeds the critical threshold.

2. System reliability assessed using conventional approaches. Here the undesired event occurs when the I&C devices are lost. However, in this approach, an I&C device is considered lost if its chiller unit or its fan fails.

These calculations were carried out assuming that all components of the system are functional at time 0, considering three different values of thermal power density emitted within the two buildings: Q = 200W.m^{-2}, 300W.m^{-2} and 400W.m^{-2}.

Next, we evaluated the system's reliability using the hybrid methodology with an initiating event. We initiated the scenario by assuming the loss of the chiller units in both buildings at time 0, with no possibility of repair. Our aim was to assess the grace period under these conditions, referred to as the probabilistic grace period. This assessment was conducted for a thermal power density of 200 W.m^{-2} emitted in both buildings.

These scenarios were simulated over a 72-hour duration.

Subsequently, we conducted a similar calculation with the exception that we excluded any possibility of failure other than that of the initiating event. Additionally, we extended the simulation period to 140 hours. The objective was to compute the grace period conventionally and juxtapose it with the probabilistic grace period.

4. COUPLING PROCEDURE

In this study, we coupled a PyCATSHOO model with a building physical model using the co-simulation principles of the FMI 2.0 standard.

The building model, represented as an FMU, comprises three main components: the chiller unit, the fan, and the I&C device. Details concerning aspects such as civil engineering structures, equipment layout and heat/material exchange managed by the FMU were considered irrelevant to this dependability study. We focused on two aspects: firstly, on the evolution of air temperature, provided by the FMU, which determines the occurrence of the undesirable event; and secondly, on the ability to introduce failures and repairs to alter the states of these three components within the FMU.

The FMI standard provides a framework for listing the variables of an FMU accessible for read and write operations by an external actor. It also specifies the functions facilitating these operations. In co-simulation mode, the FMI standard assumes that the physical model has its own differential equation solver. This aspect is particularly advantageous and promotes coupling because it eliminates the need to incorporate the physics of the phenomena studied in PyCATSHOO models and alleviates concerns regarding solver selection. Furthermore, the FMI standard defines functions allowing this resolution to be controlled, in particular those allowing one or more forward and backward time steps during simulations. PyCATSHOO builds on these functions and uses them in dichotomies to detect threshold crossings.

In this study, we developed a PyCATSHOO model, serving as the driver to control the FMU encapsulating the physical building model, which will be henceforth referred to as the driver. As depicted in Figure 2, the driver encompasses the stochastic discrete behaviour of the three components: chiller, fan, and I&C. The building itself, along with the physical phenomena occurring within it, is represented in the PyCATSHOO model by a proxy linked to an instance of the FMU encapsulating the physical model. This linkage mechanism, facilitated by PyCATSHOO, enables the driver to treat the physical state variables of the FMU as its own variables. Consequently, it can access and even modify their values without necessitating the use of the FMI standard's API, thereby alleviating the need for driver designers to have expertise in the FMI standard.

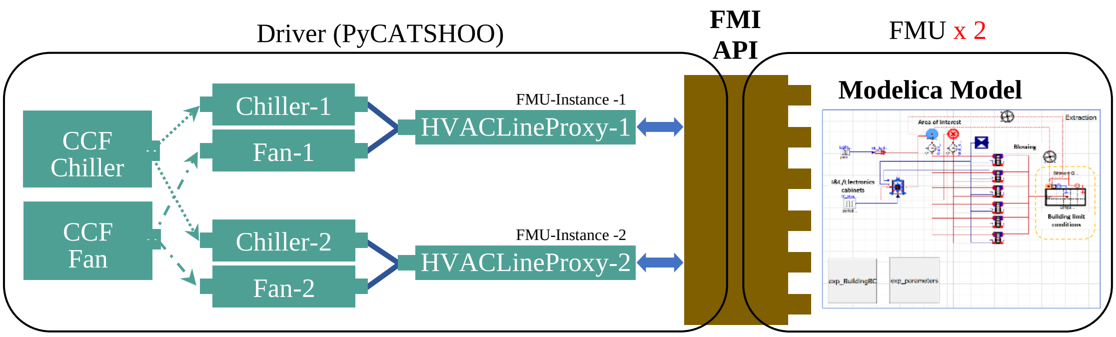

Figure 2. Coupling principles

As the two buildings are identical, a single FMU is employed to represent them. However, this FMU is instantiated twice to enable the independent evolution of the two building models during simulations.

In hybrid scenarios, PyCATSHOO models utilize the theoretical framework of piecewise deterministic Markov processes (PDMPs). This framework is practically realized through a computational entity within the PyCATSHOO library, called the PDMP Manager. It oversees the continuous variables of the system by managing the resolution of their governing equations, often embedded within the PyCATSHOO model. PyCATSHOO's ability in synchronizing the stochastic discrete behaviour of the system with the resolution of differential equations, facilitated by integrated solvers, enables this functionality.

The integration of FMI standard functionalities into PyCATSHOO aimed to maintain its operational mode while shifting the equation-solving task to FMUs, as mandated by the co-simulation approach. Consequently, the PDMP acknowledges the FMU's presence, and the variables previously managed by the PDMP through solving differential equations are treated as variables derived from explicit expressions. Conversely, during each deterministic evolution period of the PDMP, delimited by stochastic discrete events, the PDMP assumes responsibility for conveying any system changes to the FMU. This is accomplished in the driver by straightforwardly updating the shared variables with new values.

Figure 3 illustrates PyCATSHOO's operation in the absence of an FMU. It demonstrates the creation of a PDMP, the assignment of a continuous variable controlled by the PDMP through differential equation solving, and the designation of a method providing the derivatives of the continuous variables.

Figure 4 illustrates the incorporation of an FMU into the system and the link between the FMU variables and the local variables of the PyCATSHOO model.

In Figure 5, the FMU is integrated with the PDMP to support solving the differential equations. The variables managed by FMU become explicit for the PDMP. Additionally, a method is defined to be invoked by PyCATSHOO at the start of each deterministic period to assign new values to shared variables.

```
pdmp = self.addPDMPManager("pdmpManager")
self.addPDMPODEVariable   ("pdmpManager", self.v_temperature)
self.addPDMPEquationMethod("pdmpManager", "odeMethod", self.odeMethod)
```

Figure 3. Cases without FMU: Equation solving is carried out within the PyCATSHOO model. Here, "odeMethod" is a method implemented to provide the derivative expression of the continuous variable v_temperature.

```
self.fmu = self.system().addFMU("MyFMUModels/TAeZo.fmu"), "FMU")
self.v_temperature = self.fmu.variable("FMUTank.Temperature")
```

Figure 4 Here, the PDMP is informed of the presence of an FMU, and the shared variables of the latter are linked with local variables of the driver.

```
pdmp = self.addPDMPManager  ("pdmpManager")
pdmp.addFMU(self.system().FMU("FMU"))
self.addPDMPExplicitVariable("pdmpManager", self.v_temperature)
self.addPDMPBeginMethod("pdmpManager", "beginMethod", self.beginMethod)
```

Figure 5. When an FMU is used, equation solving is no longer the responsibility of PyCATSHOO. Hence, in this case, the continuous variable v_temperature is considered explicit, and the PDMP must solely ensure that the shared variables take the correct values at the beginning of each deterministic period. This is accomplished in the "beginMethod" method.

5. STUDY OUTCOMES

5.1. Technical feasibility

The primary outcome of this research is the validation of the coupling approach facilitated by PyCATSHOO, which leverages the co-simulation framework of the FMI standard. This approach maintains the modelling methodology advocated by PyCATSHOO. Specifically, shared FMU variables are treated as local variables by PyCATSHOO, eliminating the need for additional learning of modelling paradigms or the FMI standard itself.

However, this approach necessitates that the FMU can save its state at a specific simulation point and restore it upon request by the driver. In our study, we utilized the Dymola tool, capable of generating FMUs with this functionality. Nonetheless, not all simulation engines offer this feature.

FMUs are invariably accompanied by a human-readable XML file detailing their characteristics, functionalities, exposed variables, and parameters, including the ability to save and restore states. Thus, it is imperative to verify this capability before considering FMU utilization in coupling with PyCATSHOO.

Additionally, in hybrid approach implementations, simulation duration tends to be considerable, often necessitating parallel computations beyond the capabilities of individual laptops or desktops. Consequently, high-performance computing (HPC) systems become imperative, and the drivers must be proficient in leveraging all available power computing for efficient operation. PyCATSHOO models inherently support parallelization via the MPI library [8], meeting this prerequisite. In this study, we used an EDF's HPC cluster, from which we reserved 60 computing nodes each housing 48 cores. Simulation conditions are summarized in Table 3, while Figure 6 illustrates the utilization of a computing node during a simulation, demonstrating PyCATSHOO's parallelization efficiency by fully exploiting all cores across allocated nodes.

Table 3. Simulated scenarios

Scenarios	Emitted Thermal power density	Number of simulated sequences	Simulated time	Simulation time
Without initiating events	200, 300 and 400 $W.m^{-2}$	10^{+06}	72h	~ 50mn
With an initiating event	200 $W.m^{-2}$	10^{+06}	72h	~ 50mn

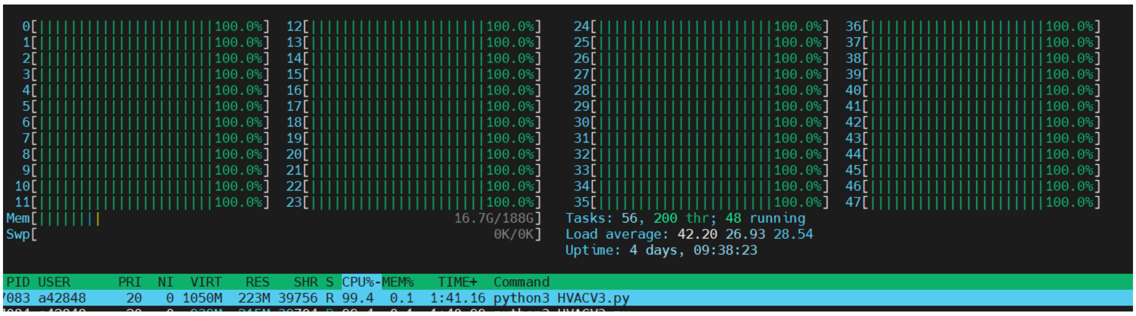

Figure 6. Cores Occupancy of a computing node during a simulation driven by PyCATSHOO

Moreover, FMUs must be compatible with various operating systems on the targeted high-performance computers. However, not all simulation engines that generate FMUs offer equal portability across different operating systems. Hence, it's essential to remain vigilant about potential performance variations among FMUs generated by these tools for different operating systems.

5.1. Outcomes and Contributions of the Hybrid Approach

5.1.1. Assessment in case of initiating event

This calculation assumes a simultaneous loss, occurring at time 0, of the chillers in both buildings. The aim is to ascertain the duration available for repairing at least one of the two chillers before the temperature surpasses the critical threshold, and even before the I&C systems encounter intrinsic failures, which become more likely with increasing ambient temperatures in both buildings.

In such a scenario of chiller loss, a conventional Boolean approach would categorize the I&C systems as lost at time 0. Hence, no comparison of occurrence probabilities between the classical and hybrid approaches will be conducted at this stage. Our focus here lies in evaluating the grace periods. We conducted an initial calculation where we disabled any possibility of chiller repair while still considering the potential occurrence of other failures on the remaining components throughout the simulated period. The outcome of this initial calculation is depicted in Figure 7.

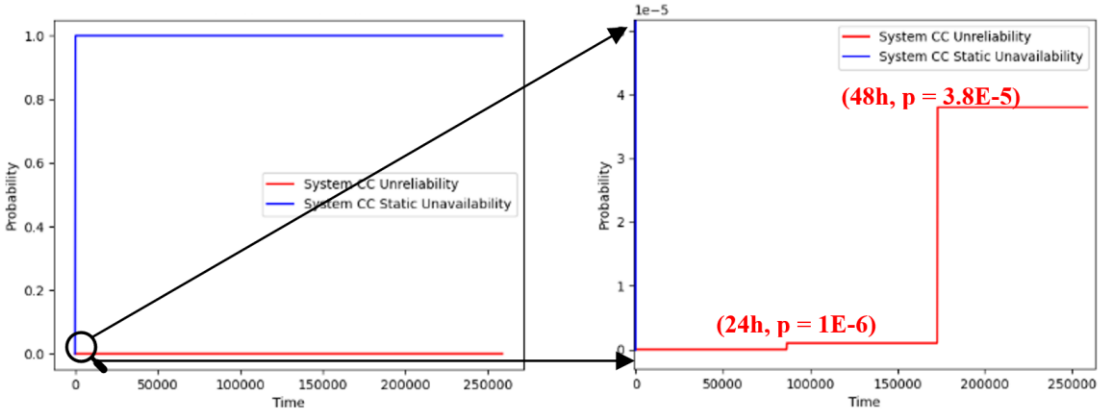

Figure 7. Unreliability in case of simultaneous loss of both I&C according to the classic approach in blue and to the hybrid approach in red

A closer examination of the unreliability curve, calculated using the hybrid approach (depicted in red in Figure 7), enables us to pinpoint the probability threshold deemed unacceptable by the operator. When plotted against the time axis, this reveals the timeframe preceding the attainment of this probability. This duration represents the grace period available for repairing at least one of the two chiller units. Assuming the unacceptable probability to be 1E-6, this grace period equates to 24 hours. Thus, the hybrid approach furnishes us with insights into a pragmatic grace period, encompassing potential failures that may manifest after the initiating event. Termed the probabilistic grace period, this information is evidently more cautious than the deterministic grace period typically derived by disregarding any possibility of post-initiator failures. Figure 8 illustrates the outcome of such a calculation, where we suppressed, in our model, all failures of the remaining system components. Only the assumption of the certain failure of the I&C systems, after surpassing the critical temperature threshold set arbitrarily at 55°C in our study, was retained. According to this approach, the deterministic grace period amounts to 84 hours. This period is notably more optimistic than the probabilistic grace period.

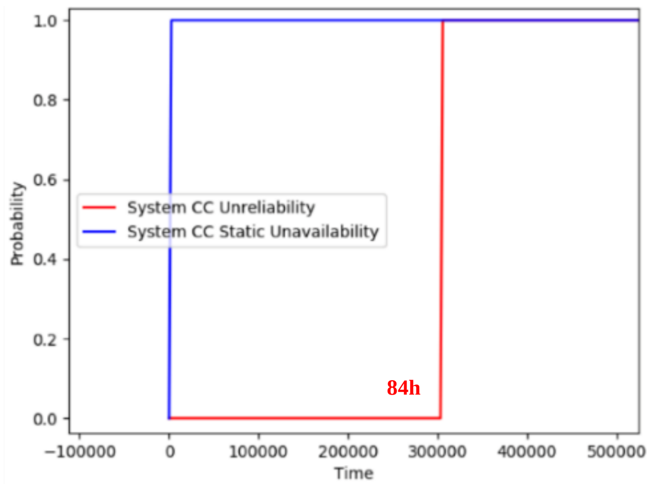

Figure 8. Deterministic grace period calculated with the classical approach.

5.1.2. Assessments without initiating events

As previously stated, we conducted simulations for three scenarios with different power density values emitted within the buildings: 200, 300, and 400 W.m^{-2}. In these scenarios, we assessed the probabilities of the undesirable event, specifically the simultaneous loss of both I&C systems in both buildings. Our aim was to compare the results obtained from conventional calculations (green curves in Figure 9) with those derived from the hybrid approach advocated by PyCATSHOO (red curves in Figure 9).

The notable observation concerns the difficulty of determining whether the conventional approach is optimistic or pessimistic. It is obvious that only simulations faithfully reflecting the real behaviour of the system can overcome this difficulty. This is demonstrated in Figure 9, where the conventional approach is pessimistic compared to the hybrid approach for thermal power densities of 200 and 300 W.m^{-2}. However, as the rightmost curves in Figure 9 show, the conventional approach turns out to be too optimistic when the thermal power density is 400 W.m^{-2}.

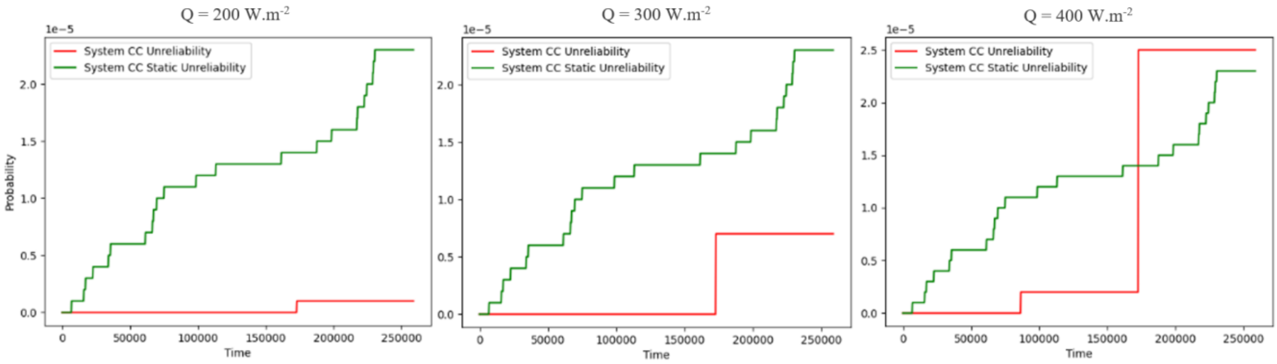

Figure 9. Cumulative probabilities of loss of both I&C according to classical and hybrid approaches, for the three thermal power densities 200 W.m^{-2}, 300 W.m^{-2}, and 400 W.m^{-2}.

6. CONCLUSIONS

We carried out a probabilistic study by closely coupling a physical model with a model reproducing the discrete stochastic behaviour of an HVAC system. We based this coupling on the FMI standard using the encapsulation of the physical model in an FMU, while respecting the principles of the PyCATSHOO hybrid simulation engine.

The technical feasibility of this integration has been demonstrated, and the effectiveness of the simulation drivers produced by PyCATSHOO has been highlighted, particularly their capability to handle parallelism on high-performance computing platforms.

Furthermore, we have shown that integrating a discrete stochastic world with a continuous deterministic physical world in probabilistic studies can provide valuable insights into various performance criteria, such as reliability and safety. The first insight regards the concept of a probabilistic grace period, offering a more realistic perspective than the classical notion. The second insight relates to the optimistic or pessimistic nature, crucial in safety studies. Our findings suggest that this nature depends on the study's data and that the hybrid approach we employed can objectively reveal it.

Although this study demonstrates the suitability of the hybrid approach for complex systems, additional efforts are still needed to address the computational time challenge. High-performance computing contributes to this effort, alongside our ongoing work to accelerate Monte Carlo simulations via variance reduction techniques such as importance sampling suitable for piecewise deterministic Markov processes.

The next phase is to formulate a methodology for developing surrogate models for our physical models, suitable for integration with discrete stochastic models. This objective poses two main challenges. Firstly, the substitution model must reproduce the multimodal character of the original physical model, which is subject to stochastic events that modify its mode of operation during a simulation. Secondly, the multitude of modes that the substitution model must be able to reproduce means that learning requires a huge amount of data. Although this data comes from simulations using the original model, the learning can be a real challenge.

References

[1] H. Chraibi, J.C. Houdebine, A. Sibler. PyCATSHOO: Toward a new platform dedicated to dynamic reliability assessments of hybrid systems. PSAM13 (2016).

[2] H. Chraibi, J.C. Houdebine, C. Picoco, V. Rychkov. Integrated dynamic probabilistic safety assessments with PyCATSHOO: a new coupling approach. PSAM16 (2022).

[3] Modelica Association. "Functional Mock-up Interface for Model Exchange and CoSimulation", Document version 2.02 (2020). https://github.com/modelica/fmi-standard/releases/ download/v2.0.3/FMI-Specification-2.0.3.pdf.

[4] Dynamic Modeling Laboratory/Dassault Systems. https://www.3ds.com/products/catia/dymola.

[5] P. Borel, F. Marsollier – TaeZoSysPro library – https://gitlab.pam-retd.fr/TAeZoSysPro

[6] Carroll, Joseph A. An MRT method of computing radiant energy exchange in rooms. System Simulation and Economic Analysis (1980): 343-348.

[7] A.B. Temsamani, S. Kauffmann, Y. Descas, B. Vandevelde, F. Zanon, G. Willems. Improved and accurate physics-of-failure (PoF) methodology for qualification and lifetime assessment of electronic systems, Microelectronics Reliability, Volumes 76–77, 2017, Pages 42-46.

[8] https://github.com/open-mpi/ompi