Towards a Common Standard for Uncertainty Quantification

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Abstract

Uncertainty Quantification (UQ) studies allow us to determine whether a model is fit for a particular purpose, as well as the operational domain in which it can be used. Standardising the UQ analysis setup and result summary enables the iterative composition of UQ information, which is a crucial step in evaluating model credibility. In this paper, we present an initial attempt to specify UQ information as a cross-layer standard for Modelica-, FMI-, and SSP-based workflows subject to two essential restrictions: (a) uncertainties can only be described in terms of parameters, and (b) analysis is limited to forward uncertainty propagation and sensitivity analysis of nonlinear models. More analysis features are planned for the future. The approach is illustrated using both a simple example and an industrial use case.

Keywords: Uncertainty Quantification, Credibility, Standardization, Operational Domain, FMI, SSP, Modelica

1 Introduction

Simulation models provide an approximation of reality with different degrees of accuracy, which has a direct impact on the context in which these models are usable. Through use case analysis in the ITEA OpenSCALING research project[1], we have identified the following workflows that rely on UQ:

- choosing a model with the appropriate level of representativeness and complexity for the specific application context,
- evaluating the model's overall uncertainty based on the propagation of uncertain parameters,
- performing model validation,
- conducting global sensitivity analysis of parameters, and
- improving the accuracy of data measurements.

In this paper, we propose a data model for capturing uncertainty quantification in a unified way across different workflows and thus facilitating the exchange of models, including metadata, between different stakeholders.

Furthermore, we show how this data model can be integrated into Modelica[2], Functional Mock-up Interface (FMI)[3], and System Structure and Parametrization (SSP)[4] based workflows.

The paper is structured as follows; Section 2 provides the motivation for the standard. Section 3 presents a simple forward UQ study while Section 4 introduces an industrial use case. The data model is outlined in Section 5, and Section 6 describes integration mechanisms with Modelica Association (MA) standards. Finally, Section 7 outlines future directions, and Section 8 concludes the paper.

2 Background and Motivation

Machine-interoperable traceability is vital for transparent model validation and reduces reliance on implicit knowledge transfer (Rosenlund et al. 2025; Otter et al. 2022). The *SSP Traceability standard* draft (SSP LS Traceability)[5] incorporates Simulation Resource Meta Data (SRMD) to capture verification activities, intended use, and operational domain, supporting automated model suitability evaluations. Embedding such structured metadata, either via SRMD or directly in models, streamlines validation, supports long-term credibility assessments, and aligns with industry standards like NASA STD-7009 [6]and LOTAR[7]. The recent Credible Simulation Process (CSP) initiative formalizes continuous simulation credibility processes using SSP-based layering (Ahmann et al. 2022; Heinkel and Steinkirchner 2021).

A model's credibility depends on how accurately it represents reality. Ensuring credibility requires rigorous verification, validation, and UQ frameworks, see, e.g., *the NASA Handbook for Models and Simulations* [8] (Roy and

[1]https://itea4.org/project/openscaling.html.

[2]https://modelica.org/language/
[3]https://fmi-standard.org/
[4]https://ssp-standard.org/
[5]https://github.com/modelica/ssp-ls-traceability
[6]https://standards.nasa.gov/standard/nasa/nasahdbk-7009
[7]https://lotar-international.org/
[8]https://standards.nasa.gov/standard/nasa/nasahdbk-7009

Oberkampf 2011; Riedmaier et al. 2021). UQ systematically evaluates confidence in model predictions. Techniques such as probabilistic analysis and sensitivity studies help quantify and propagate uncertainties, guiding confident interpretation of simulation results (Hällqvist et al. 2023; Otter et al. 2022).

Predictive capability extends validation by assessing model performance across the entire feasible input space, not just tested scenarios. Hallqvist et al. (Hällqvist et al. 2023) propose *entropy-based* (Shannon 1949; Kullback and Leibler 1951) and *coverage-based* (Atamturktur et al. 2015) metrics to quantify a model's numerical representativeness in both interpolation and extrapolation scenarios. These metrics provide a quantitative foundation for evaluating whether a model remains valid when applied outside its validated input and parameter space.

3 Simple Use-Case: DC Motor

This section presents a forward UQ study propagating uncertainties in a simple DC motor model. This kind of study can be used to answer engineering questions, such as whether at least 95% of the produced DC motors meet the requirement of reaching the declared idle speed. In other words, the aim is to assess the impact of production and material tolerances on the DC motor's steady-state idle speed.

It is assumed that a standardized procedure and supporting tooling are in place to enable this type of analysis independently of the chosen modeling tool. The task of developing a functional behavioral model of the DC motor is assigned to a simulation engineer, who is free to select the most appropriate modeling environment. The resulting model is delivered in executable form, accompanied by a specification of the experiment setup. This setup defines the static boundary conditions, parameter values, estimated distributions for uncertain parameters, and the quantities of interest to be analyzed. In addition, all metadata required to perform the analysis in the target environment in a repeatable and automated manner must be provided in a machine-readable format.

An investigation of the physical behavior of the DC motor found that the relevant dynamics can be captured by the balance equations for electrical voltage and mechanical torque, resulting in the two differential Equations (1) and (2) implemented in Modelica.

$$V = R \cdot I + L\frac{dI}{dt} + c_m \cdot \omega \tag{1}$$

$$J \cdot \frac{d\omega}{dt} = c_g \cdot I - d \cdot \omega + T_{load,mech} \tag{2}$$

In both equations, the following variables are defined:

- V $[V]$: Supply voltage,
- I $[A]$: Winding current,
- R $[\Omega]$: Winding resistance,
- L $[H]$: Winding inductance,
- c_m $[V \cdot s/rad]$: Electrical motor constant,
- $T_{load,mech}$ $[Nm]$: Mechanical load,
- ω $[rad/s]$: Motor velocity,
- $J[kg \cdot m^2]$: Rotor inertia,
- c_g $[N \cdot m/A]$: Mechanical motor constant,
- d $[N \cdot m \cdot s/rad]$: Mechanical friction coefficient.

To keep the investigations simple, only two physical parameters are defined as *uncertain parameters* and are described with the following two stochastic distributions:

- R: $\mathcal{N}(\mu = 0.1\ [\Omega], \sigma = 0.01\ [\Omega])$
- L: $\mathcal{U}([0.105,\ 0.115]\ [mH])$

The Probability Density Functions (PDFs) related to R and L are displayed in Figure 1, assuming a Gaussian normal distribution[9] $\mathcal{N}$ and resp. a uniform distribution[10] $\mathcal{U}$.

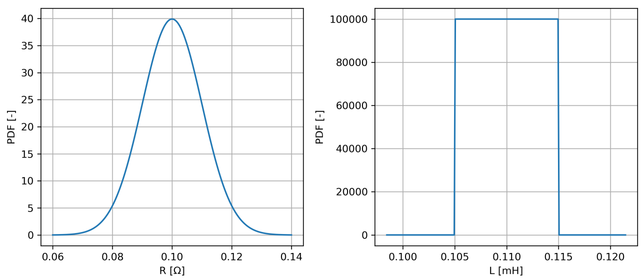

Figure 1. Representation of the uncertain parameters R and L as PDF

The remaining physical parameters are kept constant along with the voltage at the terminals and the mechanical load.

The motor is initially at rest ($I(t=0) = 0\ [A], \omega(t=0) = 0\ [rad/s]$) and accelerates in response to the input voltage V, assuming zero mechanical load torque ($T_{load,mech} = 0$), until it reaches steady-state. The objective is to quantify the uncertainty in the steady-state motor speed, expressed as ω_∞[rad/s] or equivalently $n_{\text{rpm},\infty} = \omega_\infty \cdot \frac{30}{\pi}$[rpm], based on the uncertainties in the electrical parameters R and L. To this end, the uncertain parameters are sampled using Latin Hypercube Sampling, and a simulation is carried out for each sample. The resulting data is used to estimate the Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of the steady-state motor speed.

All the information required to configure the forward UQ experiment, such as the problem description, model reference, parameter definitions, observed variables, experiment settings, and desired results, is listed in a corresponding `.xml` file. In this file, a reference to an `.ssv` file might be present, which is the standard way in SSP to store parameters and their values. The UQ XML file can be accessed via scripting during all stages of a forward UQ workflow, including pre-processing, simulation,

[9] https://en.wikipedia.org/wiki/Normal_distribution

[10] https://en.wikipedia.org/wiki/Continuous_uniform_distribution

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and post-processing. External references to result files or summaries are included where needed, see Figure 2.

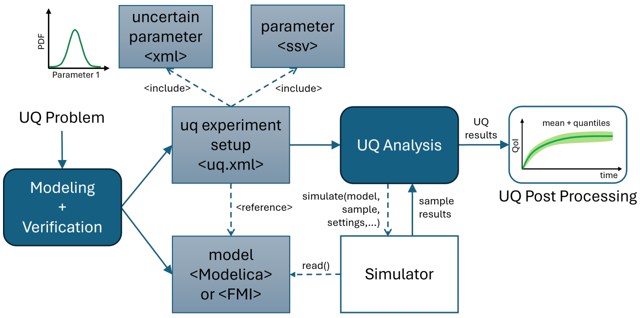

Figure 2. Forward-UQ workflow: Artifacts and processing steps

For the simple DC motor example, the following data is provided in the `.xml-file` defining the forward UQ experiment:

```
<!-- ... -->
 <uq:ParameterSet> <!-- Super set of SSP -->
  <uq:Parameters>
    <uq:UncertainParameter name="R">
      <uq:Normal mu="0.1" sigma="0.01"
         unit="Ohm"/>
    </uq:UncertainParameter>

    <uq:UncertainParameter name="dcMotor.L">
      <uq:Uniform minimum="1.05e-4"
       maximum="1.15e-4" unit="H"/>
    </uq:UncertainParameter>
  </uq:Parameters>

  <uq:Units> <!-- SSP Units -->
    <!-- ... -->
  </uq:Units>
</uq:ParameterSet>

<uq:ObservedVariables>
  <uq:ObservedVariable name ="omega"/>
</uq:ObservedVariables>

<uq:DesiredResults
  data = "dc_motor.mat"
  summary = "dc_motor_result_summary.xml"
  scope = "Trajectory"
  mean = "true"
  pdf = "true"
  cdf = "true">
  <uq:Percentiles level="0.05 0.95"/>
  <uq:SobolIndices order="2" total="true"/>
</uq:DesiredResults>

<uq:SimulationSettings
  stopTime = "0.5"
  interval = "0.01"
  tolerance = "1e-4"
  solver = "DASSL"/>

<uq:SamplingMethod>
  <uq:LatinHypercube numberOfSamples="1000"/>
</uq:SamplingMethod>
```

Note, for every uncertain parameter, a *nominal* value is required that can, for example, be used if only a single simulation run shall be performed. From this data, it is possible to perform the forward UQ experiment computations and to display typical outcomes like:

- The time response of the spreading motor speed $n_{rpm}(t)$, see Figure 3,
- The PDF of the idle motor speed in steady-state, see Figure 4 on the left,
- The CDF of the idle motor speed in steady-state, see Figure 4 on the right,
- The first-order global sensitivity analysis related to the motor speed trajectory over time, see Figure 5.

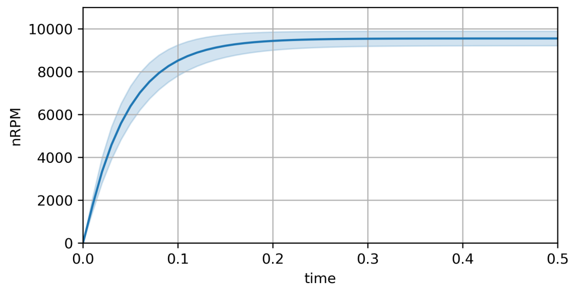

Figure 3. Mean, 5th and 95th percentile of the motor speed time response

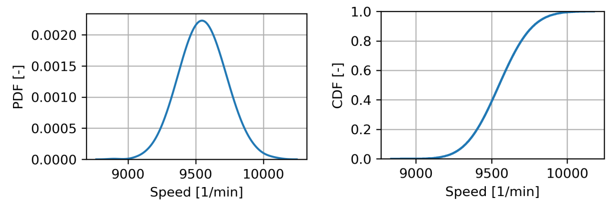

Figure 4. PDF and CDF of the motor speed at steady-state

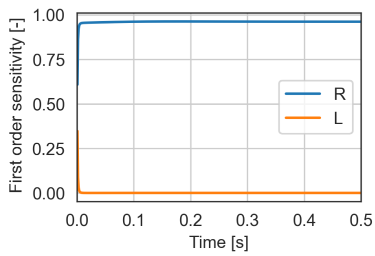

Figure 5. First order sensitivities of the motor speed w.r.t. the uncertain parameters R and L over time until reaching steady-state. The interpretation is that the uncertainty of L is of relevance only during the early start-up phase, while the uncertainty of R dominates the uncertainty of the motor speed at steady-state.

In these investigations,

- The UQ analysis of the DC motor is evaluated for only one operational point (supply voltage $V = 12\ [V]$ and constant mechanical load $T_{load,mech} = 0\ [N \cdot m]$),

- Python[11] has been used to evaluate the forward UQ experiment based on a Modelica model of the DC motor and the experiment definitions from the .xml-file, generating the samples, evaluating the simulations through OMPython[12] and OpenModelica[13], and performing the post-processing to produce the desired results.

This illustrates how the Modelica model, together with the estimated distributions of the uncertain parameter values and the .xml experiment settings based on the draft UQ standard, was used to perform Forward UQ analysis with open-source tools. The complete setup of the open-source tools is available in the draft specification[14]. In the future, the UQ .xml file will most likely be supported by many other tools, such as Modelica-based tools[15] or FMI-based tools[16].

4 Industrial Use Case: Mobile Valve

Parker Hannifin's Hydraulic Valve Systems Division Europe[17] manufactures fluid power valves for a wide range of applications. The factory in Borås, Sweden, specializes in directional valves for mobile working machines. Recently, an increased demand for valve simulation models has been noticed both from customers and internally at Parker. Simulation models are, for instance, useful in control strategy development, energy loss minimization, and functionality verification. To meet these demands, a process for auto-generation of valve models, based on valve specification data, has been developed. During this development, several challenges emerged:

- ensuring simulation tool independence,
- protecting company Intellectual Property (IP),
- shipping model credibility information, such as UQ experiments results, with the models.

The initial solution was to use the FMI standard and ship the models as Functional Mock-up Units (FMUs) providing credibility metadata in the `index.html` file inside the model's FMU directory. However, this limits the reusability of the credibility information in the simulation tool and has a negative impact on traceability, hence the need for a standardized way of shipping model credibility information with simulation models. Within the ITEA OpenSCALING project, Parker has identified a representative use case where a UQ experiment is carried out on a valve model. The UQ results are then packaged along with the model in the standard format proposed in this paper.

[11] https://www.python.org/

[12] https://pypi.org/project/OMPython/

[13] https://openmodelica.org/

[14] https://gitlab.liu.se/openscaling/work-products/d2.1-uq-layered-standard

[15] https://modelica.org/tools/

[16] https://fmi-standard.org/tools/

[17] https://www.parker.com/de/en/divisions/motion-systems-group-europe/resources/about-us/hvse.html

4.1 Valve Model

The valve model is based on the orifice equation, where the relationship between volumetric flow q and pressure drop, $\Delta P = P_1 - P_2$, across the orifice is described according to the time-invariant relationship:

$$q = A\sqrt{\frac{(P_1 - P_2)}{K}} \tag{3}$$

where the parameter K lumps the discharge coefficient and fluid density, see e.g. (Merritt 1967; Miller 1990). The orifice area, A, and K may be identified as uncertain parameters. A model of such an orifice can be defined as having two time-dependent inputs, P_1 and P_2, and two time-dependent outputs $q_1 = q_2 = q$ under the assumption of incompressible flow. The Operational Domain (OD) of this model could be viewed as a space containing all the different feasible combinations of the two inputs P_1 and P_2. The two-dimensional area, encompassing all feasible inputs, can be summarized through a set of points that define (for example) a convex hull.

The valve used in the UQ study is one work section of a proportional, load-sensing, pre-compensated mobile directional control valve in the Parker L90LS series. The core functionality of the valve is to generate a flow[18] that is proportional to an input control current, independently of pump and load pressure variations.

4.2 Scenario

A typical valve test scenario is to connect its work ports to a volume in a closed loop, feed it with constant pump pressure, and investigate the flow and counter-pressure characteristics for different input currents. Manufacturing tolerances lead to uncertainties in valve discharge coefficients, so UQ experiments must be performed to investigate the effect of these uncertainties on flow and counterpressure.

4.3 Experiment Setup

Figure 6 shows the schematics of the model used to carry out the UQ experiment. The UQ model contains the valve model, a hydraulic volume, and other valve model boundaries (e.g., constant pump supply). The valve contains Meter-In (MI) and Meter-Out (MO) orifices that are modelled according to Equation (3). The MI and MO areas (A_{MI}, A_{MO}) are determined by the main spool geometry and controlled by the main spool position via current-controlled pilot valves. In the UQ experiment described here, direction PABT is considered, which means that the main spool position is controlled by input current u_A. Pump (p_p) and load (p_A) pressure-independent flow is realized with a pressure compensator which controls the pressure drop over the MI orifice. Briefly explained, the MI orifice determines the flow (q_A), while the steady-state counterpressure (p_A) is determined by the resistance of the MO orifice for a given flow (q_A).

[18] For example, to a cylinder that controls the boom function of a forestry crane.

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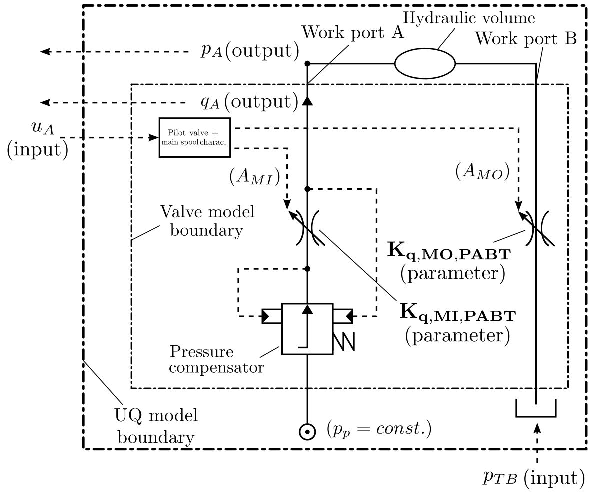

Figure 6. Schematics of the model used for UQ in the Mobile Valve use case. Variables within parentheses represent internal states.

Table 1. UQ model variables.

Variable	Causality	Description
u_A [mA]	input	Valve input A current
p_{TB} [bar]	input	Valve port TB pressure
q_A [l/min]	output	Valve work port A flow
p_A [bar]	output	Volume port A pressure
$K_{q,MI,PABT,gain}$	parameter	MI orifice discharge coefficient (rel.)
$K_{q,MO,PABT,gain}$	parameter	MO orifice discharge coefficient (rel.)

The model is packaged as an SSP-file, where the valve model FMU is connected to another FMU, exported from Hopsan [19], which contains the volume and other valve boundaries. The UQ model has the variables listed in Table 1.

According to the specification, the current $u_A \in [0, 900]$ mA, while the tank pressure $p_{TB} \in [0, 20]$ bar. The model's OD may thus be represented as a rectangle with corner points as listed in Table 2 and illustrated in Figure 7. Note that Figure 7 also shows the UQ model's Domain of Uncertainty Quantification (DoUQ), which is described in the next section.

Table 2. Valve UQ model operational domain coordinates.

Point nr.	u_A [mA]	p_{TB} [bar]
1	0	0
2	0	20
3	900	20
4	900	0

4.4 UQ Definition

For this example, UQ experiments are carried out at points whose coordinates are listed in Table 3, representing locations within the model's OD.

[19] `https://liu.se/en/research/hopsan`

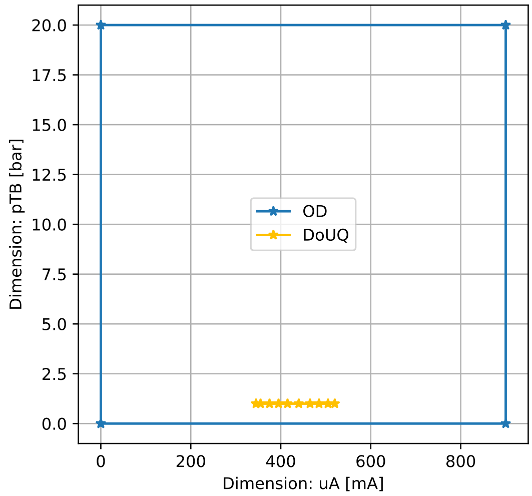

Figure 7. Operational domain (OD) and domain of uncertainty quantification (DoUQ) of the valve UQ model.

Table 3. Valve UQ model domain of uncertainty quantification points.

Point nr.	u_A [mA]	p_{TB} [bar]
1	345	1
2	355	1
3	375	1
4	395	1
5	415	1
6	440	1
7	465	1
8	485	1
9	505	1
10	525	1

Within the UQ experiment, uncertain model parameters are defined explicitly, while the resulting model output uncertainties represent the experiment outcomes. The relative discharge coefficients of the MI and MO orifices are assumed to be uncertain and follow truncated normal distributions, as specified in Table 4.

The experiments conducted here constitute forward UQ, where the uncertainties in the relative discharge coefficients are propagated through to the port A flow and pressure (q_A and p_A). For this example, the relationships between the uncertain parameters and these observed variables can be described by the simplified expressions given in Equation (4).

$$
\begin{aligned}
q_A &= A_{MI}\sqrt{\frac{\Delta p_{MI}}{K_{q,MI,PABT}}} \\
p_A &= p_{TB} + \left(\frac{A_{MI}}{A_{MO}}\right)^2 \Delta p_{MI}\frac{K_{q,MO,PABT}}{K_{q,MI,PABT}}.
\end{aligned} \tag{4}
$$

Table 4. Valve UQ model domain of uncertainty quantification coordinates. The uncertainties of the two parameters are estimated and are described with truncated normal distributions with parameters μ, σ. *: The valve model's name in the SSP-file is "valve_model".

Uncertain Parameter	Minimum	Maximum	μ	σ
valve_model.KqMI_PABT_gain*	0.8	1.2	1	0.1
valve_model.KqMO_PABT_gain*	0.8	1.2	1	0.1

4.5 UQ study in FMI

A MonteCarlo-sampling with 1000 samples was done to generate samples of the two observed variables q_A, p_A, using the UQPy python package (Olivier et al. 2020). Figure 8 shows histograms of the sample sets.

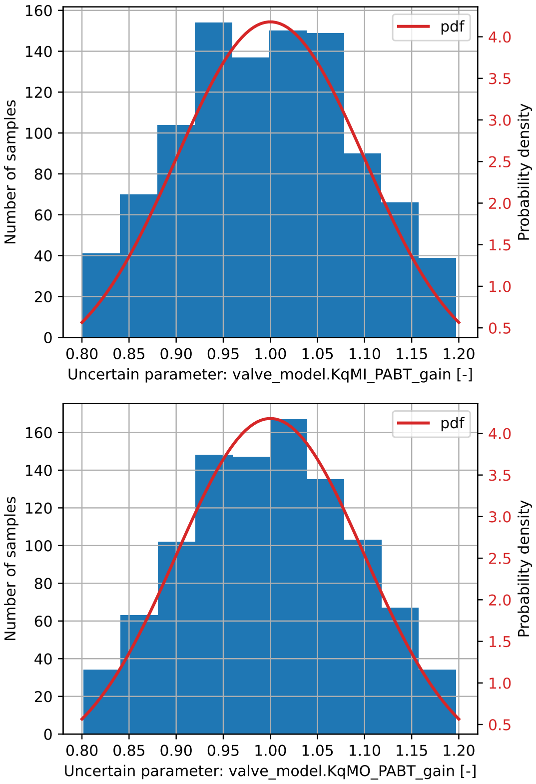

Figure 8. Histogram of 1000 samples of each of the uncertain parameters.

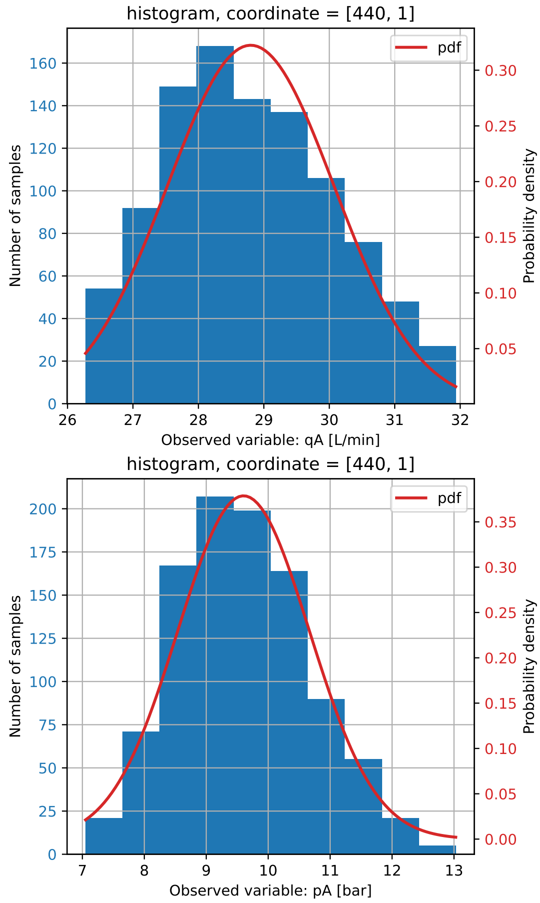

Figure 9. Histogram of 1000 samples from one Monte Carlo simulation run for each of the observed variables at operating point $u_A = 400$ mA, $p_{TB} = 1$ bar.

The UQ model was simulated with the Python API of OMSimulator. The simulation was executed for all samples at each coordinate of the DoUQ. Each simulation was run until a steady-state was reached on all model outputs. This resulted in one sample set for each output at each operating point, with 1000 samples in each set. These sample sets were then fitted to truncated normal distributions with minimum, maximum, mean (μ), and standard deviation (σ). Figure 9 shows an example of the distribution of the two observed variables at one operating point. Table 5 and 6 show the resulting fits at all experiment points for the observed variables q_a and p_A, respectively.

Figure 10 shows violin plots of the data in Tables 5 and 6. Based on these results some observations can be made:

- Uncertainty in flow q_A due to uncertainty in discharge coefficient is higher at higher current (u_A) levels, as the MI orifice area (A_{MI}) is higher at higher currents. This, in turn, results in a greater amplification $K_{q,MI,PABT} \rightarrow q_A$ (see Equation (3)). A similar reasoning may be applied to explain the larger uncertainty in p_A at higher current levels,
- Uncertainty in orifice discharge coefficients has a higher impact on the uncertainty of p_A than that of q_A. This may be illustrated by the simplified analytical expressions of q_A and p_A in equation (4); q_A primarily depends on $K_{q,MI,PABT}$, while p_A depends on both discharge coefficients.

The .xml definition of the Forward UQ Experiment and the results are shown in Listing 1 and Tables 5-6, respectively.

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Table 5. Statistical data of the observed variable q_A [L/min] for all UQ experiments fitted to truncated normal distributions.

		q_A [L/min]			
ID	Points [uA [mA], pTB [bar]]	Minimum	Maximum	μ	σ
1	[345, 1]	0.013	0.016	0.015	0.00067
2	[355, 1]	0.41	0.5	0.45	0.021
3	[375, 1]	2.6	3.2	2.9	0.13
4	[395, 1]	6.1	7.5	6.7	0.3
5	[415, 1]	12	15	13	0.6
6	[440, 1]	26	32	29	1.3
7	[465, 1]	42	51	46	2
8	[485, 1]	54	65	59	2.5
9	[505, 1]	59	71	64	2.7
10	[525, 1]	59	71	64	2.7

Table 6. Statistical data of the observed variable p_A [bar] for all UQ experiments fitted to truncated normal distributions.

		p_A [bar]			
ID	Points [uA [mA], pTB [bar]]	Minimum	Maximum	μ	σ
1	[345, 1]	1.3	1.4	1.3	0.02
2	[355, 1]	3.3	4.2	3.7	0.17
3	[375, 1]	5.0	7.3	5.8	0.36
4	[395, 1]	5.7	9.7	7.2	0.77
5	[415, 1]	6.3	12.0	8.6	0.94
6	[440, 1]	7.1	13.0	9.6	1.1
7	[465, 1]	7.3	13.0	9.9	1.1
8	[485, 1]	7.4	14.0	10.0	1.1
9	[505, 1]	7.4	14.0	10.0	1.1
10	[525, 1]	7.4	14.0	10.0	1.1

Listing 1. The `ForwardUncertaintyQuantification` element from the mobile valve use case

```xml
<!-- ... -->
 <uq:ParameterSet> <!-- Super set of SSP -->
  <uq:Parameters>
   <uq:UncertainParameter
     name="KqMI_PABT_gain">
    <uq:Normal mu="1" sigma="0.1"
      minimum="0.8" maximum="1.2"
      unit="-"/>
   </uq:UncertainParameter>
   <uq:UncertainParameter
     name="KqMO_PABT_gain">
    <uq:Normal mu="1" sigma="0.1"
      minimum="0.8" maximum="1.2"
      unit="-" />
   </uq:UncertainParameter>
  </uq:Parameters>
  <uq:OperationalDomain>
   <uq:Axes>
    <uq:Axis name="uA" unit="mA" />
    <uq:Axis name="pTB" unit="bar" />
   </uq:Axes>
   <uq:Boundary>
    <uq:ConvexHull>
     <uq:Point coordinates="0 0" />
     <uq:Point coordinates="0 20" />
     <uq:Point coordinates="900 20" />
     <uq:Point coordinates="900 0" />
    </uq:ConvexHull>
   </uq:Boundary>
   <uq:ExperimentPoints>
    <uq:PointSet id="PS1">
     <uq:Points>
      <uq:Point id="P1"
        coordinates="345 1" />
      <uq:Point id="P2"
        coordinates="355 1" />
      <!-- ... -->
      <uq:Point id="P10"
        coordinates="525 1" />
     </uq:Points>
    </uq:PointSet>
   </uq:ExperimentPoints>
  </uq:OperationalDomain>
  <uq:Units> <!-- SSP Units -->
   <!-- ... -->
  </uq:Units>
 </uq:ParameterSet>
 <uq:ObservedVariables>
  <uq:ObservedVariable name="qA"
   distributionApproximation="Normal" />
  <uq:ObservedVariable name="pA"
     distributionApproximation="Normal" />
 </uq:ObservedVariables>
 <uq:DesiredResults
  data="mobile_valve.csv"
  summary="mobile_valve_result_summary.xml"
  scope="FinalTime"
  histogram="true">
 </uq:DesiredResults>
 <uq:SamplingMethod>
  <uq:PseudoRandom numberOfSamples="1000" />
 </uq:SamplingMethod>
```

4.6 UQ study in Dymola

The proposal is that a Modelica tool will have the option to import the .xml-file and provide the user the choice to both modify, run, and verify the forward uncertainty quantification from the provided information. The tool should also be able to export any new UQ results and setups.

For this example, the mobile valve model is packaged as an SSP and imported into Dymola. This study will concern only one point, with coordinates $(u_A, p_{TB}) = (415\ \text{mA}, 1\ \text{bar})$.

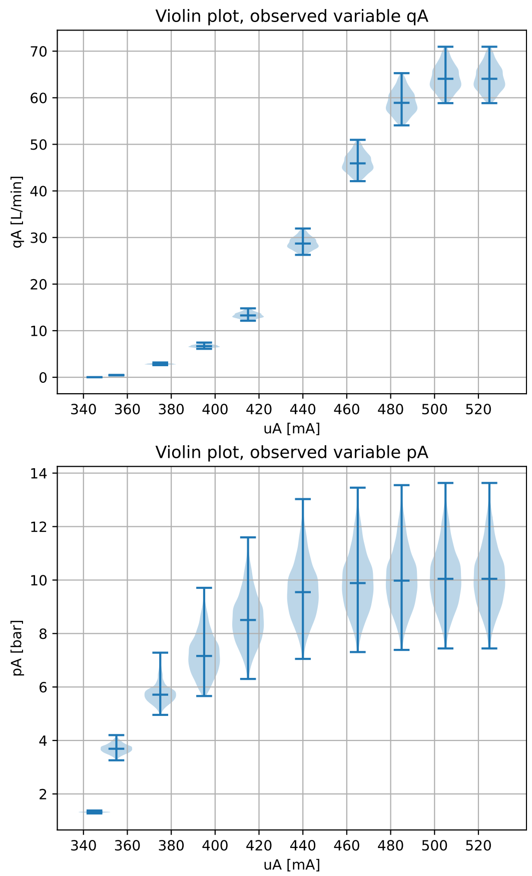

Figure 10. Violin plots of the data in Tables 5 and 6.

4.7 Verification of UQ

Using the data provided from the .xml-file, an UQ analysis with 1000 Monte Carlo samples can be performed to validate the result of previous UQ experiments. The results show that statistics such as mean value and standard deviation agree with those presented in Table 5.

In the previous step, the uncertain parameters $K_{q,MI,PABT}$ and $K_{q,MO,PABT}$ were propagated to the observed variables p_A and q_A. In addition, it can be useful to quantify exactly how much specific parameters contribute to the output variance of p_A and q_A. This helps to isolate the most important variables in a complex model with multiple parameters. The idea is to append the .xml file with additional attributes for the sensitivity analysis, such as the sampling method and the choice of sensitivity indices.

In this case, the experiment performs *global* variance-based sensitivity analysis using Sobol indices. The experiment is conducted on both p_A and q_A at the point $(u_A, p_{TB}) = (415\text{ mA}, 1\text{ bar})$. Three separate Monte Carlo runs with 10000 samples each are performed to evaluate q_A and p_A, where the uncertain parameters are sampled using the Latin Hypercube method. These 10000 samples are then bootstrapped 1000 times to provide confidence intervals for the first and total order Sobol indices.

The results are presented in Table 7. For the observed variable q_A, the first and total order indices are approximately equal, indicating that there are no interactions.

The Sobol indices for the parameters on the outcome p_A show that most of the variability comes from the parameters varying on their own, but there is no statistical significance in higher order interactions.

5 Data Model

The data model for UQ is designed to be tool-agnostic and compatible with multiple standards, including Modelica, FMI, and SSP. This ensures seamless integration across diverse simulation environments while maintaining flexibility to support both simple and complex UQ workflows. To achieve this, the model employs a modular structure where many elements are optional, allowing users to specify UQ data either inline within the model or in separate files as needed. The data model reuses existing SSP elements, such as `Units` and `ParameterSet`.

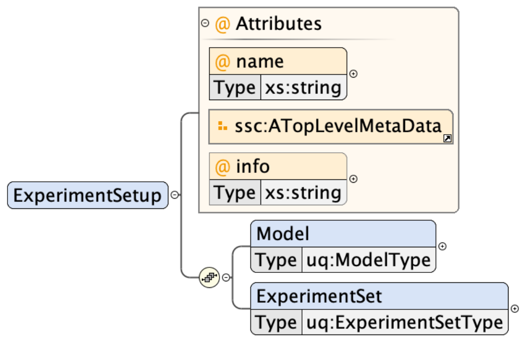

Figure 11. The structure of the `<ExperimentSetup>` element. The **`Model`** contains optional details about the simulation model, such as `name`, `file`, `model`, and `modelResourceMetaData`, the latter enabling linkage to an SRMD file for SSP traceability integration. **`ExperimentSet`** defines the experiments to be conducted on the model

The top element of the UQ model is `ExperimentSetup`, see Figure 11.
The setup can contain different types of experiments, such as `ForwardUncertaintyQuantification` (see Figure 12):

- **`ParameterSet`**: Extends the SSP `ssv:ParameterSet` by enabling the description of stochastic distributions for uncertain parameters alongside deterministic values. A reference to a standard SSP parameter file (SVV) can be used to include a standard (non-UQ) set of parameter values.
- **`ObservedVariables`**: Specifies the model variables for which results shall be computed and stored. Optionally, the attribute `distributionApproximation` may be used to indicate that the result at a given time point should be approximated by the defined distribution.
- **`DesiredResults`**: Defines which results are to be computed for all observed variables and where the resulting data shall be stored. The `data` attribute typically points to a tool-specific result file (e.g.,

Table 7. The mean values and 95% confidence intervals for the Sobol Indices of the valve model, at coordinates $(u_A, p_{TB}) = (415\text{ mA}, 1\text{ bar})$, estimated using a Monte Carlo method with 10000 Latin hypercube samples bootstrapped 1000 times.

Observed variable	Uncertain parameter	First Order	Confidence	Total Order	Confidence
pA	KqMI	48.79%	+/-0.56%	50.40%	+/- 0.41%
	KqMO	49.5%	+/-0.57%	50.37%	+/-1.32%
qA	KqMI	100.00%	+/- 0%	99.44%	+/- 2.01%
	KqMO	0.01%	+/-2.01%	-0.10%	+/-4.06%

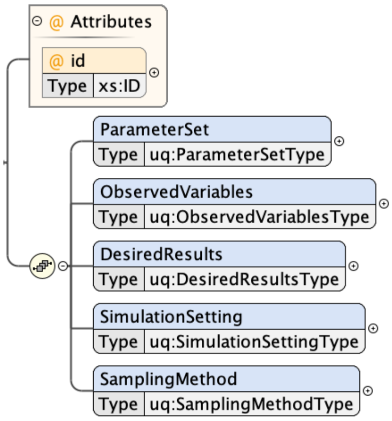

Figure 12. Structure of the `ForwardUncertaintyQuantification` element

`dc_motor.mat`) and can also refer to a directory if results are stored in multiple files. The optional `summary` attribute is used to reference a separate file that contains aggregated or post-processed statistical information.

- **`SimulationSetting`**: Specifies the most important parameters for one simulation run. Optionally, tool-specific settings can be added.
- **`SamplingMethod`**: Describes the sampling method to be used in the Monte Carlo simulation, along with all required parameters for generating samples. Tool specific parameterization can included if needed.

6 Integration with MA Standards

Uncertainty data can come from multiple sources, and it needs to be easy to export and import between tools in a unified way. For instance, a component manufacturer might evaluate the accuracy of the model for a single component in Modelica and would wish to deliver this information together with the model as an FMU. This information could then be used as input to a larger UQ study for the entire system. The suggested approach is a Cross Layered Standard that uses the same definition of UQ concepts across Modelica, FMI, and SSP models.

6.1 Integration with FMI and SSP

FMI and SSP have general extension mechanisms. Every extension must keep an FMU or SSP component still compliant, so tools can ignore elements of an extension that they do not know or support.

The extension mechanism in FMI is called *layered standard* and is described in section 2.6 of FMI 3.0[20]. It is used for the UQ standard by storing the UQ XML file in a new folder inside the FMU extra-folder and by adding the required `fmi-ls-manifest.xml` in this folder.

From the SSP Traceability layered standard perspective (i.e., which information is involved related to the modeling and simulation activity, where does it come from and where shall it be propagated), the current concept would consist of referring to the *uq.xml* file containing the UQ data e.g., from further *.xml*-files that are hosted in the different activities (i.e., Analysis, Requirements, Design, Implementation, Execution, Evaluation, Fulfillment) of the Credible Simulation Process (CSP). Each file would provide information related to a given CSP activity that could be easily read and processed by a dedicated tool (e.g., *easySSP*[21] for the Requirements, *Dymola*[22] for the Execution).

6.2 Mapping to Modelica

The Modelica Language has annotations with modifier syntax that can be used to represent the information extracted from the XML UQ file in a *backwards compatible way*. A benefit of storing the information inside the model is that references to variables are syntactically variable references and not strings, and that the information is naturally moved together with the model. The Modelica Language also supports a hierarchical `Resources` folder inside a Modelica package where the different parts are referenced using Modelica URIs. In this folder, large tables could be stored, e.g., the coordinates of the experiment points in the operational domain, including the values (that can be reused for different experiments).

On the other hand, the UQ analysis supported by a tool is typically tool-specific, and a tool could provide many more features and options as standardized by the draft specification proposed in this paper. A Modelica tool would store its UQ setup in tool-specific annotations. For this reason, currently the conservative approach is used, that which no mapping of the XML-file to Modelica annotations is defined. Instead, (a) the UQ XML file can be imported in a Modelica tool and the tool stores its UQ setup in tool specific annotations, and (b) the tool can export its UQ setup and store it in the proposed UQ XML file format (tool specific settings can be stored in tool-specific

[20] `https://fmi-standard.org/docs/3.0.2/#VersioningLayered`
[21] `https://www.easy-ssp.com/`
[22] `https://www.3ds.com/products/catia/dymola`

annotations of the XML file).

7 Outlook

The data model describes a container, which can be applied on any system level, in an iterative composition-based process. This paper showcases applications in forward uncertainty propagation and sensitivity analysis of nonlinear models. The next step is to extend the specification with model validation against in-situ measurements as presented in (Hällqvist et al. 2023).

The standard presented in this paper is driven by the analysis of existing use cases and supports common concepts used in the UQ domain. In the future, if the need for additional elements is identified, the definitions can be expanded. For instance, while the current schema includes Latin Hypercube and pseudo-random sampling, and supports basic statistical outputs (e.g., mean, percentiles), future versions may incorporate additional sampling strategies, surrogate modeling techniques, sensitivity measures, and probabilistic inference methods.

The aim is to support simple as well as advanced workflows. The presented use-cases have the modeler's role at the center of the workflow and all the information is centralised in a single file; in the future, the UQ data should be traceable via the SSP Traceability Layered Standard. This will enable quality tracking and more efficient information reuse.

Another aspect to be considered is the scalability of the approach and enabling the definition of large data quantities through references to external resources, as well as being able to associate different parameterisations to the same experiment and maximize data reuse.

8 Conclusions

Storing UQ, sensitivity analysis and validation, and verification experiments in a standardized manner is an important step toward ensuring credibility and qualifying whether a model is fit for a particular purpose.

These kinds of computations require evaluations of multiple uncertain variables, which in larger models can be a very computationally complex task. An iterative approach, where the results of a previous study for a single component can be exported and composed with the results of experiments for other components, allows for managing this complexity.

A cross-layered standard is an enabler for interoperability, where studies can be performed in different simulation tools and packaged in FMI or SSP format.

The next steps are the validation of this approach on larger use-cases with composition of UQ information from several sources and the implementation of tool support for import, export, update, and analysis of UQ data in Modelica, FMI and SSP tools.

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