Authors:
Dr Salaheddin Rahimi *CEng FIMMM*, Materials Team Lead at The University of Strathclyde's Advanced Forming Research Centre (AFRC), a specialiost technology centre within the National Manufacturing Institute Scotland (NMIS).
Dr Ioannis Violatos, Computational Materials and Process Modelling Theme Lead at the Advanced Forming Research Centre (AFRC),
Professor Bradley Wynne, Research Director at the Advanced Forming Research Centre (AFRC),
Professor Martin Jackson, Professor of Advanced Metals Processing at University of Sheffield.

The digital-twin of forging high value components

Aerospace alloys such as those based on titanium and nickel are produced from their metallic ores through energy intensive reduction and alloying processes. They are then converted to state-of-the-art high value engineering components by subjecting the material to energy intensive complex non-linear thermo-mechanical processing (i.e., forging) that results in heterogeneous microstructure, non-uniform mechanical properties, part distortion and residual stress. This necessitates significantly larger dimensions than the final geometry to be manufactured before over 70% of the material is machined away to gain the final required shape of the component and retain the 'optimum' microstructure and property set necessary for in-service performance.

This expensive and wasteful approach has led to a sector-wide effort to produce components with more homogeneous microstructures and property distributions from less material. For example, many emerging powder-derived manufacturing routes have been explored extensively over recent years. Emerging manufacturing techniques such as precision investment casting and additive manufacturing have advantages over forging in terms of material and energy usage and speed of manufacture, but they cannot produce the high integrity properties required for many structure-critical applications. For now, and an unforeseeable future, forging is here to stay, but it needs to have a 21st century makeover to be more agile, economical, less wasteful with better performing products.

Despite decades of experience and continuous improvement, forging operations still lack the precise control and tailored production that Manufacturing 4.0 requires. Therefore, for high integrity products there is enough drive and justifications to create a digital-twin of the physical forging process to empower manufacturers to provide (i) a more efficient, less conservative, and affordable process route, and (ii) improved and more consistent properties to reduce design conservatism.

Creating a digital-twin of forging is now possible, owing to recent improvements in control, sensor technology and NDT characterisation methods, coupled with improved physical understanding and modelling of the material behaviours, and computation power. But this is only achievable through new and data-centric approaches that brings together knowledge and know-how of materials behaviour, simulation and modelling, sensing, data analysis and optimisation, and most importantly artificial intelligence with decision making capability. The virtual world of a digital-twin that incorporates press dynamics, temperature, load, tool wear, and lubrication, as well as through-process microstructure and property evolution, will be the closest analogy to an equivalent real-world system or physical-twin. This is not limited to simple animation and parallel simulation of forging processes, but actually includes robust multi-scale physically-based predictive capabilities, in-process and real-time sensing, fast data optimisation algorithms embedded in a virtual reality framework with ability of decision making based on the results of simulations and real-time sensing.

But how achievable and realistic a "digital-twin" can be at this stage where (i) our understanding of micro-scale deformation mechanisms in materials (i.e., crystal plasticity) during forging at different

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temperatures are limited, and (ii) even the implementation of the existing understanding of micro-deformation mechanisms in crystal plasticity based models are limited to small sizes (i.e., far smaller than industrial scale forging) and extremely computationally intensive that cannot be used in process (i.e., real-time). So, what do we mean by "digital-twin"; microstructure digital-twin, a process digital-twin or both (i.e., everything)? Creating microstructure digital-twin is rather more difficult than a process digital-twin. This is because there is currently no NDT method for real-time in-process microstructure characterisation, and we cannot implement sensors in the microstructure during the process. Hence, we must rely on physically based models and post-mortem characterisations. The physical models are complex, time-consuming and computationally expensive, but there exist approaches for identifying relevant data from regions of interest. The process digital-twin however can rely on shape changes, temperature gradients, loads, deformation rate, and etc. from the physical-twin (i.e., physically measured data). These two are inter-related with close interactions, and feed to one another.

Inevitably , the question that arises is whether the digital-twin is '***(1) a set of carefully statistically validated simulation models for a particular process/part', '(2) a set of data collected before, during or after forging for the process and the product', or '(3) a set of real-time simulation/ predictive/optimisation tools for engineering decision making, which are built from huge data sets***'? These are fundamentally different approaches to create a digital-twin and each has its own limitations. The first is based on high fidelity modelling and statistical calibration, which is still not possible to exercise with live data due to limitations in computational power and the idealisation of the process itself. The second relies on collecting all data for the necessary key process parameter, which is practically impossible for most forging processes, and then control the process based on a baseline design or manufacturing curve. The third is more in the realms of artificial intelligence and fast surrogates such as deep-learning and neural networks, which operates blindly on large data, and is difficult and mostly expensive to generate, without making use of the physics and dynamics involved in the process. A digital-twin of forging with real-time decision-making ability is actually making use of all three approaches and combines them into a more complete and robust tool, complementing each other to extend their limitations.

Given all the limitations in the existing technologies, a microstructurally enabled digital-twin of forging can be developed which will be centred on linking high-fidelity spatially resolved full-field models for microstructure evolution and deformation with computationally efficient mean-field models using a multi-level statistical framework. The full-field models are based on advanced techniques combining the multi-phase-field method and anisotropic crystal-plasticity within a multi-physics simulation framework. These models incorporate effects of phase transformation, deformation and annealing during deformation, cooling, heating as well as transient effects, and are calibrated using a suite of characterisation techniques, such as, laboratory simulation, in-situ synchrotron and neutron diffraction, and high resolution EBSD. Mean field models employ homogenisation approaches to implicitly describe the microstructure and its evolution through crystal-plasticity based equations operating on a statistically equivalent material with average characteristics like grain size, dislocation density and texture. This high-fidelity simulation capability can be used to generate virtual datasets to supplement limited/expensive experimental data required to calibrate the microstructure digital twin (see Figure 1).

For example, consider a simple machining operation on an as-forged and heat treated high-value disc component for application in jet engines (see Figure 2). A baseline model simulating the metal forging and heat treatment processes (hot working, aging, quenching, etc.) taking into consideration microstructural changes (recrystallisation, precipitations, grain growth, etc.) using physically based and constitutive materials models, will be developed. A baseline model will also be developed for the subsequent machining operation (metal removal rate, heat generated, etc.) using simplified

approaches for metal cutting through material removal operations and integrating cutting forces, machining induced effects, and clamping configurations. These baseline models will then be adapted to create a “digital-twin” that also estimates microstructure changes, generation and evolution of residual stress, and distortion throughout the whole processes. The digital-twin will be brought to life using data acquired by in-situ measurements where the model is repeatedly updated, improved by learning algorithms and validated using sensors transmitting real-time data; e.g., using data analytic processed deformation data from digital image correlation. The dynamic digital representation of the forging process will also lend itself to augmented reality overlay communication tools enabling engineers to understand, predict, control, and optimise the performance of the manufacturing route. This will be built upon to develop a more complex digital-twin representing sequential fabrication operations, proof testing, quality control checks and component lifetime performance. This digital based technology has the potential to transform the design, manufacture and performance of high-value products, reducing asset downtime, improving productivity, and increasing market agility.

This will inform industry on the optimum processing route for a given component, enable the assessment of process route and allow the whole supply chain to be involved in the early stages of component design (when changes can still be made cheaply through the virtual digital-twin). Also, it will enable real-time production decisions, instant troubleshooting and validation for future high integrity forged components, using physics-based models and data analytics.

From a sustainability standpoint, a digital-twin of the microstructure during forging and press performance will enable the supply chain to DO MORE WITH LESS material by providing higher confidence in location-specific properties or utilising the press more efficiently (i.e., using less energy) to achieve the property goals of the design.

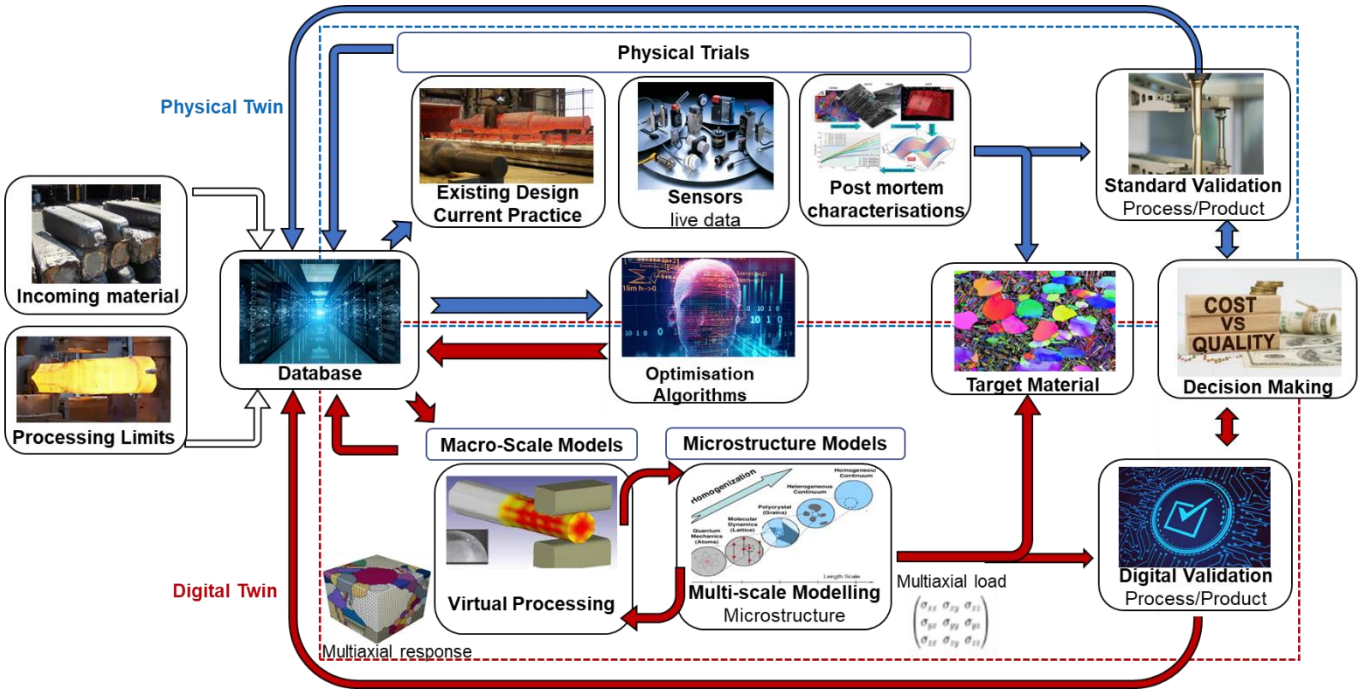

Figure 1: Schematic workflow of digital-twin of forging

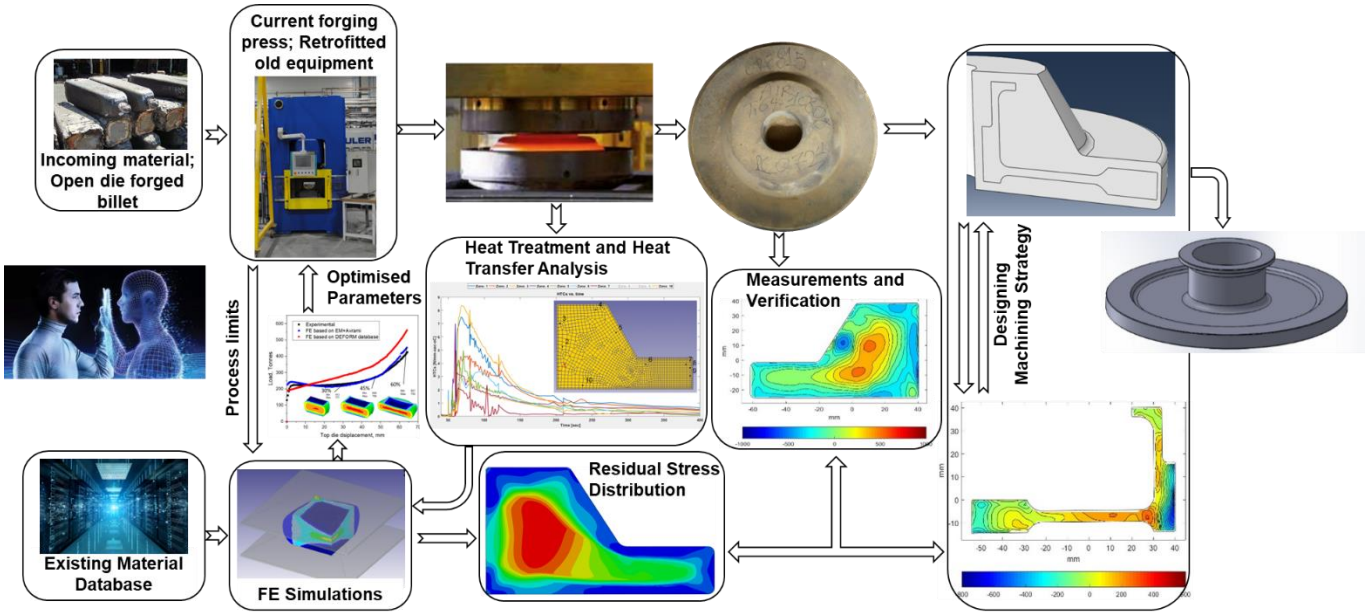

Figure 2: An example of utilising a digital-twin for controlling distortions during machining by predicting the generation and evolution of residual stress throughout forging, heat treatments and quenching – Optimisation of materials removal strategy during machining (i.e., tool path).

How can this rather sophisticated technology, which requires high-tech infrastructure and highly trained engineers, be adopted by the forging industry most of whom rely on multi-million £s legacy equipment with limited adaptability? Most manufacturers, especially SMEs, cannot afford scrapping their legacy equipment for the sake of digital transformation! Indeed, there is no need for scrapping legacy equipment as it is possible to retrofit them with data acquisition modules (and maybe even new control systems) to obtain/record some critical parameters - such as load, temperature – that can be used as input to the digital-twin. Some other necessary parameters can be obtained from historical data or verified simulation models.

Of course, the interactions between the digital-twin and a legacy equipment may not be fully automatic, but optimised process parameters, obtained from a verified digital-twin, can be implemented into conventional forging processes manually. This is a step towards digitally informed forging to achieve a part with certain microstructural characteristics and mechanical properties set.