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RISQ: RANDOM AND INTERVAL SPATIAL UNCERTAINTY QUANTIFICATION SOFTWARE

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Abstract. *This work presents a new software for spatial uncertainty quantification in high-dimensional finite element models called RISQ (Random and Interval Spatial uncertainty Quantification software). RISQ provides a wide range of spatial uncertainty tools for non-intrusive uncertainty propagation in an easy-to-use graphical user interface. The graphical user interface visualizes large finite element models and eliminates the required coding knowledge and implementation time required of end-users. Current features of RISQ include modeling of spatial uncertainty with local/global explicit interval fields and Gaussian/non-Gaussian homogeneous/heterogeneous random fields. Furthermore, RISQ facilitates the propagation of intervals or correlated random variables with standard methods such as vertex and Monte Carlo approaches. To showcase the potential of RISQ, a case study is presented to demonstrate its capabilities and efficiency in addressing spatial uncertainty in finite element models with non-Gaussian heterogeneous random fields.*

Keywords: Uncertainty Quantification, Spatial uncertainty, Random fields, Interval field

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1 INTRODUCTION

In the realm of modern manufacturing, the quest for optimizing product performance while minimizing production costs has become increasingly critical. This challenge is exacerbated by the inherent variability introduced during the production process, such as dimensional deviations [1] and material defects [2, 3], both of which can significantl affect the efficien y and reliability of the fina product. Traditional approaches to manage this variability often involve stringent quality control measures and in-line testing. While effective, these often lead to increased costs and material waste.

User interface software packages [4, 5, 6] for uncertainty quantificatio (UQ) primarily focus on inter-variability, addressing global material parameters or environmental changes across different product realizations. These software packages often fall short in capturing intra-variability, i.e., the spatial variations and local defects within a single product. This gap in current UQ techniques limits the ability to identify and mitigate regions within a product that are particularly sensitive to variability, thereby hindering efforts to enhance both robustness and cost-efficien y.

The RISQ software aims to address these limitations by providing a comprehensive framework for spatial uncertainty quantification By integrating advanced modeling and propagation techniques, RISQ enables the inclusion of intra-variability in the numerical evaluation of product performance. This approach not only offers a more detailed understanding of how spatial uncertainties affect product reliability but also paves the way for targeted design and manufacturing improvements. In addition, RISQ's graphical user interface aims to guide the user step-by-step through the uncertainty quantificatio process, making reliability analysis accessible even to those with limited expertise or limited coding experience.

This paper is organized as follows: Section 2 discusses the theoretical framework to perform uncertainty quantification Section 3 discusses how the software architecture of RISQ implements this theoretical framework. Section 4 provides an example problem that outlines the steps required to perform an uncertainty quantificatio study in RISQ and highlights its spatial variability modeling capabilities. Section 5 discusses the current state of RISQ. Finally, Section 6 draws conclusions.

2 THEORETICAL UNCERTAINTY QUANTIFICATION FRAMEWORK

RISQ's high-level theoretical workfl w hinges on an uncertainty quantificatio framework presented by de Rocquigny et al. [7]. Figure 1 shows that this framework divides uncertainty quantificatio into four broad steps:

1. **Model definition**: The firs step requires the definitio of a parametric (deterministic) numerical model, its input parameters and its output quantities of interest. An example of such a numerical model is the finit element representation of a mechanical component, whose displacement and stress state can act as output quantities of interest.

2. **Input uncertainty definition**: The second step requires the identificatio of uncertain inputs to the numerical model and quantify their uncertainty. The uncertain nature of the input (e.g., aleatory or epistemic) affects the modeling framework choice that is used to represent it (such as probability theory, fuzzy arithmetic or interval arithmetic).

3. **Uncertainty propagation**: Uncertainty propagation consists of repeatedly solving the numerical model define in step 1 for different combinations of input parameters, sampled from step 2.

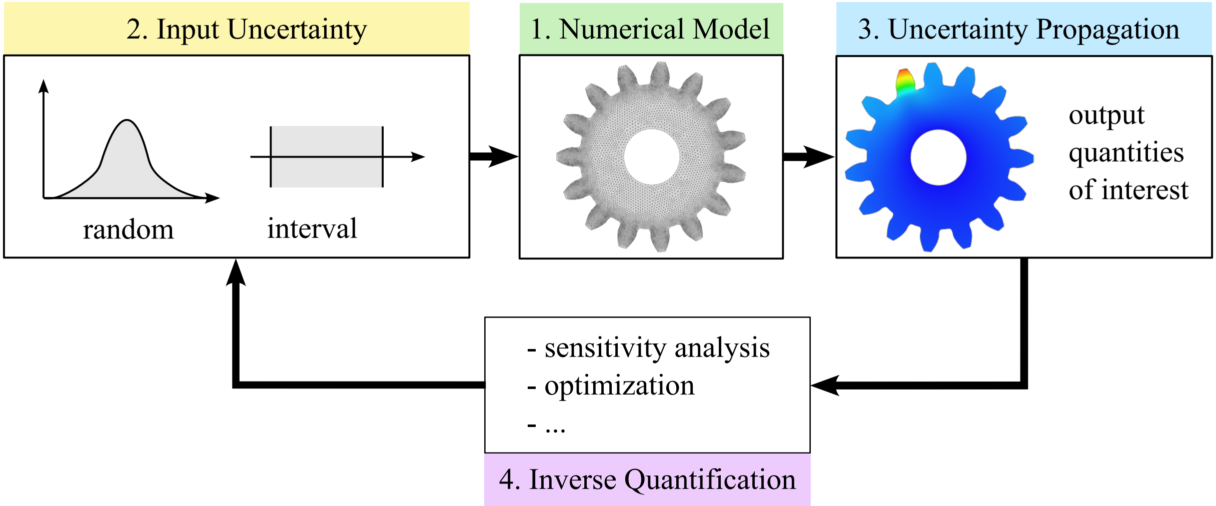


Figure 1: Uncertainty quantificatio framework schematic used by RISQ.

4. **Inverse quantification** : If needed, the output quantities of interest can be used to perform inverse quantificatio or sensitivity analysis on the input uncertainties.

By integrating these steps, RISQ provides a comprehensive framework for spatial uncertainty quantification

3 FRAMEWORK IMPLEMENTATION AND RISQ ARCHITECTURE

The theoretical framework for uncertainty quantification as outlined by de Rocquigny et al. [7] in Section 2, is implemented in the RISQ software to provide a practical and user-friendly approach to spatial uncertainty quantificatio in numerical simulations. The following steps detail how this framework is translated into an actionable workfl w within RISQ. Coloured circles indicate how each step is linked to the theoretical framework in Section 2. Figure 2 provides a schematic illustration of these steps.

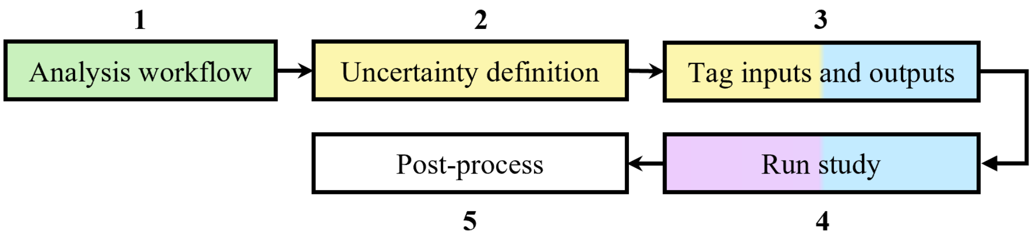


Figure 2: Schematic illustration of RISQ's uncertainty quantificatio workfl w.

- **Define analysis workflow**: In RISQ, each analysis workfl w is structured as a sequence of analyses (numerical simulations), with a clear execution order. An analysis is define by its inputs and outputs, allowing users to map out the fl w of data through the system. Pre-existing analysis portals help users interface with inputs and outputs of numerical models set up with other software, such as commercial finit element analysis software.

Define input uncertainty: Users specify the number of uncertain inputs within the workfl w, and select an appropriate modeling framework for each, whether probabilistic, interval or parametric. For each modeling framework, additional tools are available to further specify the input uncertainty (e.g., defi ition of probability distribution and autocorrelation structure for probabilistic inputs).

Tag input uncertainty and output quantities of interest: Users can tag input uncertainties to specifi analysis input parameters. In addition, tagging output quantities of interest allows RISQ to store these outputs for later post-processing.

Run study: Users select the type of study they wish to conduct, such as "forward propagation", "sensitivity analysis" or "parameter optimization". Users can then run the study when it has been properly set up. Tagged inputs and outputs can then be used for later post-processing within RISQ.

Post-process: RISQ offers a set of post-processing tools designed to help users visualize and interpret the results of their studies, such as histogram and simulation mesh plots.

By following these steps, RISQ translates the theoretical framework into a practical, user-friendly software solution. This implementation not only facilitates the quantifi ation of spatial uncertainties, but also empowers users to make informed decisions to enhance product robustness and cost-efficien y.

4 EXAMPLE: PROBABILISTIC COMPOSITE PLATE BUCKLING

RISQ currently contains several tools for the uncertainty quantificatio of spatial variability. This Section studies the probabilistic buckling of a composite plate, subject to a spatially uncertain ply angle, through forward uncertainty propagation utilizing Monte Carlo sampling.

4.1 Analysis definition

Figure 3 shows the dimensions and mesh of a simple unidirectional carbon-fibre-reinforced composite plate. Table 1 provides the material properties of the composite material. Figure 3 illustrates that the plate is subject to an in-plane compressive force. Nastran SOL105 is used to calculate the firs eigenfrequency and eigenmode of this buckling problem. The model formulation is define as a Nastran input fil (bulk data fil .bdf) using Simcenter 3D as a pre-processor. Running the Nastran solver provides us with an ASCII output fil (.op2) of the nominal (deterministic) problem that contains our output quantities of interest (i.e., the eigenfrequencies and eigenmodes). Within RISQ the Nastran analysis is run multiple times for uncertainty quantification

Table 1: Material properties used for the composite plate in the example problem.

Property	Value
E_{11}	$139.27\,\mathrm{GPa}$
$E_{22/33}$	$7.70\,\mathrm{GPa}$
$\nu_{12/13}$	0.299
$G_{12/13}$	$4.03\,\mathrm{GPa}$
G_{23}	$2.74\,\mathrm{GPa}$

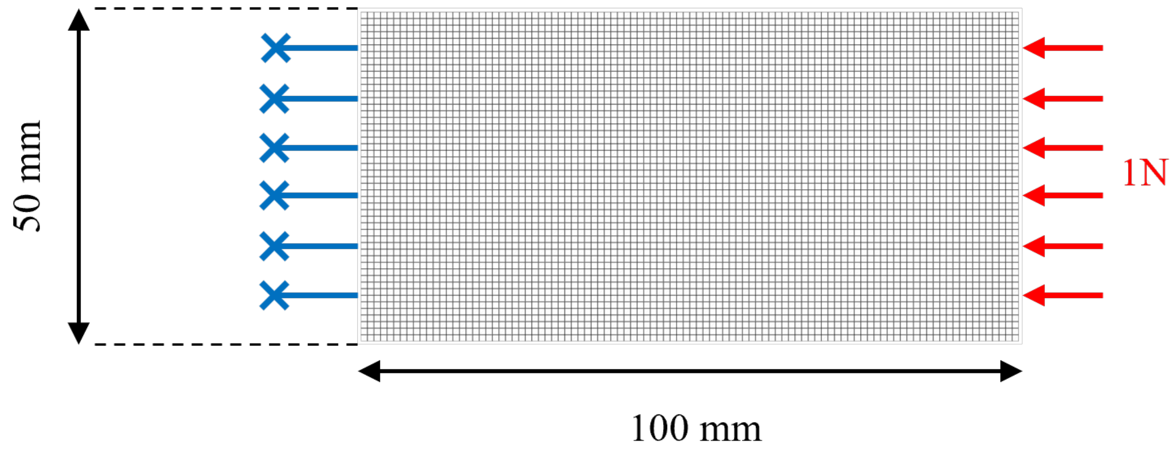


Figure 3: Unidirectional composite plate mesh with loads and constraints in red and blue, respectively.

4.2 Input uncertainty definition

The next step consists of specifying uncertain inputs within the analysis workfl w. As an example, we consider the ply orientation of the unidirectional composite plate to be stochastic. We further specify the ply angle to follow a Gaussian distribution with zero mean (i.e., the nominal fibe orientation aligns with the load direction) and a standard deviation of $5°$. The ply angle exhibits spatial variation that we introduce by specifying a two-dimensional auto-correlation structure. The auto-correlation structure uses a modifie exponential kernel K_{XX}:

$$K_{XX}(\tau) = \frac{e^{-|\tau|/b}}{1 + |\tau|/b}, \tag{1}$$

where τ represents the spatial lag between two positions and b is a parameter that determines the decay rate of the kernel. For each dimension of the random field we specify a distance at which a certain correlation should remain. Both values are used by RISQ to iteratively calculate the parameter b internally, depending on the kernel choice of the user. The random fiel is discretized using the stepwise covariance matrix decomposition method [8].

4.3 Input and output tagging

By pointing our Nastran analysis to a pre-existing nominal input and output file the analysis portal provides the user with GUI to select the input parameters contained within the Nastran analysis. In our case, the Nastran input fil contains as input parameters: orthotropic material properties and laminate properties. We tag our “uncertain ply angle” to the “ply angle input parameter” of the firs (and only) ply contained within our laminate. The tag changes the nominal value of the input parameter to an uncertain input. Likewise, RISQ provides the user with a graphical user interface to show the output parameters contained within the nominal Nastran analysis output file In our case, the Nastran output fil contains both displacement and modal results. We tag both the eigenmode and eigenvalue results as quantities of interest for later post-processing steps.

4.4 Run study

The next step consists of definin our uncertainty quantificatio study. In our example, we use standard Monte Carlo sampling with 100 samples in total with 5 parallel processes to speed up the uncertainty quantification

4.5 Post-processing

Figure 4 shows a histogram made with RISQ of the firs eigenvalue for the 100 samples created in Section 4.4. Figure 5 shows a mesh plot of a realization of the spatially variable ply angle on the composite plate and its corresponding firs eigenmode.

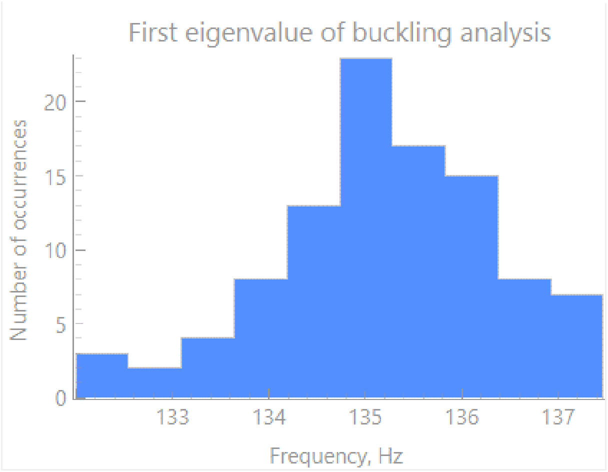
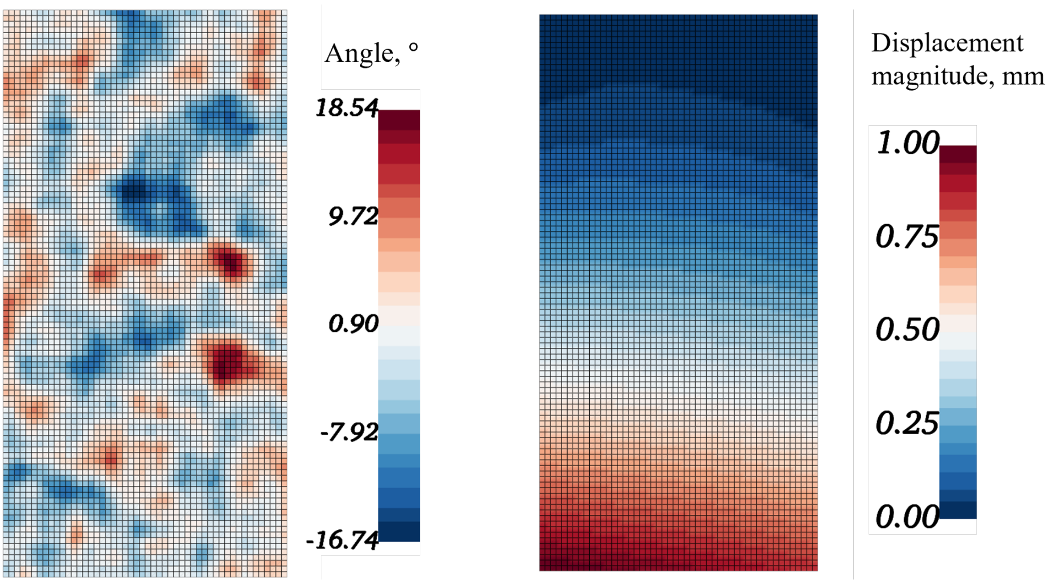


Figure 4: Histogram plot of 100 stochastic realizations of the firs eigenvalue of the corresponding uncertain composite plate.



(a) Ply angle

(b) First eigenmode

Figure 5: Mesh plots of (left) a ply angle random fiel realization and (right) the firs eigenmode of the corresponding uncertain composite plate.

5 CURRENT STATE OF RISQ

The current state of RISQ provides the core structure required to perform spatial uncertainty quantificatio as outlined in Section 3. The non-intrusive architecture allows RISQ to interact with a wide range of software packages, such as Nastran, Matlab and Python.

RISQ currently supports a wide range of (non-)spatial input uncertainties: (Probabilistic) Support for definin a wide range of univariate parametric distributions, cross-correlated multivariate distributions and auto-correlated multivariate distributions using Gaussian and non-Gaussian random fiel theory. (Interval) Support for definin both scalar intervals and local and global explicit interval fields Advanced techniques are implemented to efficientl propagate these uncertainties the study workfl w to the quantities of interest. Finally RISQ also supports a range of, inverse identificatio techniques, such as sensitivity analyses.

After the analysis, a wide range of visualization tools including mesh plots, histograms and scatter plots are available for post-processing.

6 CONCLUSION

This paper presents RISQ as a software capable of performing spatial uncertainty quantifi cation. Its software architecture is based on the theoretical uncertainty quantificatio framework described by deRocquigny et al. [7]. Through its graphical user interface, RISQ aims to significantl reduce the expertise and coding effort required to perform comprehensive spatial uncertainty quantificatio on numerical simulations, rendering it useful to both academic and industrial actors. The case study of a composite plate buckling simulation with spatially uncertain composite properties illustrates RISQ's workfl w and some of its features. Future developments will focus on extending software compatibility with commercial finit element analysis software, and further increasing its computational efficien y, opening up a wider audience for RISQ.

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