The Digitally Enabled Supply Chain: Maintaining Data Provenance in a Global Manufacturing Supply Chain

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ABSTRACT

Digitally enabled supply chains, which exploit the capabilities of digital technologies and sensing systems, will enable supply chains to be more resilient to market risks, to be more responsive to market opportunities, and to remain competitive. However, digitally enabled supply chains depend critically on the management and analysis of data and, in turn, on establishing trust and confidence in those data processes. In this paper we discuss the benefits that come from digitising global manufacturing supply chains, and the requirements and challenges associated with that digitisation. In particular we describe the use of component and process data, as well as component and process models in the form of digital twins, in the context of strategies for smart assembly and automated process control.

1.0 INTRODUCTION

Global manufacturing is on the cusp of a transformation. The increasing availability and capability of digital technologies and computing power, as well as cheaper sensors and sensing systems, will enable interconnected end-to-end supply chains that are more resilient and responsive. Making these supply chains 'digitally enabled' will become essential for global manufacturing supply chains to stay competitive and to improve operational efficiencies.

At the heart of digitally enabled supply chains sit data, its connections, analysis and interpretation between suppliers and end users. The end user has to have trust and confidence in the data, starting from its collection by sensors and flowing through to (often automated) decision making. The analysis and usage of this data can lead to reduction in scrap rates, improvements in product quality, and increases in manufacturing efficiency.

Trust and confidence through data traceability and provenance will therefore become critically important to ensure that sound manufacturing decisions are made on the basis of well-understood and reliable data. To enable trust in the data, it is necessary to ensure accurate measurements are traceable to internationally accepted standards, with the complication that the traceability is often through legacy equipment and in challenging manufacturing environments. To enable confidence, it is necessary to understand what the data means and the provenance of the data. If the user has trust and confidence in the full supply chain data as a basis for decision making and product approval, the amount of testing and inspection required can be significantly reduced, along with the related costs and delays.

As well as increasing confidence, gaining a clearer understanding of what the data means will ensure that operators, and software systems, are trained on data that is fully understood, validated and auditable in terms of the operational situations it covers. This data confidence will support the validation and quantitative assessment of predictive and di The Digitally Enabled Supply Chain agnostic outputs, which is essential in

convincing end users and regulators to accept technology advances.

This paper describes the current activities and areas of research in NPL's Digitally Enabled Supply Chain (DESC) programme. The aim of the programme is to stimulate adoption of digitised global manufacturing supply chains by providing industry with the necessary skills, guidance, infrastructure and confidence, as well as developing a framework for data provenance. The DESC programme has been designed to address challenges and barriers to manufacturing digitisation by focusing on data collection, data validation and trust of data across sectors. Initial work is focussing on fundamental research, and is demonstrating the results on examples from the automotive and drinks sectors.

2.0 BENEFITS OF DESC OVER OTHER APPROACHES

The digitally enabled supply chain aims to make best use of all the data associated with an end product and its component parts and raw materials that is gathered during manufacturing. It is an umbrella term covering multiple concepts rather than a one size fits all approach. It is strongly linked to concepts such as "industry 4.0" and "factory of the future", which use a combination of data and artificial intelligence approaches, such as deep learning, to automate decision making in manufacturing.

Whilst the extra investment required to generate a DESC seems daunting, a lot of manufacturing equipment comes with fitted sensors and internet connectivity and all that is required is to enable that capability and to store the data appropriately. Additionally, in many cases useful data are already being generated throughout the supply chain, but are not used or shared to full advantage (within the terms of contracts and IP agreements). Data sources that are typically generated within a supply chain and can be used in a DESC setting include:

- material property data associated with the raw materials used by suppliers;
- measurements made by suppliers during manufacture;
- measurements made for acceptance testing;
- measurements made during assembly, whether of the individual components or of the partially assembled end product;
- CAD drawings used for visualisation and aesthetics;
- numerical multi-physics models of product performance under operating conditions.

Supply chains at the moment are generally based on managing tolerances and using sampling statistics. The purchaser specifies acceptance criteria, generally stated as tolerance limits, which the components must meet to be acceptable. Suppliers select a subset of components during manufacture and test them against the criteria, and statistical approaches are used to show that (for instance) the probability that 99 % of the components meet the criteria is greater than 95 %.

This approach inevitably leads to waste, because there is a non-zero probability that some of the components will not meet the criteria. In many cases, the components not meeting the criteria are only identified after some further processing and assembly steps have taken place, potentially leading to waste of energy and of components provided by other suppliers.

Another problematic aspect of this approach is that the most obvious way to improve product quality and reduce waste is to require the components from suppliers meet reduced tolerances, but the cost of manufacture increases exponentially as tolerances are reduced. The end result is either increased cost or

reduced margins for someone in the supply chain, often for a small increase in quality.

A digitally enabled supply chain makes smarter use of resources to avoid waste and improve quality. Consider a simple example, where a pin from one supplier is required to fit through a hole in a block from a different supplier. The pin diameter and the hole diameter each have associated tolerances. If no further information is available and pins and blocks are paired up randomly and are rejected if the pin will not fit into the hole, then it is inevitable that some components will be rejected. The DESC approach instead associates a measurement of the pin diameter with each pin and of the hole diameter with each block, making it possible to reduce the rejection rate by careful choice of pairs of block and pin. This approach to assembly is illustrated in simplified form in figure 1.

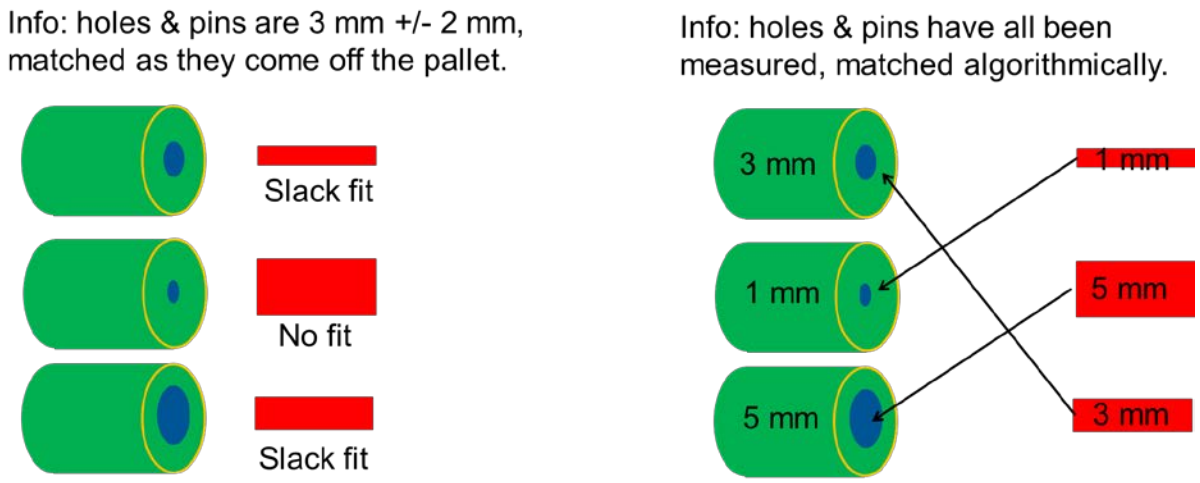

Figure 1: Illustration of the use of DESC for product assembly.

2.1 A simple assembly example

The benefit of this approach can be demonstrated by considering a simple and idealised example, based on the matching of pistons and cylinders in the automotive industry. Suppose that Supplier A manufactures a block containing a cylindrical hole whose diameter is h, and Supplier B manufactures a block with a cylindrical pin attached whose diameter is p, with the pin intended to fit in the hole. Supplier A manufactures parts with holes whose diameters differ by no more than 0.2 mm from a nominal value of 10.00 mm, and Supplier B manufactures parts with pins whose diameters differ by no more than 0.2 mm from a nominal value of 9.6 mm.

Figure 2 illustrates the theoretical distributions of the diameters h and p of parts manufactured by the two suppliers. These distributions are rectangular with limits of, respectively, 9.8 mm and 10.2 mm (for holes) and 9.4 mm and 9.8 mm (for pins).

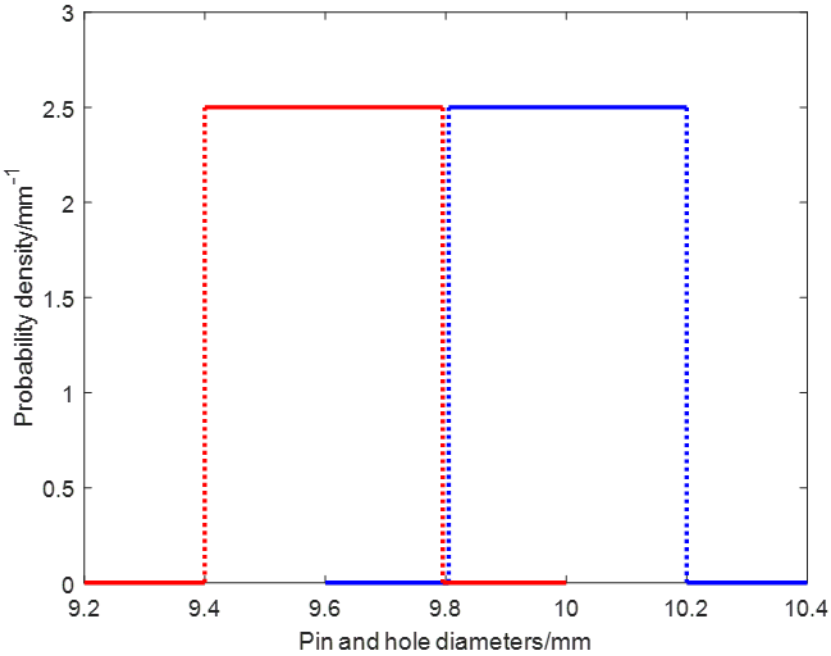

Figure 2: Theoretical distributions of, respectively, the diameters *h* and *p* of a hole (blue) and a pin (red) manufactured by the two suppliers.

With these specifications on the parts, the difference between the diameters of any manufactured hole and any manufactured pin is between 0.0 mm and 0.8 mm, and so it would seem that a pin manufactured by Supplier B will always fit in a hole manufactured by Supplier A. But it is important to the functionality of a product assembled from two parts that the fit is not too tight or too slack, and so a product is only accepted if the difference between the diameters of the hole and pin is between 0.05 mm and 0.75 mm, and is otherwise scrapped.

Figure 3 illustrates the theoretical distribution of the difference $d = h - p$ of the diameters of a hole and a pin in an assembled product. The figure also shows the limits between which d is required to lie for the assembled product to be accepted. In addition to this specification on d, a product quality function $Q(d)$ is used to express quantitatively the quality of an assembled product according to its value of d. The function is defined to be zero for $d \leq 0.05$ mm and for $d \geq 0.75$ mm as required by the specification, and takes a maximum value of one at $d = 0.1$ mm, which defines the optimum fit of a pin and a hole. This function, here taking the form of a piecewise linear function, is shown in figure 4.

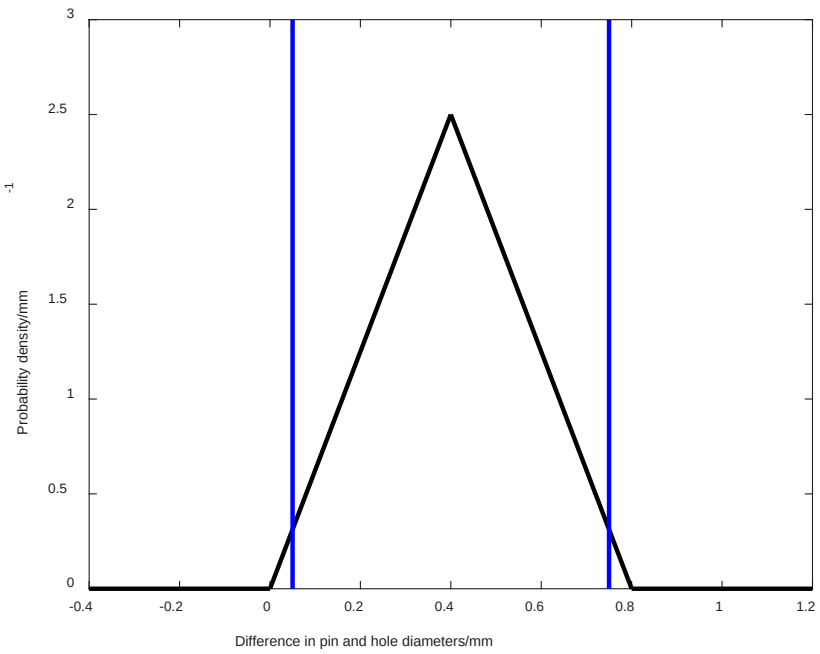

Figure 3: Theoretical distribution of the difference *d* = *h* - *p* of the diameters of a hole and a pin in an assembled product. The vertical lines specify the limits between which *d* is required to lie for the assembled product to be accepted.

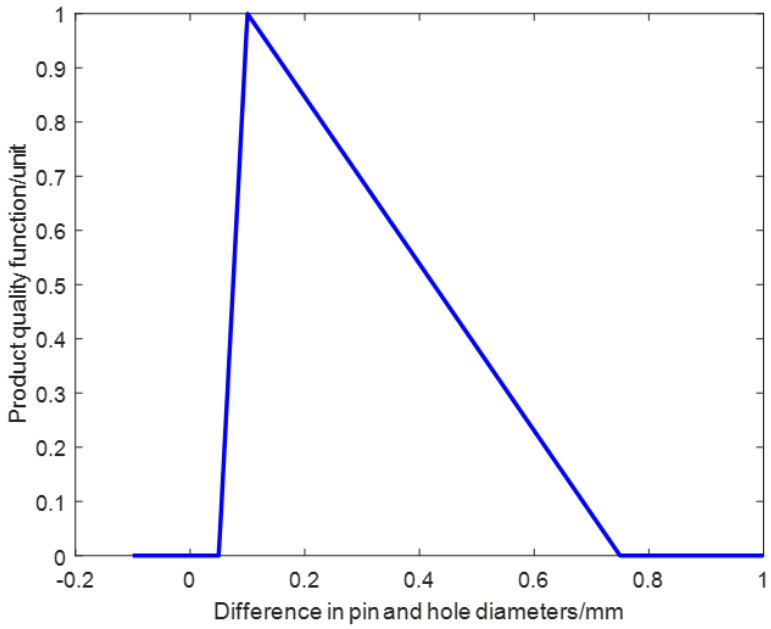

Figure 4: Product quality *Q* as a function of the difference *d* in the diameters of the hole and pin used in the assembly of the product.

If the pins and blocks are paired at random (undirected assembly) and a random sample of size 1 000 is taken, figure 5 shows the frequency distribution of corresponding product quality values. In this case, products are assembled with quality values spread across the interval zero to one. Some products are assembled with quality values of zero, and these correspond to those products that are scrapped. Some products are assembled (by chance) with quality values close to one, and these correspond to products for which *d* is approximately 0.10 mm, the optimal fit. The distribution of quality values has a median value of 0.54 and a standard deviation of 0.24.

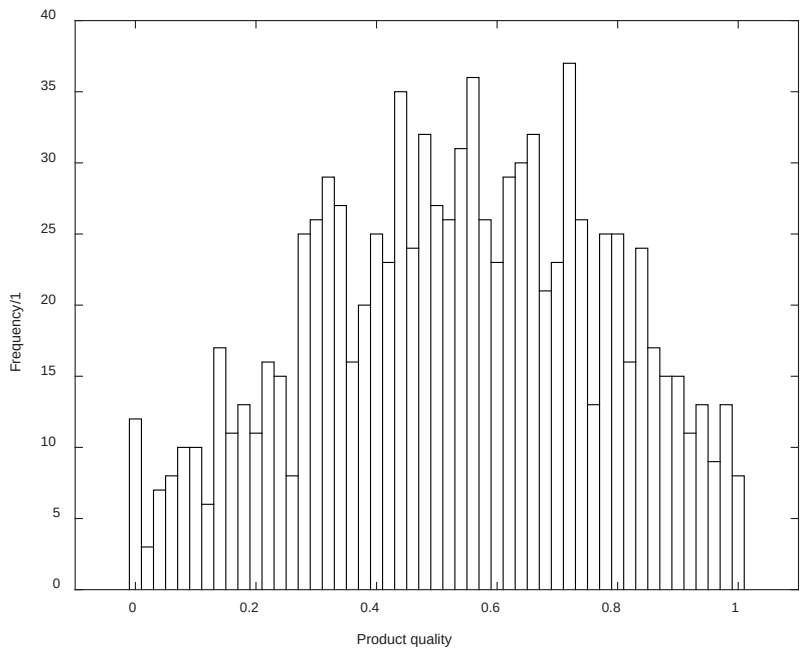

Figure 5: Frequency distribution for values of the product quality function for products assembled in a randomized or undirected way.

An alternative assembly method is to use ‘directed’ assembly in which a strategy is designed and applied to decide which pins are to be fitted in which holes. For this simple simulation scenario, a possible strategy would be to order the parts delivered by Supplier A such that the diameters of the holes are in increasing order, and to order likewise the parts delivered by Supplier B. The hole with the smallest diameter is then assembled with the pin with the smallest diameter, and so on. Figure 6 shows the distribution of product quality values for the products assembled in this way. In this case, the quality values have a median of 0.55 and a standard deviation of 0.0063, which indicates that a very consistent set of products is obtained, scrap is eliminated, but no product having optimal quality is assembled.

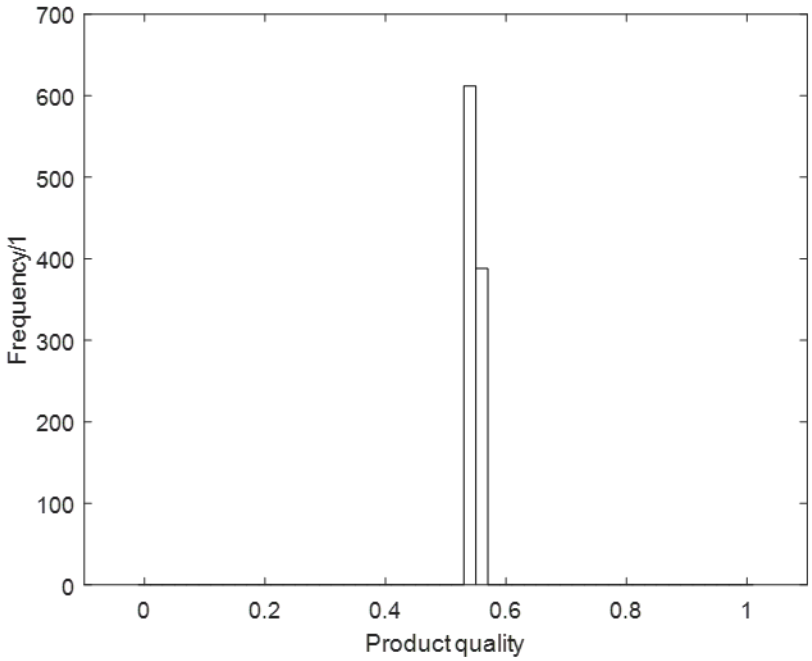

Figure 6: As figure 5, but for products whose assembly is directed using a strategy based on arranging the component parts so that their respective diameters are in increasing order.

This example is clearly a very simplified version of real problems. The approach ignores the fact that there is a cost associated with measuring all the parts (not just knowing that they all conform) and physically ordering them. Ongoing research at NPL is looking at more complex situations where efficient algorithms are needed to optimise the way the parts are assembled, and at simpler strategies (such as binning) for part classification.

2.2 Digital twins and automated process control

The approach described in the previous section to assembling components is clearly not suitable for all products, as the measurement costs can make it uneconomic for suppliers of high volume low value components. However, the information generated by acceptance tests carried out by suppliers of such components can be used to reduce costs and improve quality by using the calculated statistics in a model of the fully assembled final product (a “digital twin”).

Measurements made during assembly can be used to update the current state of knowledge about a part or structure based on a model (this model is described as a “digital twin”). Suppose that the supplier of a supporting beam in an assembled structure has supplied batch-level information about beam stiffness, and that a finite element model of the assembled structure is available that can be used to predict the deformation of the structure under gravitational self-loading. If measurements are made of the self-loaded shape of a complete assembly, then a data assimilation approach can be used to assign an estimate of beam stiffness to the assembly based on the prior knowledge given by the supplier, the finite element model and the measured shape. Doing so is useful because it means that an improved estimate of beam stiffness can then be used in further models of part lifetime and worst-case loading to improve confidence in the structural integrity of the overall assembly. Additionally, if the beam stiffness is thought to be inadequate, remedial action can be taken to avoid scrapping the assembly at the final testing stage or before catastrophic part failure in service.

Historical data gathered during manufacture can also inform smart process control and maintenance. Many

process control systems use current and recent data to set PID controllers and alarms based on expert knowledge and previous experience. A typical sensing system contains multiple sensors gathering different data throughout a manufacturing process, leading to a data set that is too large and too complicated for a human to analyse intuitively to identify the factors leading to good quality products. Machine learning and other artificial intelligence algorithms can combine supply chain information with manufacturing data to identify clusters, patterns and correlations that can improve process control. Time series analysis can fuse maintenance records and process data to identify data trends that precede emergency maintenance events to support failure prediction and enable preventative measures to be taken before catastrophic damage occurs.

3.0 REQUIREMENTS AND CHALLENGES

The value of DESC is entirely dependent on trust. In particular the purchaser needs to have trust in the supplier's data and in their own data, and the suppliers need to have confidence that the data they supply is being used in a way that will not compromise their business.

The level of trust required of data depends on the purpose for which the data is being used: data used for business-critical decisions will require a much higher level of trust than data for low-risk choices. Generation of trust requires confidence that:

a) the sensors used to gather the data are appropriate for the task,

b) any subsequent processing of the data has been carried out using reliable algorithms, and

c) the data has not been altered (maliciously or accidentally) subsequent to any processing.

In addition, if historical data are being considered, there must be confidence that the data are appropriate for their intended use.

Confidence in data gathered by sensors can be partially addressed by associating metadata with the data. Metadata ("data about the data") captures aspects of the measurement process that may affect the reliability and future usability of the data, for instance:

- sensor type and capabilities (precision, standard uncertainty, known sensitivities to environment, etc.),
- date of last sensor calibration and any other traceability information,
- operator (if relevant),
- time of data collection,
- sensor location, etc.

For the metadata to be of the greatest possible use, standards for metadata need to be common across industries, because most types of sensor are used in multiple industries. Metadata also plays a key role in the use of curated and historical data. The structuring of metadata ("ontology") has a strong effect on the ease of carrying out data searches, particularly for data sets with multiple levels of metadata. The ability to carry out this type of search efficiently underpins the ability to merge data sets that are gathered at different points in time and space but relate to a single object, a task crucial to the effective use of process data.

The Data Science group at NPL is working to develop metadata protocols that ensure that data has appropriate, and appropriately structured, information associated with it. The work is using the FAIR

("Findability, Accessibility, Interoperability, and Reusability") principles of data curation as a starting point, and is identifying the unique requirements of measurement data that will need special consideration. Initial efforts are focussing on automated data and metadata capture for measurements carried out in the laboratory. It is expected that the resulting data structures will share many common features with data gathered during factory floor measurements, meaning that the outputs of the work can be rapidly transferred to industrial applications.

NPL is also carrying out research into data reliability measures. The most important, and most familiar, measure is the measurement uncertainty associated with the data, but there are other aspects that can be quantified and used to assess data reliability and the suitability of data for a given application. Uncertainty evaluation for DESC data sets is generally very challenging: data sets are multimodal, are gathered by sensors of varying quality, and are large scale. An aspect that is generally neglected is correlations within these data sets: it is obvious that measured data gathered by the same sensor are correlated, but data collected at the same time using different sensors also may be correlated if, for instance, the measurements are made in a thermally uncontrolled environment and the behaviours of the sensors are temperature-dependent. More generally, data reliability needs to be linked to an understanding of the application for which the data will be used: as was mentioned above, data for business- and safety-critical decisions requires a higher level of reliability than for less important decisions. This concept is linked to the idea of "data readiness levels".

The reliability of algorithms used to process data is a growing concern, particularly with the increasing use of algorithms that are trained using data sets and use probabilistic approaches to obtain internal parameter values. The probabilistic aspects of the algorithms mean that they may not generate the same results if given the same input data sets on different occasions. The use of data to train the algorithms means that care must be taken to provide a training data set that includes every possible outcome that needs to be recognised or identified. The use of incorrect training data can lead to unpredictable behaviour of the algorithm. These aspects make standard approaches for software testing and for uncertainty evaluation for data processed by such algorithms unsuitable. Many artificial intelligence or machine learning algorithms have these features, and NPL is working to develop appropriate guidance and uncertainty evaluation techniques to ensure that the reliability of these algorithms is well understood.

A related topic that needs to be considered for the use of digital twins is model reliability. The models used to obtain a state of belief about a product need to go through a validation process to ensure that they accurately capture the physics of the situation, ideally culminating in a comparison between model prediction and measurement. However, this comparison must be distinct from the model updating process to ensure that the updating is not a self-fulfilling prophecy. NPL is working on appropriate validation methods that take the uncertainties associated with model results and validation data into account.

Perhaps the most challenging area is data security, particularly for data sharing. Blockchain is a potentially important technology that allows for secure sharing of data and avoids many of the vulnerabilities of centrally-stored data, thus reducing the security concerns that hinder many potential data-sharing activities. In addition to these benefits, NPL is investigating the use of blockchains' time-stamping facility to provide a distributed approach to traceability and uncertainty evaluation.

If suppliers are reluctant to share commercially sensitive data with their customers, it may still be possible for mutually beneficial use of the data to occur. Suppose that the customer has a commercially sensitive calculation that they wish to carry out using a supplier's data, and that the supplier refuses to release the data in (raw) unencrypted form. Homomorphic encryption and related techniques enable general computation to be carried out on encrypted data, producing an encrypted output, without the need for the data or any intermediate results to be decrypted. These technologies are still at an early technology readiness level as there are problems with computation time and with the effects of noise within the encrypted calculation, but may be of benefit in the future.

4.0 CONCLUSIONS

DESC is at an early stage in most industries, and there are many challenges yet to be overcome. Recent developments in mathematics and computer science have generated new technologies that address problems in automated decision-making, secure data sharing, and data quality measures that will support further growth of the DESC approach. In order to gain full benefit, these innovations must be linked to a sound understanding of measurement data and its associated uncertainties, leading to reliable decision-making based on trusted data. The DESC programme at NPL is placing these new technologies in a metrological framework to support industrial uptake with minimal disruption to existing practices.