Assessing the quality of full-field measurements of a plate subject to thermoacoustic loading

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Introduction

Computational models are used extensively in industry to make predictions about the behaviour and performance of engineering components. Confidence in the models can be established through model validation which provides a decision-maker with evidence of the extent to which the model is an accurate representation of reality. An ASME standard [1] for the validation of computational solid mechanics models, defines validation as 'the process of determining the degree to which the model is an accurate representation of corresponding physical experiments from the perspective of the intended uses of the model'. A step-by-step methodology for performing the necessary validation steps for computational solid mechanics models can be found in existing frameworks such as a CEN guide [2], which recommends that fields of data from computational models, such as displacement and strain fields, are compared against the corresponding full-field measurement data, e.g. from Digital Image Correlation (DIC) [3]. A key challenge associated with existing validation frameworks is the assumption that there will be a richness of measurement data available for comparison with predictions. For systems where this richness is absent and the amount of measurement data cannot be increased, one approach is to establish the quality of the dataset and incorporate a measure of its quality into existing validation methodologies.

Method

A method, outlined in Fig. 1, for assessing the quality of datasets has been developed using ideas incorporated in the Analytical Hierarchy Process (AHP) [4] and the rational decision-making process [5]. The quality of the dataset is established by a panel of experts who score, on a scale of 1 to 5, how well the dataset possesses attributes from the National Physical Laboratory Good Measurement Practice Guide [6] and also assess the importance or weight of the attributes for the problem of interest, similarly on a scale of 1 to 5. The score, s_i and weight, w_i of each attribute are combined in a quality factor, QF:

$$QF = \frac{\sum_i (w_i \times s_i)_{real}}{\sum_i (w_i \times 5)_{perfect}} \tag{1}$$

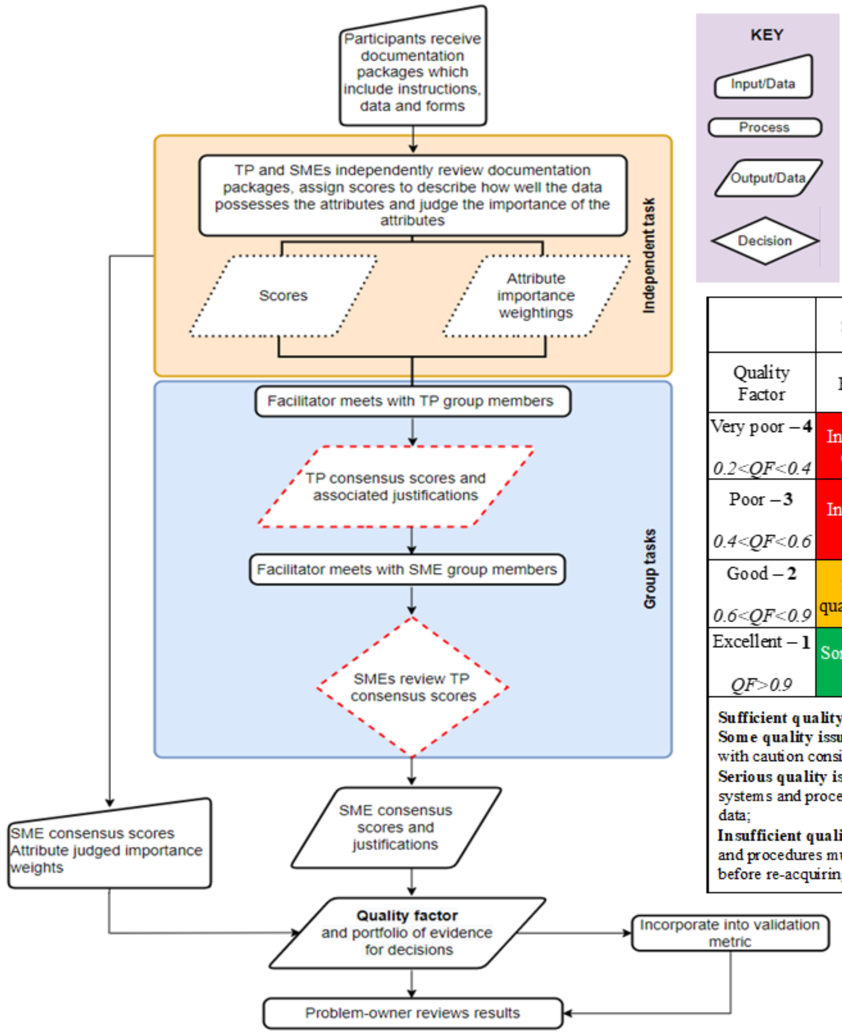
where the numerator refers to the data being assessed and the denominator refers to a perfect or ideal set of data. The Delphi method is used to arrive at consensus values for the scores amongst the panel of experts and a portfolio of evidence for the decisions made. The value of the quality factor ranges between 0.2 to 1; where 1 indicates that the dataset has received perfect scores. To determine if the quality factor value is sufficient for the problem of interest, an assessment matrix has been developed based on a risk assessment matrix which compares the quality factor against the socioeconomic consequence of the problem of interest, see Fig. 1.

Industrial case study

A case study in structural mechanics was conducted to demonstrate the new data quality methodology. The case study used full-field measurement data, obtained using digital image correlation, of a plate subjected to thermoacoustic loading [8]. The participants for this case study consisted of three technical panel members and two subject matter experts, who were supported by a facilitator. Using the scores assigned to the dataset and the judged attribute importance weightings, the quality factor was calculated to be 0.83. This can be described as good quality in the assessment matrix, and if the level of socioeconomic consequence is assumed to be medium, this leads to a recommendation that there are serious quality issues associated with the data – i.e. the data is of insufficient quality for the intended purpose and the measurement systems and procedures must be reviewed and improved before re-acquiring data; whereas, if the level of socioeconomic consequence is assumed to be low then the data would be considered to only have some quality issues and could be used with caution taking account of the likely impact of the issues on decision-making.

Conclusions

In cases where the measurement data available for comparison with a corresponding set of predictions does not have the richness assumed in validation processes, the quality of the data can be assessed and incorporated into the validation process. Using a new method, the quality of the data is assessed for how well it possesses a set of attributes from a good practice guide. The quality factor obtained from the method allowed an assessment of the quality of data fields from thermoacoustic testing of panels and this factor can be incorporated into a probabilistic validation metric to provide information on the extent to which predictions were representative of measurement data.



	Socioeconomic consequence of problem of interest			
Quality Factor	High - 4	Medium - 3	Low - 2	Very Low - 1
Very poor – 4 $0.2<QF<0.4$	Insufficient Quality	Insufficient quality	Serious quality issues	Some quality issues
Poor – 3 $0.4<QF<0.6$	Insufficient quality	Serious quality issues	Serious quality issues	Some quality issues
Good – 2 $0.6<QF<0.9$	Serious quality issues	Serious quality issues	Some quality issues	Sufficient Quality
Excellent – 1 $QF>0.9$	Some quality issues	Some quality issues	Sufficient Quality	Sufficient Quality

Sufficient quality – dataset can be employed without concerns;
Some quality issues – some issues with the quality of the dataset, proceed with caution considering the likely impact of the issues on decision-making;
Serious quality issues – dataset of insufficient quality, measurement systems and procedures must be reviewed and improved before re-acquiring data;
Insufficient quality – dataset of insufficient quality, measurement systems and procedures must be reviewed and substantially improved or replaced before re-acquiring data

Figure 1 (left): Flowchart outlining key steps of proposed data quality assessment method in which TP denotes technical panel, SME denotes subject matter expert and the black and red dashed lines relates to steps which incorporate the analytical hierarchy and rational decision-making processes respectively; and (right) assessment matrix based on the quality factor and socioeconomic consequences of the intended use.

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