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# Identifying challenges in quantifying uncertainty: case study in infrared thermography

Alex Grenyer[a]*, Sri Addepalli[a], Yifan Zhao[a], Luke Oakey[a], John A. Erkoyuncu[a], Rajkumar Roy[a]

[a]*Through-life Engineering Services Centre, Cranfield University, Cranfield, MK43 0AL, UK*

* Corresponding author. Tel.: +44-1234-75-8555; fax: +44-1234-75-8292. *E-mail address:* a.h.grenyer@cranfield.ac.uk

**Abstract**

Complex engineering systems present a wealth of uncertainties concerning aspects ranging from performance measurements to maintainability and through-life characteristics. A quantifiable understanding of these uncertainties is vital to system optimisation and plays a key role in decision-making processes for manufacturing organisations worldwide; impacting profit, product availability and manufacturing efficiency. The aim of this paper is to examine challenges and complications that arise when quantifying uncertainties in complex engineering systems that rely on expert opinion. A thermographic inspection system is utilised as a use case. Contractor-client and supervisor-maintainer relationships are examined. Key challenges highlighted involve accurate depiction of error margins and corresponding uncertainties of components where data is only heuristically obtainable, as well as the influence of environmental conditions and skill of the maintainer.



*Keywords:* Uncertainty quantification; Challenges; Insustrial Product Service System; Complex engineering system; Thermography

## 1. Introduction

Assessment methodologies of statistical uncertainties are well documented, but the quantification of technical uncertainties determined by expert opinion (heuristic) in the context of complex engineering systems (CES) is broadly overlooked. This paper examines a use case where measurement data is obtained from subsystem components to determine statistical measurement uncertainties. These are then combined with relevant heuristic components for each subsystem, which are in turn combined to obtain an estimate for the total uncertainty of the system.

Rapid digitalisation and connectivity is creating opportunities in IPS$^2$. This paper considers digitalisation in the context of the use case, which can aid in the evaluation of component health.

When considering the maintenance of CES, this approach raises more questions than answers. Once statistical uncertainty estimates are obtained from recorded data, it is necessary to also question the way in which these recordings were made, their accuracy and how such approaches may differ in various operating conditions. The complexity in answering these questions emanates largely from the fact that the decisions made for one component or subsystem can have unforeseen effects on others in the CES. An example of one such system is the maintainer. The degree of uncertainty associated with the maintainer's discretion in the quality of maintenance carried out is significant due to the number of variables that may influence such decisions; such as training level, measurement quality and environmental conditions.

Industrial Product-Service Systems (IPS$^2$ ) are the result of the rapidly changing nature of industrial service provision whereby a client may interact with a product in their possession, but not take ownership [1]. Maintenance responsibilities are therefore shifted back to the product provider (contractor), who must manage varying customer requirements and adhere to a defined level of quality and time constraints. These service contracts are increasing in scale and complexity, now accommodating highly complex and dynamic systems. Operational life cycles of such systems promote extensive


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relationships between the contractor and client. The availability, reliability and maintainability of these systems and equipment is therefore essential in logistical contracts and through-life support services. Some significant maintenance technologies that support these services are non-destructive testing (NDT) and degradation assessment, repair and remote maintenance that sustain maintenance activities [1,2]. These should therefore be profitable to the contactor, but also ensure supply chain sustainability and customer affordability [3].

The approach to a specific maintenance task by a contracted maintainer may differ from that of the client's maintainer on the same task. Decisions made here raise several heuristic uncertainties from both sides that are naturally problematic to quantify. Contributing factors such as those mentioned above will impact the quality of work carried out. A clear picture of both heuristic uncertainties from the maintainer's perspective and statistical uncertainties from recorded data will aid decision making process for cost-effective maintenance planning.

The aim of this paper is to examine challenges that arise when quantifying heuristic uncertainties in the maintenance context of CES, considering the dynamic nature of system requirements over time and the effect these may have on the through-life maintainability of CES from the perspective of IPS[2].

## 2. Literature review

### 2.1. What is uncertainty?

Uncertainty is the difference in the amount of information that is required to perform a task and the amount of information already possessed [4–6]. The relevance of information, or lack of information, should be specified concerning the functionality of the organisation or application in question [7]. Grote [4] discussed these distinctions in a broad sense of incomplete information, inadequate understanding of existing information and undifferentiated response alternatives [8]. Uncertainty is caused by variability in the environment, human error and/or human ambiguity and can result in a negative, positive or neutral impact on the overall performance [9].

The terms 'error' and 'uncertainty' are often used interchangeably. It is important to differentiate these concepts. A statistical error is the (unknown) difference between the measured value and true value, following probability distributions. Measurement uncertainty is the lack of information about the magnitude of these errors. The degree of uncertainty associated with a measurement can be utilised to aid decision making.

### 2.2. Types of uncertainty

There are two key types of uncertainty estimate; Type A, which are sourced from standard deviations of statistical data, and Type B, which are obtained from heuristic estimates [8]. Such estimations should be distributed to assess their validity.

Uncertainties can be further defined as aleatory and epistemic, although accurate allocation of these terms for a given variable of either uncertainty type is largely dependent on the measurement model [10]. Epistemic uncertainties are those that could be known in principal, but are not known in practice [11,12]. This may be due to inaccurate measurements or the measurement model neglecting certain characteristics. Epistemic uncertainties can, therefore, be reduced by obtaining more data or by refining models. Aleatory uncertainties, on the other hand, cannot be reduced as they represent variables that differ each time a given experiment is carried out [11–15].

This distinction is largely necessary to identify where uncertainty can be reduced. Failure to accurately distinguish between these types of uncertainty may result in underestimation or overestimation of the probability of failure in a system, which could have significant knock-on effects [10].

### 2.3. Uncertainty analysis

NASA [8] published a document based on general rules and recommendations given by the Guide to the Expression of Uncertainty Measurement (GUM) [6]. The measurement process should be clearly described to provide information and clarity about the measured quantity (measurand). This should include measurement set up, equipment used, environmental conditions during measurement, and the procedure used to obtain the measurement. This can then be used to identify sources of error and uncertainty [8,16].

The core uncertainty analysis procedure defined by the GUM involves five key steps: define the measurand, identify error sources and distributions, estimate uncertainties, combine uncertainties, report analysis results. Once the error sources have been identified, appropriate statistical distributions are selected to characterise the nature of measurement errors, which are quantified by standard deviation.

### 2.4. Uncertainty estimation methods

Statistical uncertainty quantification (UQ) for measured data can be achieved through a variety of documented methods, the most apparent of which are Monte Carlo, Bayesian, Latin Hypercube and Kalman filtering.

Helton and Davis [17] examined Monte Carlo simulation methods along with Latin hypercube sampling in uncertainty analysis for complex systems. Latin hypercube sampling generates a sample of parameter values from a multidimensional distribution. It is often used alongside Monte Carlo simulation.

Monte Carlo simulation is stated to provide the most effective approach to the propagation and analysis of uncertainty in many situations for various combinations [17]. It allows extensive sampling of uncertainty ranges for individual variables to be achieved without the use of surrogate models [17]. Analytical procedures can be developed that allow the propagation of results through systems of linked models [16].

Bayesian analysis is a statistical process that answers questions regarding unknown parameters through probability distributions. NASA [8] describes Bayesian analysis as a method for deriving and expressing the probability of an event occurring given that a prior event has occurred as a probabilistic function of the two events occurring independently or together. This process is a core part of determining measurement accuracy, decision risks and calibration processes.

Kalman filtering is an algorithmic process that observes measurements over a set timeframe, allowing educated estimations to be made about a dynamic system [18]. These measurements can include statistical variances, inaccuracies, and unknown variables. The algorithm uses aspects of Bayesian analyses to estimate joint probability distributions in each timeframe. Kalman filters are used in a range of fields including navigation, signal processing and robotics [18].

Monte Carlo simulation is the most diverse and adaptable method of the four discussed here, so will be used in this study to inform statistical validation of the variables obtained to estimate component uncertainties.

### *2.5. How does uncertainty effect IPS²?*

Service cost assessments for the support of long-term projects is a challenge shrouded in uncertainty owing to the variable nature of such services and unpredictable changes in customer requirements [19,20]. Further uncertainties are found in highly variable equipment usage rates, lack of information to make accurate forecasts, importance of creating the right incentives around long-term maintenance and accurately predicting schedules [21]. These uncertainties present an inherent degree of risk to IPS², which can be utilised as a measure of future uncertainties in achieving performance within defined cost, schedule and performance constraints.

Erkoyuncu et al. [22] examined cost estimation methodologies at the bidding stage for IPS² from a number of sources.. The resulting Uncertainty Tool for Assessment and Simulation of Cost (U-TASC) was based on an amalgamation of various standard qualitative and quantitative methodologies. The challenge of incorporating heuristic qualitative assessments in the in-service phase of IPS² in a manner that can be incorporated with quantitative estimates was highlighted.

### *2.6. Research gaps*

Ideally methods to quantify the compound effects of different types of uncertainties would exist to capture their full system impact. Modern CES feature a range of subsystems interacting simultaneously and nonlinearly with each other and the environment on multiple levels that create challenges to UQ, resulting in over or under estimation.

NASA [8] covered an approach to quantify system uncertainty, but approaches that support the system of system perspective to UQ are lacking. That is, a system in which individual components in uncertain states with levels of importance dependent on operational condition and system environment, represented in context by CES. UQ relating to IPS² is still a relatively new field of research. The scientific determination of Type B (heuristic) uncertainties and their effect on aggregated system of system uncertainty is necessary to capture their full system impact.

Maintenance and modelling techniques are well versed in literature, with clear benefits different approaches for varying applications. Overall, there is a lack of guidance in literature to quantify compound uncertainties in CES when considering heuristic attributes.

## 3. Use case: Thermography system demonstrator

The use case for this paper considered a conventional pulsed thermography system as described by Zhao et al [23] to demonstrate the challenges in compound UQ considering heuristic and statistical variables. This system consisted of four core subsystems; an Infrared (IR) camera, flash box, composite sample of known emissivity and data processing computer (Fig 1). Each subsystem consisted of its own inherent mix of uncertainties. This made it a relatively simple system of system setup compared to those utilised in modern CES and IPS², but presented much the same challenges faced in operational environments for UQ. For example, the positioning of the camera, movement of the sample and operator bias are assumed to be uniform throughout the experiment with negligible error margins. However, these error limits, and therefore the breadth of uncertainty, can vary significantly in real-world environments where, for example, varying atmospheric temperatures or windspeeds will impact the accuracy of recorded data or of the subjective opinion of a maintainer. Operating conditions will have further impacts, for example cramped spaces or working at heights.

Optical flash thermography is a Non-Destructive Testing (NDT) process in which a sample is heated by a very brief, uniform pulse of light from a flash box. The IR camera monitors sample surface temperature response over time to the thermal impulse. The transient heat flow is obstructed in areas of the sample closest to a wall or unintentional defect, causing a local increase in temperature at the surface [24]. This process can be used in several conditions to identify defects and in a variety of materials.

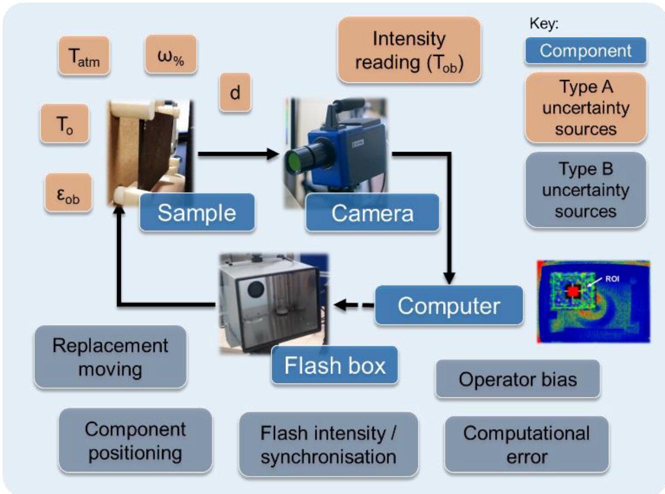


Fig 1. Setup diagram with uncertainty in thermography system

### *3.1. Identification of uncertainties*

The combined uncertainty resulting from measured data and heuristic estimates from each module was considered to quantify the compound system of system uncertainty.

The measurand was the digital level of the reconstructed temperature decay profile from the IR camera. The intensity is a dimensionless true value obtained from polynomial fitting. Components of each module were subject to a degree of error that, directly or indirectly, influenced the compound uncertainty of the measurand. These uncertainty sources are displayed in Table 1.

### *3.2. Experimental procedure*

The sample was placed in a pre-built mount on a level bench and positioned in parallel with the flash box and camera. The sample was introduced and removed from its mount between ten repetitions using a pair of tongs with rubber handles to simulate positional uncertainty associated with the operator and sample positioning. Three trials per repetition were recorded to create a sufficiently large sample size; a total of thirty temperature measurement datasets. The same acquisition parameters were used for all recordings. Atmospheric temperature in Kelvin and humidity were recorded for each of the ten runs using a digital thermometer.

Table 1. Subsystem components and associated uncertainty sources

| Subsystem | Uncertainty source | Nominal / mean value | Error margin | Probability distribution, uncertainty type |
|---|---|---|---|---|
| IR Camera | Atmospheric T., K ($T_{atm}$) | 294.34 | ±0.1 | Normal, A |
| | Humidity, % ($\omega_{\%}$) | 61 | ±0.1 | Normal, A |
| | Distance, m (d) | 0.26 | ±0.01 | Uniform, A |
| | Intensity reading ($T_{ob}$) | 5.13 | ±0.001 | Normal, A |
| | Positioning | 0 | ±0.001 | Uniform, B |
| Flash Box | Flash intensity, % | 75 | ±0.001 | Uniform, B |
| | Synchronisation, s | 0 | ±0.001 | Uniform, B |
| Sample | Emissivity ($\varepsilon_{ob}$) | 0.85 | ±0.02 | Uniform, A |
| | Temperature, K ($T_o$) | 294.34 | ±0.1 | Normal, A |
| | Mount Positioning | 0 | ±0.001 | Uniform, B |
| | Replacement moving | 0 | ±0.02 | Uniform, B |
| Computer | Operator bias | 0 | ±0.01 | Uniform, B |
| | Computation error | 0 | ±0.01 | Uniform, B |

To increase accuracy and minimise error in readings from each run, the tripod on which the camera sits, sample mount and flash box were fixed in the same position for every recording. Each data capture was initiated with a single flash at 75% power. Recordings were taken at a frame rate of 25Hz, recording 1000 frames in 40 seconds. An area region of interest (ROI) of 15x15 pixels was used to record a mean value of each frame. The resulting thermal image is shown in Fig 1. The circular pattern in the centre of the image is a reflection of the camera lens. The ROI was taken from an unaffected area to avoid the effect of non-uniform heating on the measurement. A cooling time of 15mins between each run ensured the sample cooled to the optimum working temperature. This assumed that atmospheric temperature was equal to sample temperature. These measurements would have a different mean value, but the same standard deviation and, therefore, the same uncertainty.

### 3.3. Uncertainty estimation

To obtain statistically significant assessments of the uncertainty in each subsystem component, Monte Carlo analysis was used to generate random variables within specified error limits. For statistical recordings, the standard deviation of the mean of each run was considered equal to the uncertainty in the recorded values [8].

The component uncertainties of each subsystem were combined using sensitivity coefficients and appropriate effective degrees of freedom in accordance with the GUM [6,8]. Uncertainty estimates for each subsystem were then combined using the Root Sum Square (RSS) method [8,22] with a 95% confidence level, assuming negligible correlation between the subsystems. The results are identified in Table 2.

Heuristic uncertainty estimates, such as the positioning of the camera, movement of the sample and operator bias in the computer assume a uniform distribution with a highly concentrated mean as the error limits were negligible throughout the recordings. However, these error limits, and therefore the breadth of aleatory uncertainty, can vary significantly with environmental and operating conditions. The degree of error from each subsystem component will have a notable impact on the resulting system uncertainty. The specific effects from these components is detailed in Table 3, along with a reiteration of the uncertainty sources for each subsystem and their relative uncertainty type. The greater the error margin in the recording equipment, such as the digital thermometer, the greater the degree of epistemic uncertainty will be. Environmental conditions can fluctuate over time, which increases aleatory uncertainty in the mean values obtained from measurements such as temperature and humidity. Accidental adjustments in the positioning of components will alter the camera focus, which will result in less accurate readings. This kind of error is more likely to have a negative impact in the context of real-world CES in uncertain dynamic operating conditions.

Table 2. Subsystem and system combined uncertainty estimates

| Subsystem | Subsystem Mean Combined Uncertainty | System Combined Uncertainty (RSS) |
|---|---|---|
| IR Camera | 0.1203 (12%) | 0.1773 (17.7%) |
| Flash Box | 0.0014 (0.1%) | |
| Sample | 0.1295 (13%) | |
| Computer | 0.0141 (1.4%) | |

## 4. Identifying industrial challenges in heuristic UQ

In this laboratory set up, heuristic uncertainty estimation was relatively straight forward. In a real-world industrial environment, these estimations become considerably more complicated owing to additional sources of uncertainty. These can range from primary factors such as: subsystem interconnectivity, interoperability of the whole system that is dependent on subsystems and understanding of the whole system of system as a single system – to tertiary factors such as: maintainer wellbeing, equipment availability and additional environmental factors. These are expanded in the following sections. When considering IPS$^2$, the quality of NDT processes such as thermographic inspection for maintenance of a given component of CES carried out by a contractor may differ significantly to that of work carried out by the client.

The main challenge faced in the use case was accurately assessing error margins and corresponding distributions for components from which statistical data was not obtainable. The degree of error contributed by such components influences the uncertainty in the measured value. In a real-life environment, these estimations are sourced from expert opinion. Maintenance activities are carried out based on such opinions and live or historic data. The quality of such data, accuracy of expert opinions and environmental conditions all drive the quality of maintenance carried out, which drives a highly dynamic level of uncertainty.

Table 3. Influence of error sources on resulting uncertainties

| Subsystem | Uncertainty source | Uncertainty type (A/B) | Influence on compound uncertainty |
|---|---|---|---|
| IR Camera | Atmospheric temp. | A | Greater variations in temp. increase uncertainty in readings |
| | Humidity | A | Greater variations in humidity increase uncertainty in readings |
| | Distance | A | Changes in distance will move ROI and alter camera focus - keep constant |
| | Measured reading | A | Small, constant temperature fluctuations in air result in variations in values per frame |
| | Positioning | B | Changes in position and angle will move ROI and alter camera focus - keep constant |
| Flash Box | Flash intensity | B | Variations in flash intensity will cause changes in sample surface temperature per recording |
| | Synchronisation | B | Flash must occur for the first recorded frame to give constant accurate recordings |
| Sample | Emissivity | A | Sample emissivity is constant - difficult to accurately obtain values for composite materials |
| | Temperature | A | Influenced by flash - must be allowed to cool to room temperature before starting next recording |
| | Mount positioning | B | Changes in position and angle will move ROI and alter camera focus - keep constant |
| | Replacement moving | B | Held in place by mount - changes in position and angle may still occur |
| Computer | Operator bias | B | Operator may input inaccurate readings or make incorrect measurements |
| | Computation error | B | Operator may make incorrect calculations |

### *4.1. Industrial perspective of challenges faced in UQ for maintenance practice*

Four 2-hour interviews have been held with the head of support and research and technology manager of a major defense contractor. A key aspect discussed was the nature of relationships between the contractor and a client in long-term IPS$^2$ contracts and how they evolve over time. In many cases, the contractor will have their own integrated maintenance and delivery teams. Systems often maintained by the original equipment manufacturers (OEM), dictated by the contractor. The client will operate the given asset and carry out repairs where necessary while in operation, whereas the contractor will diagnose faults and carry out routine maintenance or larger repairs [1,2,25]. A board framework representing the relationship between contractor and client is shown in Fig 2.

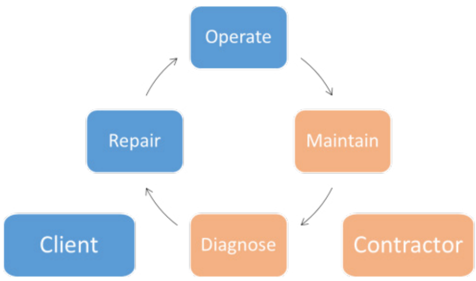


Fig 2: Contractor-client relationship in IPS$^2$ contracts

Experience, expertise and training have a momentous influence on decision making. Decisions made directly affect the quality of maintenance carried out, and therefore drive a significant degree of uncertainty that is substantially complex to quantify [21,22,2]. Equipment quality may vary for the contractor or client, thereby affecting the accuracy of resulting measurements. Maintenance regimes used by the contractor or client may also differ, therefore holding a greater degree of uncertainty. In CES, where a change in uncertainty in one system has an unknown impact on another, this issue is amplified as different components may be maintained by different parties in the same system, which may restrict the availability of data about specific components and the impact they will have on interlinked systems.

Insufficient training for a given task, environmental conditions and stress levels of the maintainer will further impact the quality of maintenance carried out. A supervisor should check the maintainer's work. However, these checks may not be carried out effectively, depending on the maintainer-supervisor relationship. If the supervisor knows and trusts the maintainer, they may not sufficiently check the quality of work, despite having a better subjective opinion, which can increase the uncertainty of the quality of maintenance.

Stress levels and working conditions further influence this uncertainty, as a heightened degree of each will negatively impact the quality of maintenance. It is incredibly difficult to obtain data on maintainer wellbeing as unions do not like to give or authorise the collection of such information. In many cases, more attention is given to critical and complex components. Non-critical components therefore receive less attention. For example, bypass valves could be considered non-essential until they fail.

To address these situations, maintenance support systems such as DRACAS – Defect Reporting and Corrective Action System – are used to report failures and track corrective actions. However, the way in which operators may use these systems or the way data is handled can further increase uncertainties in maintenance practices. Data concerning work carried out may not be inputted correctly, or alerts may not be responded to appropriately.

## 5. Conclusions

The aim of this paper was to examine challenges that arise when quantifying heuristic uncertainties in CES in the context of IPS$^2$, considering training, relationships, environmental factors and the effect these may have on the maintainer and resulting quality of maintenance. A use case utilising a thermographic inspection system was examined to demonstrate the challenges of heuristic UQ in CES.

The key challenge encountered was the accurate depiction of error margins and corresponding uncertainties of components where data is only obtainable though subjective opinions.

Maintenance work for assets carried out in IPS$^2$ is often conducted by the contractor, as well as a degree of diagnosis work, while the client will typically operate and carry out minor reactive repairs. For CES, additional support systems are used to actively report failures and track corrective actions.

Maintainers should therefore be well trained in standard maintenance procedures, but also capable of executing reactive maintenance. A multitude of uncertainties arise here, influenced by the working environment and skill of the maintainer, as well as equipment availability.

The use of Monte Carlo simulation to measure the level of uncertainty in heuristic attributes within subjective error margins addressed the research gap identified in this context, but further research is required to establish how such attributes may differ, for example, from a manager to a maintainer.

The level of uncertainty obtained in the use case is relatively low, but in the system of system context in CES, which encompasses substantially additional interlinked subsystems, the challenge of accurately determining the degree to which uncertainty in one subsystem will affect another can have severe effects on the level of compound uncertainty and, therefore, the cost of service provision and performance targets in IPS$^2$. The ability to track changes in such uncertainties over time will enable far more accurate cost estimations to be made for long-term service contracts.

Future work in this subject area should examine strategies to obtain statistically viable data concerning the quality of maintenance in dynamic working conditions and asset condition, skill of the maintainer and trends in active decision making for given reactive, corrective or preventive maintenance activities.

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