# Uncertainty Analysis of a Hardware in Loop Setup for Testing Products Related to Building Technology

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***Abstract*****—**Hardware in Loop (HIL) testing is done to test and validate a particular product especially in building technology. When it comes to building technology, it is more important to test the products for their efficiency. The test rig in the HIL simulator may contribute to some uncertainties on measured efficiency. The uncertainties include physical uncertainties and scenario-based uncertainties. In this paper, a simple uncertainty analysis framework for an HIL setup is shown considering only the physical uncertainties. The entire modeling of the HIL setup is done in Dymola. The uncertain sources are considered based on available knowledge of the components and also on expert knowledge. For the propagation of uncertainty, Monte Carlo Simulation is used since it is the most reliable and easy to use. In this article it is shown how an HIL setup can be modeled and how uncertainty propagation can be performed on it. Such an approach is not common in building energy analysis.

***Keywords*****—**Energy in Buildings, Hardware in Loop, Modelica (Dymola), Monte Carlo Simulation, Uncertainty Propagation.

## I. Introduction

The HIL methodology considers the system dynamics and encompasses a comprehensive investigative system [1]; the advantage is that this method allows one to study the product under realistic dynamic boundary conditions. In such methodology, the three important challenges are the test rigs that emulate the realistic and the dynamic boundary conditions. A simulation model of the building validated against experiments represents the real system. The actual period of one year could be reduced to a smaller set of representative days. In literature, there are many ways to choose representative days for testing, as shown in [2], in order to obtain the seasonal efficiency of the product by extrapolation later onwards. The next question is will there be uncertainty due to the test bench components on the efficiency that is being measured. There are experimental and parametric uncertainties, the parametric uncertainties are to be treated in this article. In this article, the emphasis is given for the physical uncertainty, since for the scenario based uncertainty, one requires extensive real-time testing. The schema of the HIL setup is shown in Fig. *1*. This HIL setup is then modeled in Modelica. The virtual part contains a single zone building that requires space heating for the winter season. The building has 70 $m^2$ of floor area and is only a single zone; the windows are sized to 40% of the wall area on all four walls. The product to be tested is the boiler with a maximum heat flow output of 22.3 kW and a minimum heat flow rate of 8 kW. The maximum heating requirement of the single zone building is 15 kW. The single zone building has a hydronic system and radiator that distributes heat for the building.

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## II. Test Rig

In a real-world operation, the test rig consists of a Plate Heat Exchanger (PHEX) with the primary side connected to the boiler and the secondary side connected to the cooling unit. The pump in the primary side receives the mass flow setpoint from the building model. The pump in the secondary side receives its return temperature setpoint for each time step from the building model based on the space heating requirement. Based on the return temperature setpoint from the building model, the secondary pump draws cold water for the heat exchange in PHEX for replicating the heat transfer in the building. The heat exchanger in the test rig is the representation of the building in the Dymola model. The test rig with the heat exchanger, the pumps, the boiler and the cooling unit form the real part of the HIL setup. The mass flow rate setpoint is used for supplying the hot water to the building; the input temperature is taken from sensors in the test rig which measures the supply temperature of the boiler. While the building model in Dymola forms the virtual component. For the hardware in loop simulation OPC 2.0 protocol is used for the closed loop communication. This entire setup is then modeled in the Dymola (including both the real and the virtual part) for performing the Monte Carlo Simulation.

### *A. Assumptions on Modeling*

The model of the test rig is done based on the expert knowledge and physical inspection (physical model of the test rig is shown in Fig. *2*). Some of the assumptions are: The cooling unit is replaced by a cool boundary source with a constant temperature of 15 °C. The existing model of the boiler in the Buildings library in Dymola is used. No heat losses in the pipes are considered and there are no heat losses between the test rig and the surroundings. This can be later added to the Dymola model when the test rig will become operational. The pipes are considered ideal pipes and no losses are assumed. The weather data chosen are for Trappes, France. The representative days for testing are chosen based on K-means clustering. More information on the K-means clustering and other clustering techniques is available in [2]. The number of days chosen are seven days (selected from a year's data). The supply temperature of the hot water from the boiler for the space heating is set to 55 °C while the return temperature is left freely which is a direct effect of the heat transfer in the building. The entire HIL setup operation is studied virtually using Dymola. Such an approach for modeling the Real Time Hybrid Setup (RTHS) is accepted widely, as explained in [3].

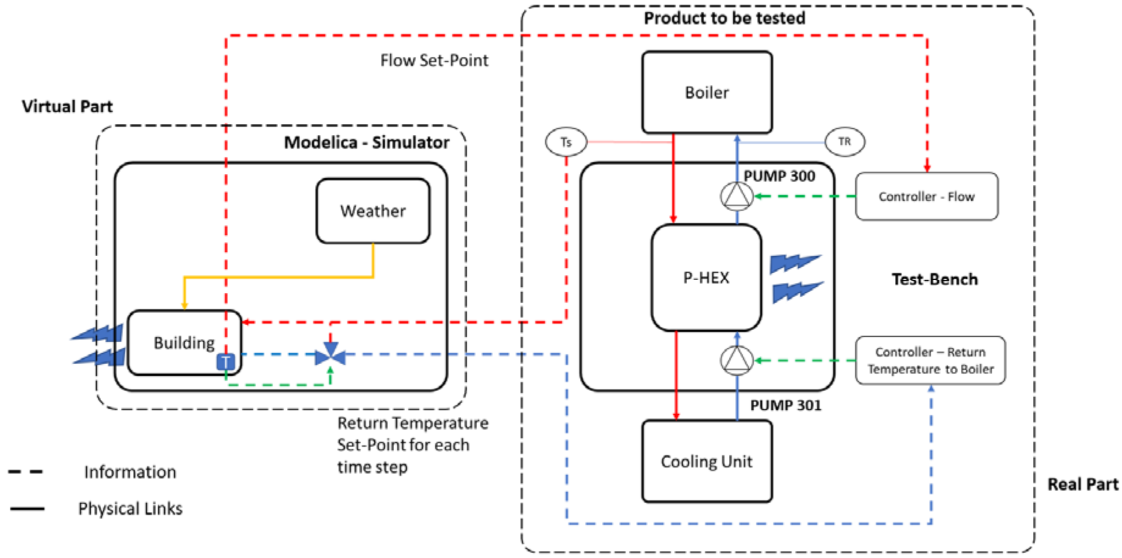


Fig. 1 Schema of HIL simulator

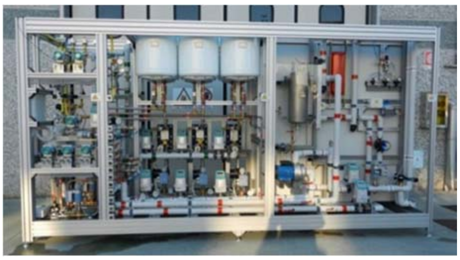

Fig. 2 Physical view of the test bench

Before going into further experimentation with the Dymola model, it is important to check if our modeling process is correct. This can be verified by comparing the heat flow rate in the building model and the heat exchanger model, such that both should be same at least in the steady state, as shown in Fig. *3*. The temperature measurement inside the building is used to vary the flow rate of the hot water from the building since it is just a single zone building.

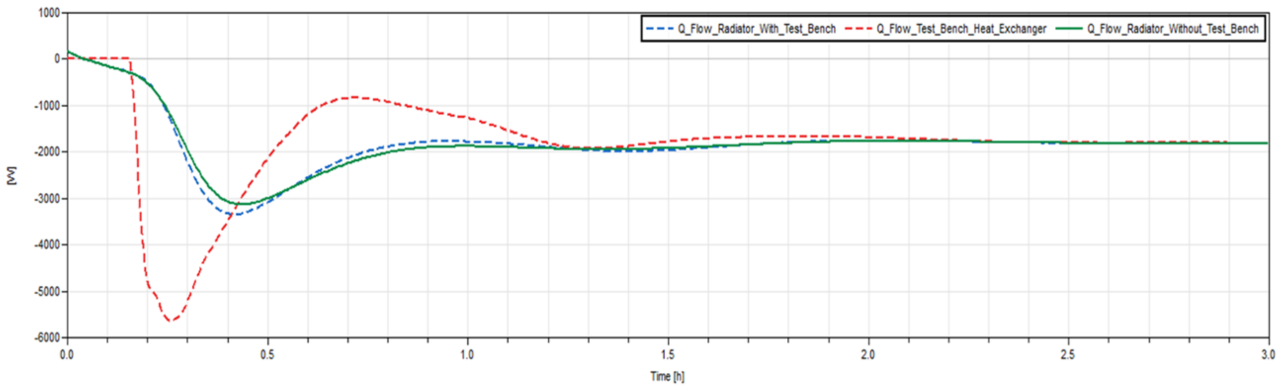


Fig. 3 Verification of the model by comparing heat flows between building and heat exchanger

## III. Uncertainty Propagation

For the propagation of the uncertainty there are four steps. The first step is to develop the model of the system. The second step is to identify the sources of uncertainties; in this case we consider only the physical uncertainties (parametric uncertainty) of the test rig and assigning the probabilistic distributions to the uncertain parameters. The third step is to perform the uncertainty propagation and the fourth step is improving the process by gaining knowledge on the system.

The modeling was done on Dymola and the previous section gave a brief explanation about the modeling.

### A. Sources of Uncertainty

Considered sources of uncertainty are the parameters of the test rig. It includes the temperature sensor uncertainty; the nominal heat flow value of the heat exchanger is important because the Dymola model uses this value to generate the heat effectiveness coefficient which in turn affects the operation of the heat exchange. The uncertainty in the bends is considered because the increase in the diameter and the radius of curvature of the bends can cause pressure losses. The angles of the bends also affect the pressure loss in the test bench, but the knowledge of this angle is available from physical inspection and also from the data sheets. There are two types of uncertainty, one is the inherent physical uncertainty and the other is uncertainty due to the absence of knowledge as mentioned in [5]. For physical uncertainties it is better to represent the uncertainties in the form of probability distributions [6].

### B. Uncertainty Ranges and Distribution

The uncertainty ranges for the sources chosen are determined from both the data sheets of the components and also based on expert opinion. The probability distributions for the uncertainties are fixed as uniform distribution. The reason is that it is a common approach as mentioned in [5]. Otherwise for parametric uncertainty distributions, one can choose readily the normal distribution also explained in [5]. The sources of uncertainty, their ranges and the distribution are shown in Table I. There are around 16 bends of three types; altogether there are around 35 parameters which are uncertain as per the understanding at the time of writing this article.

TABLE I
UNCERTAIN SOURCES, RANGES AND DISTRIBUTIONS

| Uncertain Source | Range | Distribution Type |
|---|---|---|
| Temperature sensor supply side | -0.3 °C to +0.3 °C | Uniform |
| Temperature sensor return side | -0.3 °C to +0.3 °C | Uniform |
| Nominal heat flow value of heat exchanger | 29.83 kW to 34.245 kW | Uniform |
| Bend Type A- Hydraulic Diameter | 39.74 mm to 40.74 mm | Uniform |
| Bend Type B – Hydraulic Diameter | 33.2 mm to 34.2 mm | Uniform |
| Bend Type C – Hydraulic Diameter | 26.4 mm to 27.4 mm | Uniform |
| Bend Type A – Radius of Curvature | 46 mm to 50 mm | Uniform |
| Bend Type B – Radius of Curvature | 36 mm to 40 mm | Uniform |
| Bend Type C – Radius of Curvature | 27 mm to 31 mm | Uniform |

### C. Monte Carlo Simulation

For the uncertainty propagation, the method chosen is based on classical Monte Carlo simulation since it is one of the simplest and a reliable method. The Dymola model is subject to an N number of simulations, picking a random draw for all the 35 uncertain parameters. A more detailed description of the Monte Carlo simulation is explained in [4]-[6]. The only downside of the choice of the Monte Carlo simulation corresponding to this case is that since the model is so detailed, the time taken for higher number of Monte Carlo sampling results in unfeasibly longer time.

## IV. Results and Analysis

The Monte Carlo simulation is performed for the HIL setup model using the Design library in DYMOLA. The simulation is run for N = 1000 samples. The choice is made for N based on the available computing power of the PC performing the simulation. The results obtained from the Monte Carlo simulation for the efficiency of the boiler over 7 days is shown in Fig. *4*.

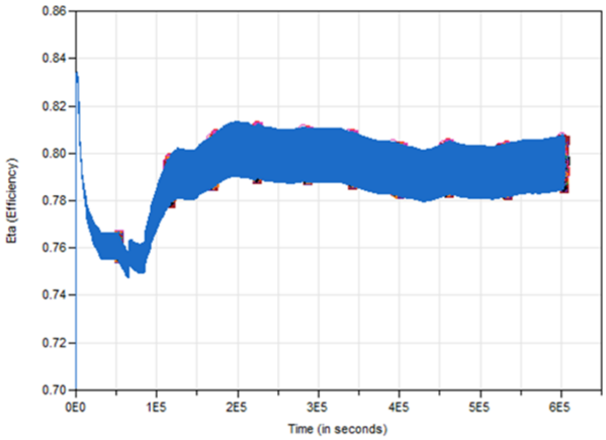


Fig. 4 Monte Carlo simulation results for efficiency over 7 days

From Fig. *4*, it can be seen that the value of efficiency does not vary too much over the period of 7 days since it consistently hits the 79% to 81% over the time. Moreover, from the simulation, the expected value for the boiler efficiency is 0.797056 and the standard deviation is 0.0050624. This shows that the uncertainty related to the physical aspects do not cause much uncertainty. This could be further asserted with the fact that the standard error for the efficiency could be found as ± 1.6 e-4. The cumulative probability is obtained as shown in Fig. *5*. The cumulative distribution shows that the more frequent value is 0.797556, based on the slope. The standard deviation and the expected values for the different number of samples are shown in Fig. *5*. It can also be inferred that more than the physical uncertainties, it would also be important to consider the scenario-based uncertainties. This could be established with solid experiments once the test rig will become operational. Different values of the expected values and the standard deviation are shown in Table II.

Since the number of samples becomes the deciding factor for the confidence interval for the same 1000 samples for the 95% confidence interval, the uncertainty can be represented as 0.797 ± 3.14 e-4. Examining the cumulative distribution function, it is evident that not a lot of values fall under this range. Hence, from the result it is evident that more samples of Monte Carlo simulations are required to confirm the accuracy and to finalize that the physical uncertainty can be neglected and more emphasis can be given to the scenario-based uncertainty. But the problem here is the computing resource. Moreover, from Table II it is relevant that by increasing the number of samples for the Monte Carlo simulation, one can achieve the required confidence interval.

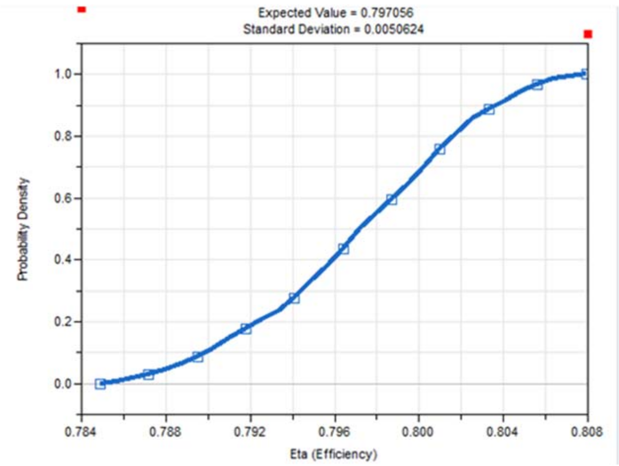


Fig. 5 Cumulative distribution for 1000 samples

TABLE II
MONTE CARLO SIMULATION BASED ON NUMBER OF SAMPLES

| N | Mean | Standard Deviation |
|---|---|---|
| 50 | 0.796745 | 0.00402496 |
| 100 | 0.797243 | 0.00471830 |
| 200 | 0.796624 | 0.00461927 |
| 500 | 0.797391 | 0.00479472 |
| 1000 | 0.797056 | 0.0050624 |

## V. CONCLUSION AND FUTURE SCOPE

From the uncertainty framework adopted it is evident that one needs to have a very fast model. The model used here is a very detailed model and of a very higher order, moreover in the uncertainty propagation one requires a very high number of samples to compute the uncertainty. The very next issue is that the choice modeling the uncertainty also decides the in the future it would be important to use a probability box as shown in [4], where one can assign the probability distribution to both the physical parameters and also the hyper parameters of the Probability Distribution. This is very important because when the knowledge about which distribution is absent, it could be very important to use the second order probability. It would also be important to perform a model order reduction or to develop a surrogate model for performing the uncertainty propagation. It would also be interesting to project the controller gains as an uncertain parameter since a small change in these values could lead to a different outcome. We take the case of the secondary pump control in the test rig, by making a very small change in the controller gains, the return temperature value varied considerably when compared to the return temperature from the building, meaning that this could lead to different heat flow values between the building and the PHEX. The next step is to add the scenario uncertainties as well. Finally, such modeling of the HIL setup could allow us to make simulations in order to make useful inferences before engaging in the real testing of the components. Another future work could be making a sensitivity analysis on such models to find out the most important parameter that could affect the outcome. For the future, weather data could also be considered where one could add the uncertainty on the temperature and the irradiation data. The next steps will be also to focus on a convergence criterion for the Monte Carlo simulation; one method could be to also use stochastic accelerated approaches to reduce drastically the simulation time. It would also be useful to consider the dynamic boundary conditions with uncertainty.

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