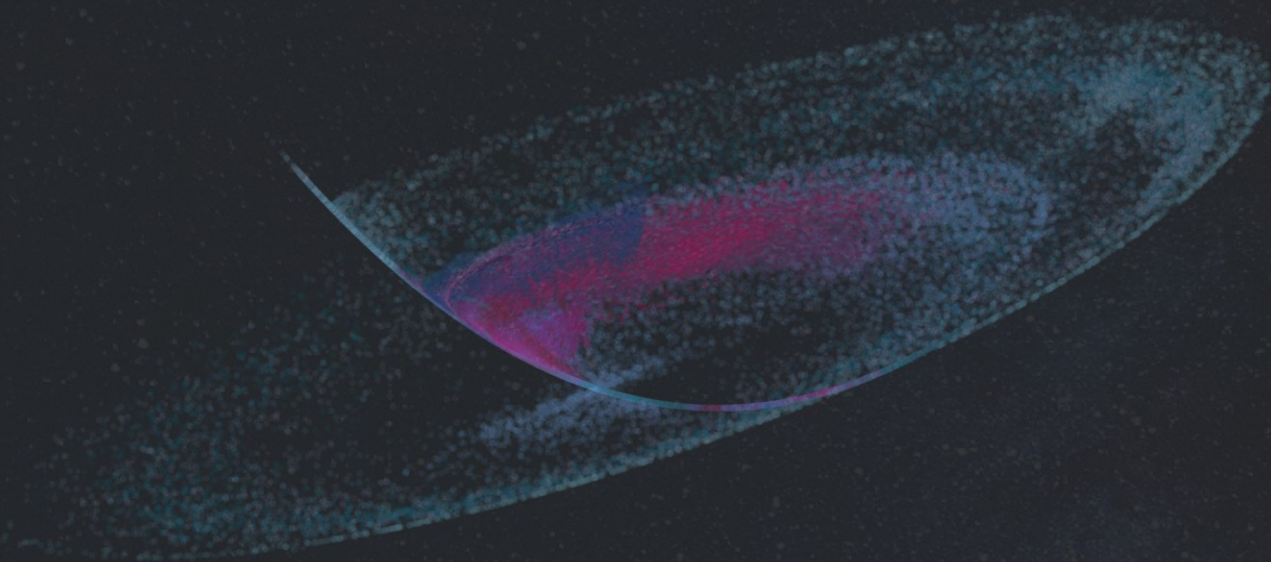


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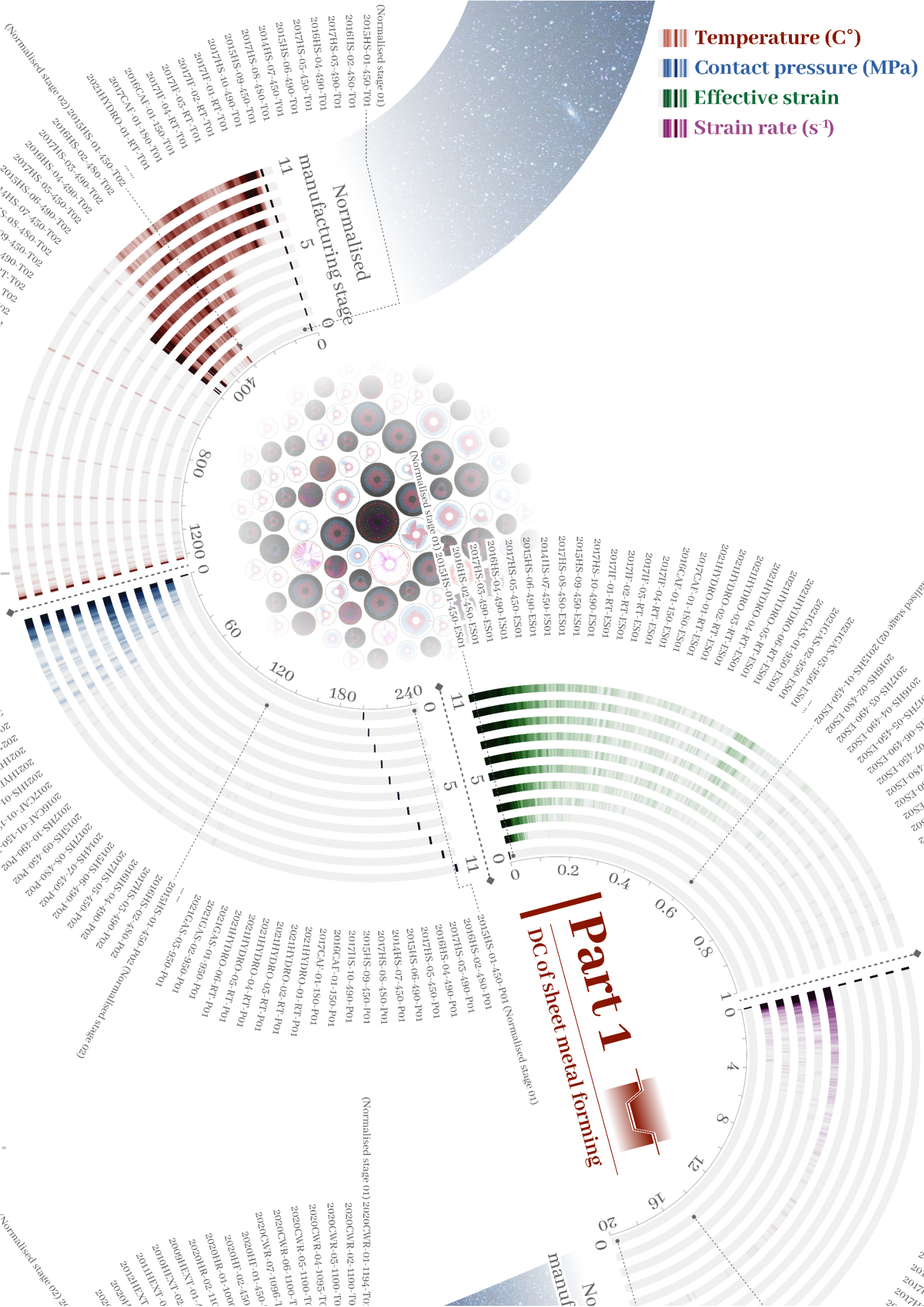
Data science in manufacturing: Unlocking digital characteristics (DC) of metal forming processes

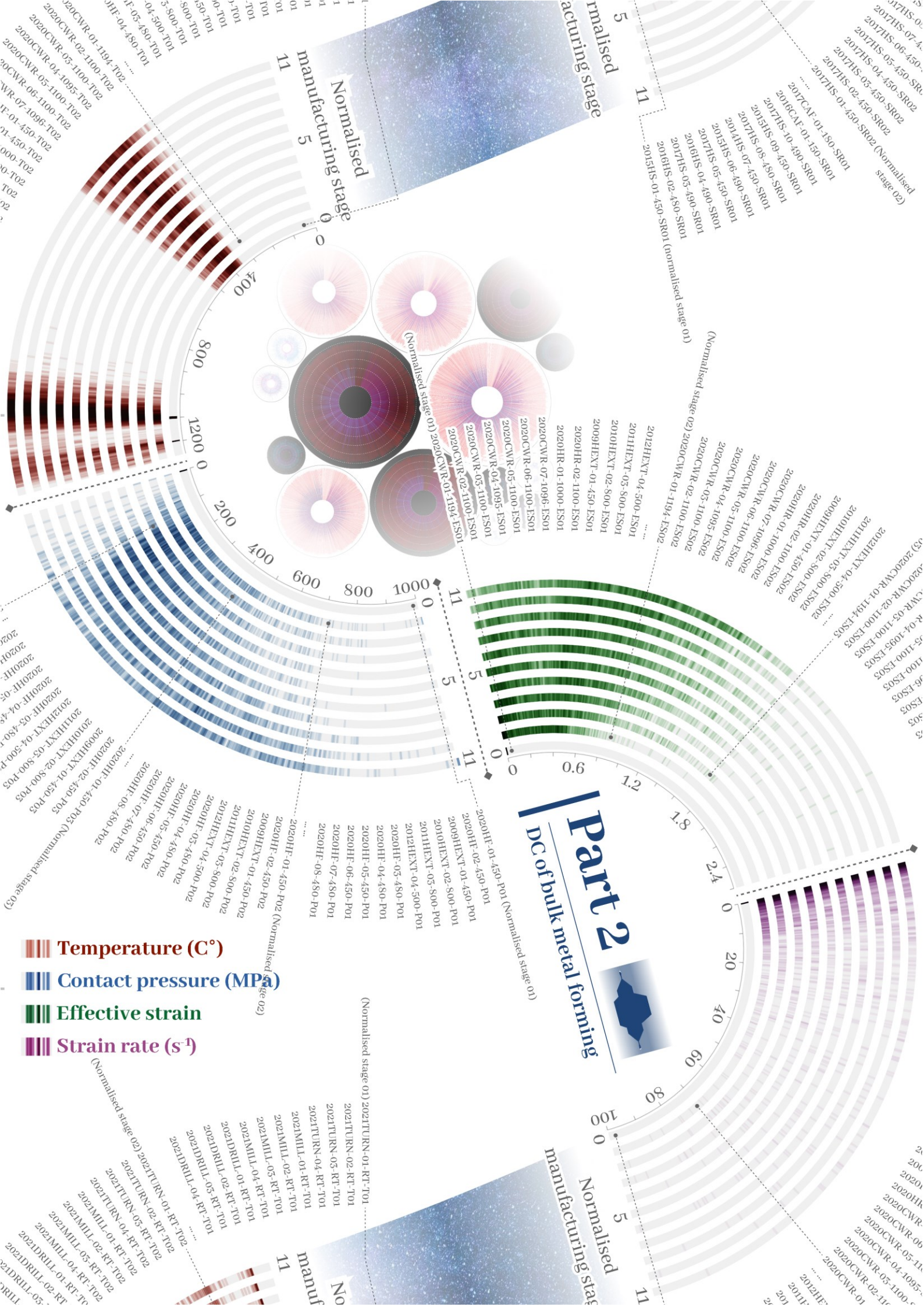


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Submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy in Mechanical Engineering of
Imperial College London
and the Diploma of Imperial College

July 2023





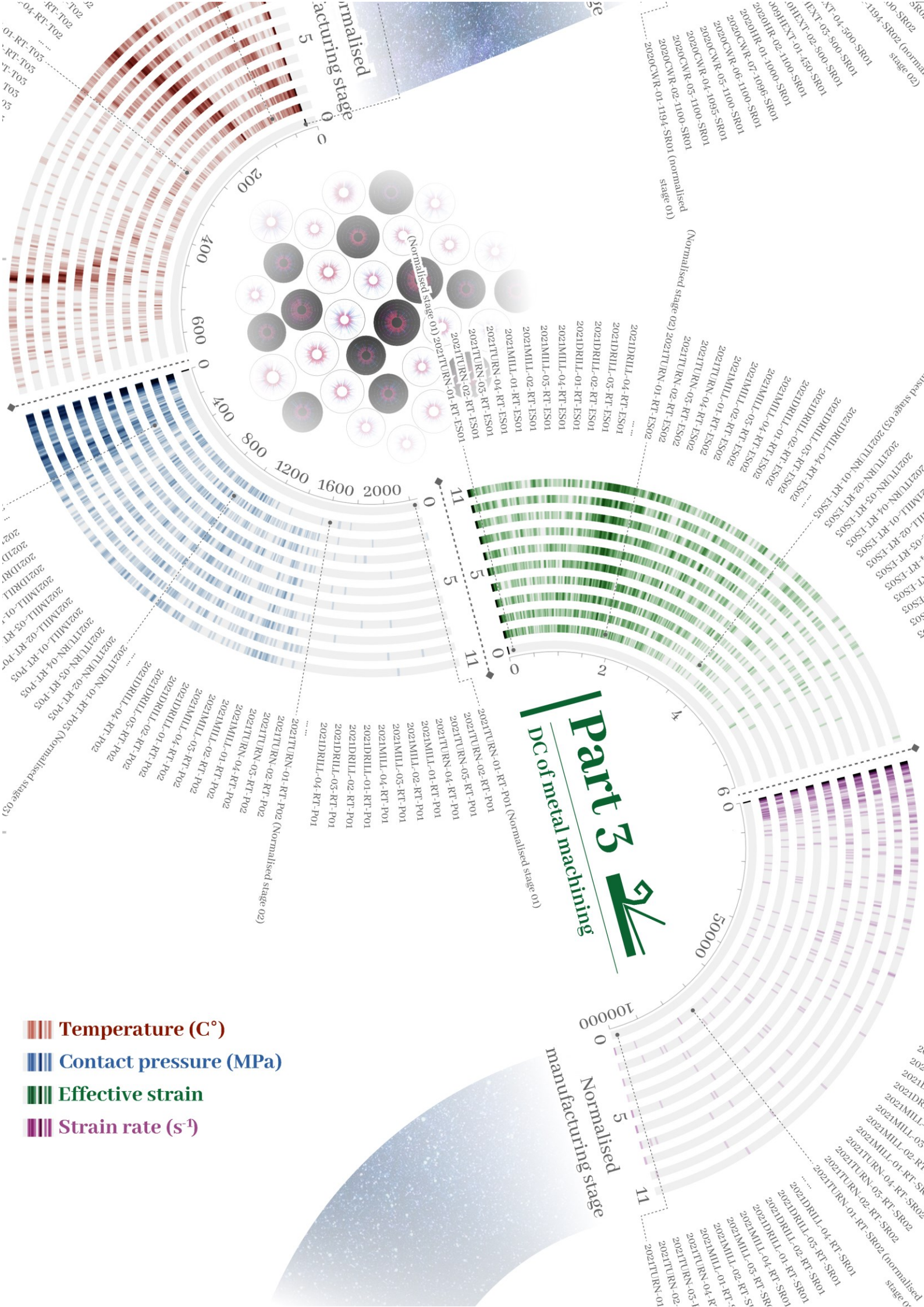


Figure A | Digital characteristics (DCS) of manufacturing processes. The DCS is developed based on experimentally verified manufacturing metadata (filed in 201 functional data modules with unique ID numbers, as shown in this figure, for searching and referring, see Methods) stored in the data repository through key enabling approaches in terms of information absent data processing techniques (e.g., the physical-based Evolutionary Binary algorithm, see Chapter 3) and data characterisation techniques (e.g., the development of digital characteristics, see Chapter 3). Using these technologies, the DCS is composed of digital characteristics (DC) of over 140 manufacturing processes covering sheet metal forming and bulk metal forming processes, and its volume is continuously expanding with DC developed based on newly processed manufacturing metadata (see Chapter 5). Therein, in each part, each ‘ring’ represents a dataset of a manufacturing process, and the size of the ‘ring’ represent the data volume of this dataset. To present the DCS of manufacturing processes, the evolutionary temperature data, contact pressure data, strain data and strain rate data are mapped against normalised manufacturing stages, which are four representative thermo-mechanical data that are distinct in terms of different manufacturing processes. In Part 1 of the DCS, at present, the DC of the sheet metal forming processes show that across the end-to-end manufacturing stages, the temperature data values range from room temperature to 1267.0 °C, contact pressure data values range from 0 to 243.3 MPa, effective strain data values range from 0 to 0.95, and strain rate data values range from 0 to 18.8 s⁻¹. In Part 2 of the DCS, at present, the DC of the bulk metal forming processes show that the temperature data values of bulk metal forming processes range from 306.2 °C to 1254.3 °C, contact pressure data values range from 0 to 1000.0 MPa, effective strain data values range from 0 to 2.5, and strain rate data values range from 0 to 99.9 s⁻¹. In the Part 3 of the DCS, at present, the DC of the machining processes show that the temperature data values range from room temperature to 642.6 °C, contact pressure data values range from 0 to 2,258.3 MPa, effective strain data values range from 0 to 5.94, and strain rate data values range from 0 to 10,000 s⁻¹.

Declaration of Originality

This is to certify that the intellectual content of this thesis is the product of my own work under the supervision of Dr. Liliang Wang at the Department of Mechanical Engineering of Imperial College London. I have clearly referenced all sources used in this thesis. This thesis has not been submitted yet for a degree or diploma at any other university or institution.

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17.07.2023

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Abstract

As one of the most important manufacturing crafts, the metal forming industry accounts for 15-20% of the national GDP of modern industrialised nations¹. Over 160,000 engineering materials and nearly 90% (wt. %) of products made of metals are manufactured by metal forming processes^{2,3}. Approximately 90% of steel products⁴ and 67% of aluminium products⁵ are manufactured by at least one metal forming process. Meanwhile, voluminous data, proliferated daily at an ever-greater scale during production, research, and development activities, have driven scientific advances in the manufacturing sector towards the era of digital manufacturing. These data are essential to unlock insightful features that can facilitate comprehensive scientific understanding of metal forming technologies. To date, there has been limited research in approaching metal forming from the perspective of data, not to mention that most collected data lack critical information to fully characterise a metal forming process. This is mainly due to limitations of data collection capabilities and data privacy, which hinders the extraction of insightful digital information from underlying scientific patterns.

In this thesis, a cloud-based data repository was established that currently contains 201 functional data modules of diverse manufacturing processes. Each data module consists of experimentally verified manufacturing metadata and essential information with a globally unique and permanent ID which provides open access for scientific communities. Tackling the long-standing challenges on processing information absent data requires an emerging research field combining knowledge of metal forming and data science. Here, a physical-based Evolutionary Binary (EB) algorithm was developed for enabling information absent data processing. Results demonstrate that the EB algorithm yields a highly efficient recognition of missing features for a metal formed product with nearly 95% of overall accuracy with sparsely labelled data points ($\leq 1\%$). By using this technology, the digital characteristics (DC), a novel concept has been developed to denote the visualisation of manufacturing metadata for a targeted manufacturing process incorporating essential information spanning the design, manufacturing and application stages of manufactured products, for sheet and bulk metal forming processes. The DC of a representative metal forming process are visualised and analysed in terms of specific features such as the geometric features.

Moreover, the unique DC have been identified for over 140 manufacturing processes, leading to the establishment of the digital characteristics space (DCS) of manufacturing processes that provides access for scientific communities to the most up-to-date and

information-rich cloud-based repository. Using the DCS as a pairing reference, the origins of a set of unknown fragmental data were successively identified with a minimum length of 10 data points. This is realised by pairing the representative thermo-mechanical features of fragmental data with the existing thermo-mechanical DC in the DCS by using machine learning approaches. Subsequently, the unique thermo-mechanical DC, represented by the temperature DC, contact pressure DC, effective strain DC and strain rate DC, of the pair manufacturing process were developed and analysed. This thesis established a framework of data science in manufacturing/metal forming including the manufacturing metadata collection that leads to the development of a cloud-based data repository, information absent data processing that leads to the development of the physical-based EB algorithm, data characterisation and analysis that leads to the development of DC and DCS of manufacturing processes, and digitally-enhanced research and DCS application highlighted by the fragment data pairing.

Acknowledgements

Here, I would like to express my great gratitude to the following individuals who have played instrumental roles during my PhD journey. Due to the Covid 19 epidemic since 2020, I have never been home during the past four years since 2019. Their unwavering support, guidance, care and encouragement have been invaluable throughout this tough journey.

First and foremost, I would like to express my deepest appreciation to my supervisor, Dr. Li-Liang Wang, for his exceptional mentorship, patient supervision, insightful inspiration, rapid feedbacks and consistent trusts, like always. Dr Wang's expertise, passion and dedication on the sciences and technologies have been very impressive and remarkable. Without his strong support, I cannot even study in Imperial College London. I am immensely grateful for the valuable opportunities provided by him and the knowledge imparted, which have significantly shaped the outcome of my PhD.

Then, I am indebted to my amazing teammates and colleagues, and true friends, in the Metal Forming and Modelling Group (MFG, present and past): Dr. Denis J. Politis, Dr. Omer El Fakir, Dr. Mateusz Kopec, Dr. Yiran Hu, Dr. Xi Luan, Dr. Yang Zheng, Dr. Qunli Zhang, Dr. Xiaochuan Liu, Dr. Yuhao Sun, Dr. Zhaoheng Cai, Dr. Xiao Yang, Dr. Dhawan Saksham, Dr. Mozammel Mia, Ms. Xiangnan Yu, Ms. Lemeng Zhang, Mr. Bozhou Di, for their kind collaboration and supports. Their knowledge, enthusiasms, and willingness to brainstorm novelties have been instrumental in completing this project. In addition, the MFG was awarded the prestigious President's Medal by Imperial College. This award selects only one research team among a variety of research groups and research labs at Imperial, which is a huge honour not only for the team, but also for the individuals of the team that make contributions. It was absolutely enjoyable working with these talented researchers.

To my beloved parents, I am eternally grateful for your unwavering support and love. Your encouragement, understanding and sacrifices have supported me through my entire academic journey during such a difficult time due to Covid 19. Your belief in me, even in the moments of my self-doubt, has never ended, and I cannot thank you enough for always being there for me.

I would like to express my sincere appreciation to my partner, Yuhan, for her constant support, patience, and understanding throughout my PhD. Your encouragement and belief in

my abilities have been a source of my strength and motivation. Your love has kept me going through the most difficult and demanding times.

Last but not least, I would like to acknowledge the countless other individuals who have provided their assistance, insights, and encouragement. Your supports have made a significant impact during my PhD, and I am grateful for your contributions.

Completing this project would not be possible without the guidance, support, and love of these exceptional individuals. I really appreciate every support, opportunity, help and encouragement given by the above individuals or teams. Without them, I won't be able to make the current accomplishment. I am deeply grateful for their contributions and impacts on shaping my academic and personal experiences.

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List of publications

Peer-reviewed journal publications

1. **Liu, H.**, Dhawan, S., Politis, D. J., Yang, X., Zheng, Y. & Wang, L*. *Unlocking digital characteristics of metal forming processes*. Nature Communications. (2023) (revision under review).
(This research was presented as **Keynote Speech** at 19th International Conference on Experimental Mechanics, Kraków, Poland, 17-21 July 2022)
2. **Liu, H.**, Dhawan, S., Shen, M., Chen, K., Wu, V., & Wang, L*. *Industry 4.0 in metal forming industry towards automotive applications: A review*. International Journal of Automotive Manufacturing and Materials. 1.1 (2022): 2.
3. Mia, M., Zhang, L., Anwar, S. & **Liu, H.***. *Development of Digital Characteristics of Machining based on Physics-guided Data*. Journal of Manufacturing Systems. (2023) (in press).
4. Yang, X., **Liu, H.**, Dhawan, S., Politis, D. J., Zhang, J., Dini, D., Hu, L., Gharbi, M. M. & Wang, L*. *Digitally-enhanced lubricant evaluation scheme for hot stamping applications*. Nature Communications. 13.1 (2022): 1-9.
5. Yang, X., **Liu, H.**, Zhang, L., Hu, Y., Politis, D. J. & Wang, L*. *Interactive mechanism and friction modelling of transient tribological phenomena in metal forming processes: a review*. Friction. (2023): 1-21.
6. Di, B., **Liu, H.**, Dhawan, S., Wang, K., Liu, X.* & Politis, D. J. *Mechanics-Based Failure Model of Tube Hydro-Bulging Test*. Frontiers in Mechanical Engineering. 8 (2022): 908375.
7. Yang, X., Liu, X., **Liu, H.**, Politis, D. J., Leyvraz, D. & Wang, L*. *Experimental and modelling study of friction evolution and lubricant breakdown behaviour under varying contact conditions in warm aluminium forming processes*. Tribology International. 158 (2021): 106934.
8. Chantzis, D., Tracy, M., **Liu, H.**, Politis, D. J., Fu, M. & Wang, L*. *Design Optimization of Hot Stamping Tooling produced by Additive Manufacturing*. Additive Manufacturing. (2023) (in press)
9. Yu, X., Jin, Y., **Liu, H.**, Rai, A., Kostin, M., Chantzis, D., Politis, D. J. & Wang, L*. *A Review of Renewable Energy and Storage Technologies for Automotive Applications*. International Journal of Automotive Manufacturing and Materials. 1.1 (2022): 10.

10. Yang, X., Zhang, L., **Liu, H.**, Politis, D. J., Gharbi, M. M., Shi, H. & Wang, L*. *Effect of tooling temperature on the transient lubricant behaviour in hot metal forming processes.* steel research international. (2022): 2200306.
11. Liu, X., Di, B., Yu, X.*, **Liu, H.**, Dhawan, S., Politis, D. J., Kopec, M. & Wang, L. *Development of a Formability Prediction Model for Aluminium Sandwich Panels with Polymer Core.* Materials. 15.12 (2022): 4140.

Conference paper

1. **Liu, H.**, Yang, X., Zheng, Y. & Wang, L*. *Experimental Study on Galling Behavior in Aluminum Stamping Processes.* Physical Sciences Forum. Vol. 4. No. 1. 2022. (oral presented at 19th International Conference on Experimental Mechanics, Kraków, Poland, 17-21 July 2022)

Intelligent products (software copyright) on SmartForming®

1. **Liu, H.**, Wang, L. *Data Space*® (of manufacturing processes). 2023. SF ID: SFDS11-MANUF. A cloud-based data repository that currently contains 201 functional data modules with experimentally verified dataset(s) and essential digital information with globally unique and permanent IDs.
(<https://app.smartforming.com/store/modules/all?categoryId=18>)
To get access to *Data Space*®, please refer to the instructional video:
<https://youtu.be/Y0ibUrkuXXs>
2. Weill, M., **Liu, H.** *Auto-PamStamp*®. 2023. SF ID: 2023AGR-01-PY-PS. An executable application that automatically generates ASCII scripts to extract all the desired data from PamStamp software, after which the data are formatted into clean and ready-to-use CSV files. This was applied to enable the automatic data collection in this thesis.
(<https://app.smartforming.com/store/modules/616>)

Plenary and Keynote speeches

1. **Liu, H.**, Dhawan, S., Politis, D. J., Yang, X., Zheng, Y. & Wang, L. *Unlocking digital characteristics of metal forming processes*. **Keynote Speech**, 19th International Conference on Experimental Mechanics, Kraków, Poland, 17-21 July 2022.
2. Wang, L., **Liu, H.** **Plenary speech**, International Conference on Advanced Materials Netshape Forming, Chongqing, China, 8-10 September 2023.

Nomenclature

General symbols:

FEA	Finite element analysis
IoT	Internet of things
CPS	Cyber-physical systems
AI	Artificial intelligence
FAIR	Findable, Accessible, Interoperable, Reusable
DC	Digital characteristics
DCS	Digital characteristics space
HFQ	Solution heat treatment, forming, and in-die quenching
SHT	Solution heat treatment
FAST	Fast light alloys stamping technology
I-CPS	Industrial cyber-physical system
I-IoT	Industrial internet of things
BDA	Big data analytics
CC	Cloud computing
AM	Additive manufacturing
ML	Machine learning
ANN	Artificial neural network
SVM	Support vector machine
QPSO	Quantum-behaved particle swarm optimisation
MLP	Multilayer perceptron
CNNs	Convolutional neural networks
MaaS	Model-as-a-Service
SaaS	Software-as-a-Service
IHTC	Interfacial heat transfer coefficient

BH	Blank holder
FB	Flat bottom
SW	Side wall
3Us	‘Unified’, ‘Unique’ and ‘Useful’
FD	Fragmental data
L100-FD	Fragmental data with a length of 100
L50-FD	Fragmental data with a length of 50
L40-FD	Fragmental data with a length of 40
L30-FD	Fragmental data with a length of 30
L20-FD	Fragmental data with a length of 20
L10-FD	Fragmental data with a length of 10
CWR	Cross wedge rolling
FT-CWR	Flat type cross wedge rolling
NDT	Non-destructive testing
PLC	Programmable logic controller

Symbols for illustrating the Evolutionary Binary (EB) algorithm and machine learning algorithms:

EB	Evolutionary Binary
TMF	Thermo-mechanical filter
$f_i(t)$	Thermo-mechanical data
f_c	Critical value
s	Model parameter
$\langle n \rangle$	The parameter was normalised
t_c	Manufacturing stage
$\varepsilon_{1,i}^{\langle n \rangle}(t_c)$	The normalised major strain at the normalised stage t_c
$\varepsilon_{\text{eff},i}^{\langle n \rangle}(t_c)$	The normalised effective strain at stage t_c

$P_i^{<n>}(t_c)$	The normalised contact pressures at stage t_c
$T_i^{<n>}(t_c)$	The normalised temperatures at stage t_c
t_0	Initial manufacturing stage
CDS(s)	Calibration dataset size(s)
TeDS(s)	Test dataset size(s)
DT	Decision Tree
KNN	K-Nearest Neighbour
MLP	Multilayer Perceptron
TDS(s)	Training dataset size(s)

Chapter 1. Introduction

1.1 Background

Manufacturing is one of the largest sectors of the economy, with the total value of the global manufacturing big data market increasing from USD 3.22 billion in 2018 to USD 9.11 billion by 2026⁶. Of these, metal forming has long been an important and popular metal forming craft during the technology evolution, which are widely used in automotive, aerospace engineering and construction industries⁷. The metal forming industry accounts for 15-20% of the national GDP of modern industrialised nations¹. It is estimated that over 160,000 engineering materials and nearly 90% (wt. %) of products made from metals are manufactured by metal forming processes^{2,3}. In addition, approximately 90% of steel products⁴ and 67% of aluminium products⁵ are manufactured by at least one metal forming process. Empowered by modern experimental and finite element analysis (FEA) investigations, advanced metal forming technologies enable the efficient manufacturing of complex-shaped components with remarkable reduction in raw material usage, high formability and high post-form material strengths. The corresponding technologies have been successfully integrated in manufacturing plants, especially in automotive and aircraft plants over the past decades⁸⁻¹², together with the development of other theoretical and experimental metal forming related technologies including coating¹³⁻¹⁵, lubrication¹⁶⁻²⁰ and tool design^{21,22}.

Empowered by the Fourth Industrial Revolution, namely the Industry 4.0²³, a concept initiated in 2011 and popularised in 2015, the business models for the entire manufacturing industry are being digitally transformed and revitalised towards mechanical automation by key enabling technologies covering communication, controlling and intelligence, that enhance the manufacturing productivity and flexibility²⁴⁻²⁶. Industry 4.0 is shaping the metal forming industry. During the daily manufacturing and academic activities, voluminous metal forming metadata are being produced daily at an ever-greater scale during manufacturing, research and development activities. It is estimated that manufacturing will generate nearly 2,000 petabytes of data per year in the near term, which is more than communications, finance, energy, healthcare and retail²⁷. The surging metal forming data can be captured by wireless sensor networks utilised in Industry 4.0 key technologies such as internet of things (IoT)^{28,29}, cyber-physical systems (CPS)^{30,31}, cloud computing^{32,33} and digital twins^{34,35}. In addition, FEA of metal manufacturing processes has been an indispensable tool in the development of the supply chain. Material modellers have developed and published advanced models in peer-assessed

work with enhanced predictive functionalities realised via user-defined subroutines. Therefore, large amounts of metal forming metadata can be collected from experimentally verified FEA models to enable proactive prediction and analysis before the real forming process commences^{3,36}.

This unprecedented surge in metadata availability presents a revolutionary opportunity to enable the data mining of more insightful information for the metal forming technologies, and profoundly characterise and understanding these technologies from the perspective of data that incorporates essential manufacturing information through the entire production process^{37,38}. The fast development of digital technologies, especially modern artificial intelligence (AI) algorithms²⁷, with their burgeoning industrial applications^{39–43}, aim to take great advantage of the rapidly increasing manufacturing metadata. Great efforts are being made to promote the data management, reuse and movement by industry, academia and funding agencies to develop new technologies, products and services, as guided by a concept of increasing importance named the FAIR (Findable, Accessible, Interoperable, Reusable) data principles^{44,45}, which is a well-known guiding principle for enhancing data management and stewardship (especially scientific data).

1.2 Motivations and objectives

Data sciences in manufacturing is becoming an emerging research area and effective tool to enable the digital transformation in manufacturing. However, a long-standing challenge for decades is that most of the manufacturing metadata are information absent, and fragmental data that contains extremely scarce information are widely observed and has become a long-standing research challenge in data sciences of manufacturing due to lacking effective techniques for fragmental data processing. the metadata collected via sensor networks could, intrinsically, be fragmental, e.g., temperature metadata captured by thermo-couples from a small specific region of the workpiece over a short production period, not to mention the failures and malfunction of sensor networks, the challenges of metadata storage, management or retrieval, or the policies of data privacy and protection, which has become the first priority in the manufacturing sectors^{46,47}.

The information absent data refers to data lacking the critical information for a single or some data points, or a specific dataset, for example, physical or geometric features of the

products or the underlying thermo-mechanical metadata. The absence of such information hinders the progress of knowledge management, reuse and movement, further deteriorating the long-standing challenge regarding the shortage of labelled data and subsequent challenges that arise in data manipulation, in-depth analysis and visualisation^{48,49}. Furthermore, the fragmental data usually contain extremely scarce essential information and thus posing great challenges on extracting insightful information from them, and significantly hinders the subsequent data-driven research and development on relevant manufacturing processes.

Due to these long-standing challenges, to date, there has been limited research in illustrating, characterising and analysing the metal forming processes from the perspective of data, leading to the incomplete digital understanding on the manufacturing processes. Hence, the following objectives are conducted to achieve the aim of this thesis:

1. Developing a scientific guidance on the development of digital characteristics (DC) of manufacturing processes. The guidance contains details of essential elements represented by manufacturing metadata collection from multiple sources, data pre-processing and information absent data processing technologies.
2. Establishing a cloud-based data repository of manufacturing processes that provides access to experimentally verified functional data modules. Each functional data module consists of experimentally verified dataset(s) and essential digital information including a globally unique and permanent identifier (ID) for stimulating the knowledge movement in scientific communities.
3. Developing a physical-based algorithm that enables the accurate and efficient processing of the information absent data to enhance the profound understanding on the metal forming processes. This algorithm, named the Evolutionary Binary (EB) algorithm, was developed following the thermo-mechanical principles. As the most important element in the EB algorithm, the embedded thermo-mechanical filters (TMFs) were developed by analysing the unique thermo-mechanical evolutionary characteristics of missing features of a specific metal forming process, thus the data points with such characteristics were able to be identified using the EB algorithm.
4. Developing DC of the representative metal forming processes to map and analyse the unique characteristics from the perspective of the data incorporating various evolutionary thermo-mechanical information. The DC can be characterised by three characteristics named 'Unified', 'Unique' and 'Useful'.

5. Establishing the digital characteristics space (DCS) of manufacturing processes. The data processing (e.g., EB algorithm) and characterisation (e.g., DC) technologies enabled the establishment of the DCS of manufacturing processes. The DCS is providing an open access to the most comprehensive, up-to-date and information-rich DC to the scientific communities.
6. Exploring the potential applications of DC and DCS of manufacturing processes highlighted by the fragmental pairing. The origins (e.g., which manufacturing process and stage) of unknown fragmental data pieces that contain extremely sparse information were identified using machine learning algorithm with the DCS as a pairing reference. This was achieved by comparing the thermo-mechanical DC of the fragmental data and that of the existing DC stored in the DCS. The pairing model was validated using a benchmark hot stamping dataset.

The structure of this thesis and the sequential relationships between the main chapters are shown as follows:

Chapter 1 presented the background, motivations and key issues in digital manufacturing, especially the challenges focusing on the manufacturing metadata collection, processing and characterisation, and explained the main objectives to be addressed in this thesis. **Chapter 2** presented a comprehensive literature review on the key industry 4.0 digital technologies that are widely used in the manufacturing sectors, and the recent research and development on the key technologies in manufacturing data processing. To characterise the metal forming processes from the perspective of metadata, **Chapter 3** provided a scientific guidance on developing the digital characteristics (DC) of manufacturing process covering metadata collection, information absent data processing and data characterisation. Using an information absent benchmark dataset of a representative metal forming process, **Chapter 4** developed a physical-based algorithm, named the Evolutionary Binary (EB) algorithm, for recognising the absent features (i.e., the geometric features) from the information absent data. The recognition performance was compared to that of three classic machine learning algorithms (i.e., Decision Tree, K-Nearest Neighbour and Multilayer Perceptron algorithms) in terms of accuracy and efficiency. Subsequently, the DC of this metal forming process were developed and analysed in terms of the recognised geometric features. **Chapter 5** established the digital characteristics space (DCS) of manufacturing processes based on the most up-to-date and comprehensive manufacturing DC developed using the EB algorithm. Therefore, taking the manufacturing DCS as a pairing reference, **Chapter 6** proposed a machine learning-based approach to identify

the origins (e.g., which manufacturing process and stage) of an unknown manufacturing dataset. Based on the pairing results, the DC were developed and analysed for this paired manufacturing process. Finally, **Chapter 7** presented the overview of the thesis, summarised the key contribution on the establishment of data science in manufacturing and main conclusions of this work, and explained the future research plans.

Chapter 2. Literature review

The global manufacturing industry currently produces 200 kg of steel and 7 kg of aluminium per person per year that are transformed into a variety of goods satisfying universal demand, of which over 90% are metal working products⁵⁰. Of these, approximately 90% of steel products⁴ and 67% of aluminium products⁵ are manufactured by at least one metal forming process. As one of the most important manufacturing crafts, the metal forming industry accounts for 15-20% of the national GDP of modern industrialised nations¹. During the past decades, advanced metal forming technologies have been developed to enable the efficient production of complex-shaped metal components, which are widely used in automotive, aircraft, naval and domestic appliance applications, with high raw material usage, high post-form material strength, and achieve remarkable reduction in weight and CO₂ emissions^{9,10}. For instance, the solution heat treatment, forming, and in-die quenching (HFQ) is one such sheet metal forming technology, where the blank is first heated to its solution heat treatment (SHT) temperature, and transferred to a cold die, formed rapidly and then held in the cold dies to achieve a fast quenching to obtain the desirable microstructure that is critical for post-form strength^{8,51}. Another advanced metal forming technology, named the fast light alloys stamping technology (FAST), facilitates mass production by using ultra-fast heating of the alloy sheets that retain a similar strength to the as-received material in the formed components, with the springback effect being reduced or eliminated⁵². In addition, the metal forming related technologies such as coating¹⁴ and lubrication¹⁸ are fast developed to enhance the post-form strength and formability of products.

Voluminous manufacturing data, proliferated daily at an ever-greater scale during production, research and development activities, have driven scientific advances in the metal forming sector towards the era of digital manufacturing. Data sciences in metal forming will become an emerging research area and effective tool to tackle this unprecedented surge in metal forming, and manufacturing metadata availability. This is being witnessed by the ongoing efforts made on developing the key digital technologies, including the industrial cyber-physical system (I-CPS), industrial internet of things (I-IoT), digital twin, big data analytics (BDA) and cloud computing (CC). These technologies are expected to enhance most stages during the metal forming, including the supply chains, raw material provision, tool design and manufacture, forming operations, energy consumption, cost, quality control and customer services. However, according to a survey carried out in 2020 for global manufacturers,

approximately 52% of the participating manufacturers indicated that their companies lack the expertise and culture to explore and use digital technologies. This can be further proved by the fact that only 28% of these responders have tried to integrate any digital technology to optimise their manufacturing processes⁵³. The subdued inclination for uptake of these digital technologies leads to significant challenges when achieving the industry-scale transformation of digital manufacturing⁵³. This chapter aims to review the recent development and implementations of key digital technologies towards data science in metal forming industry.

2.1 Review on key digital technologies in Industry 4.0

2.1.1 Industrial cyber-physical system (I-CPS)

A rapid growth has been witnessed in the development of diverse cyber-physical systems (CPS). Of these, as shown in Fig. 1, the industrial cyber-physical system (I-CPS) can be defined as a combination of the industrial cyber and physical systems that synergistically enable precise and efficient manufacturing production applications^{25,30} enabled by computing, communication and control⁵⁴. The I-CPS can be characterised in three influential components, i.e., (1) human component focusing on learning, technique and modelling, (2) cyber component focusing on data management and services, and (3) physical component focusing on configurations, sensing and communications. The interfaces of human-cyber, cyber-physical, and human-physical act as major roles in integrating all components to a unified system⁵⁵.

The I-CPS is expected to strengthen the operation stages throughout the entire metal forming plant, especially including the supply chains⁵⁶, raw blanks or billets production^{57,58}, manufacturing operation and quality prediction⁵⁹, energy saving⁶⁰, cost reduction and customer services⁶¹. The implementation of I-CPS in manufacturing requires sophisticated interactions among different digital technologies. Taking the digital transformation of a rolling mill as an example, the full integration of I-CPS in the rolling mill incorporates the sensing technology for collecting real-time big data, big data processing technology, and data visualisation technology for mapping the effects of milling parameters⁶².

Despite the progress of these research and development, challenges also need to be paid attention when promoting the I-CPS and related technologies in metal manufacturing industry. The main challenge of its application can be found in the capabilities, management, engineering, infrastructures and information systems³⁰, and unifying the standards in I-CPS with diverse

roles and functions such as the terminology standard, measurement standard and quality standard⁶³.

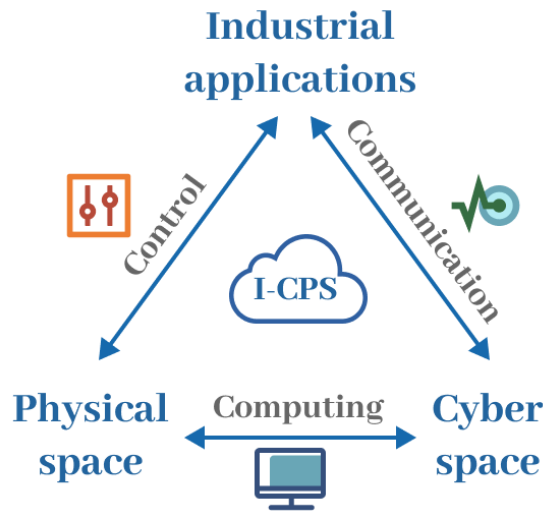


Figure 2.1 | The configuration of I-CPS²². I-CPS creates an interactive connection among the physical space, cyber space and industrial applications.

2.1.2 Industrial internet of things (I-IoT)

First introduced in 1999, the idea of internet of things (IoT) enables the inter-connection of ‘Anything’ in ‘Anywhere’ at ‘Anytime’. Specifically, it is described as a smart system incorporating the physical world into a digital ecosystem^{61,64}. Therein, the ‘things’ indicates the unprecedented amounts of electronic devices including wireless sensing networks, external recorders and other subsystems⁶⁵. The IoT has attracted significantly increasing attention, and the total value of global IoT technologies is projected to reach \$6.2 trillion by 2025⁶⁶.

The industrial IoT (I-IoT) is the application of IoT in industrial activities, which is dedicated to improve the productivity, efficiency, safety, flexibility, scalability, customer service and enhancing intelligence of the manufacturing and industrial systems^{25,67}. I-IoT offers seamless interoperability and connectivity among industrial devices, systems, services, networks, and in particular the control systems. I-IoT can be defined in three tiers from the industrial perspective²⁵, i.e., Tier 1: physical layer, consisting of various hardware devices like sensors and external recorders; Tier 2: communication layer, providing shared manufacturing big data and connecting the physical layer to the Tier 3, the application layer, which is represented by the smart factory, smart plant and smart supply chain.



Figure 2.2 | Typical sensing network of metal forming workshops in I-IoT⁶⁸.

Advanced sensing technology is one of the key factors for realising the I-IoT in metal forming industry via connecting the physical layer with the application layer⁶⁹. As shown in Fig. 2.2, the typical sensing network in metal forming workshops operated in I-IoT enable the sensing of protection of security, IT environment, power system and facilities around the factory⁶⁸. The metal additive manufacturing (AM) has seen rapid growth over the past decade, with applications expanding into industrial grade requirements^{70–72}. The significant growth rate stems from rapidly improving technologies for part accuracy, quality, and strength. The metal AM can be regarded as an essential ingredient in the intelligent production systems, and can be intelligently driven by integrating the Industry 4.0 technologies in CNC machines, especially the I-IoT technology⁷³. Challenges in traditional metal AM, such as the poor repeatability, improper material property, interlayer imperfection, data management and low efficiency, can be improved by associating I-IoT⁷⁴. In addition, the I-IoT technology has been implemented in servo presses in metal forming processes for improving the tool life⁷⁵, in which the artificial intelligence (AI) is expected to be integrated to predict the future maintenance requirements. With overall monitoring of the metal forming workshop, including die casting⁷⁶ and forming processes⁶⁰, the I-IoT technology can improve the energy efficiency and management of the metal forming enterprises.

2.1.3 Digital twin

Introduced in 2003 via a course named ‘product lifecycle management’ by Grieves⁷⁷, digital twin has become one of the most promising technologies for realising Industry 4.0. Digital twin can be defined as the seamless integration between the cyber and physical spaces³⁵. Specifically, in industrial applications, it integrates the physical manufacturing entities to their respective cyber entities and includes diverse decision-making algorithms, modules or platforms for

industrial activities^{34,78}. Using the real-time data collected from embedded sensors, sophisticated high-fidelity models (virtual entity) are established to reflect the real-time state (such as information model and functional elements) by almost mirroring the entire life-cycle of the manufactured products (physical entity)³⁴.

The implementation of Digital twin in metal forming industry has been widely considered to improve the production from various perspectives, including the real-time component geometric precision and tolerance⁷⁹, tools or forming machines⁸⁰, energy consumption⁷⁷, and design roadmap of the metal forming process⁸¹. For instance, a digital twin-driven modelling method was proposed for reflecting real-time state of sheet metal forming process focusing on the die wear conditions⁷⁷. The updating coefficient of friction, blank holder force, punch force, and punch displacement were monitored and captured by the force and displacement sensors. The optimisation results demonstrate that a 14.35% reduction was achieved in the maximum thinning region of the stamped part, as well as 8.9% reduction in the energy consumption through the forming process.

The DT technology is now being actively considered as a supervisory role in metal AM process through real-time monitoring and control^{82–88}. In addition, a digital twin-based CPS was proposed to predict whether a product can be formed in abnormal scenarios involving automotive body production lines⁸⁹. The information models of the product, process, plant, etc., were established for the automotive body production lines. Experimental results demonstrate that an average prediction accuracy of over 96% was achieved in the actual production line. A hybrid data-driven and model-based framework for establishing a combined monitoring and control system was proposed in the complicated automotive sheet metal forming processes⁹⁰. This framework used the retrieved data (such as the material information and coatings) and the captured real-time metal forming data (such as temperature, sheet thickness and tribology behaviours) as an input for the process models to predict the product/process settings as the output, then this would be utilised for optimising the product properties or process settings. However, the computational cost of the process model needs to be reduced to provide faster response, and further lab-scale validation is required on this framework, and the main challenge of digital twin remains as big data processing, and the privacy and security issues⁹¹.

2.1.4 Big data analytics (BDA)

Big data (BD) refers to the datasets that are too large or complex to be tackled by traditional data-processing methods, thus requires new technologies to mine insightful information from it. Nowadays, BD can be characterised in five well-accepted dimensions, namely the ‘7Vs’ representing ‘Volume, Velocity, Value, Veracity, Variety, Visualisation and Variability’⁹². In addition, the well-known FAIR (Findable, Accessible, Interoperable and Reusable) data principles provided a foundational guideline for researchers to generate, store, utilise and manage scientific big data⁴⁴. The FAIR data principles act as valuable guidebook since volumes of data are being generated and captured during daily manufacturing and academic activities.

Big data generated during the metal manufacturing processes are mainly captured by the sensing networks^{32,37}. In addition, the metal forming data can also be collected from the experimentally verified finite element analysis (FEA) simulations^{36,93}. Fig. 2.3 shows the data mapping of the hot stamping datasets collected from the experimentally verified FEA models containing the thermo-mechanical information (e.g., temperature data, contact pressure data, strain rate data) of the stamping and quenching operations^{8–10,52}. These FEA models simulated the hot stamping of representative automotive components such as side beams, B-pillars and door inners. This data collection method can be proactive by providing optimisation suggestions through data processing and analysis before the actual forming process commences.

The AI technology leads the investigations on big data processing in metal forming, spanning the material design⁷⁸, forming force prediction⁹⁴, tribological characteristics^{95,96} and product surface quality⁹⁷, geometric accuracy⁹⁸, process formability⁹⁹, tool path design and generation¹⁰⁰ (especially for incremental sheet metal forming¹⁰¹), product¹⁰² and die designs¹⁰³, in-process defect monitoring¹⁰⁴, etc. Therein, various AI methods, especially machine learning (ML) algorithms, including the artificial neural network (ANN) algorithm¹⁰², support vector machine (SVM)⁹⁵, quantum-behaved particle swarm optimisation (QPSO) algorithm⁹⁷, multilayer perceptron (MLP) algorithm¹⁰⁵ and convolutional neural networks (CNNs)¹⁰⁰, are widely utilised. In terms of the applications of AI in sheet metal forming, supervised ML is still the predominant AI method⁹⁴. However, one of the limitations of ML algorithms is that the generalisation performance is always required to draw conclusions on a different metal forming process, if the dataset of that process is not included in the training data¹⁰⁰. The generalisation refers to the ability of ML algorithms to perform well on unseen or new data which have not been specifically trained on. For instance, if a supervised ML algorithm was trained using the labelled data from metal stamping process, then its prediction performance can be very unstable

and inaccurate when processing the unseen data from another manufacturing process such as extrusion.

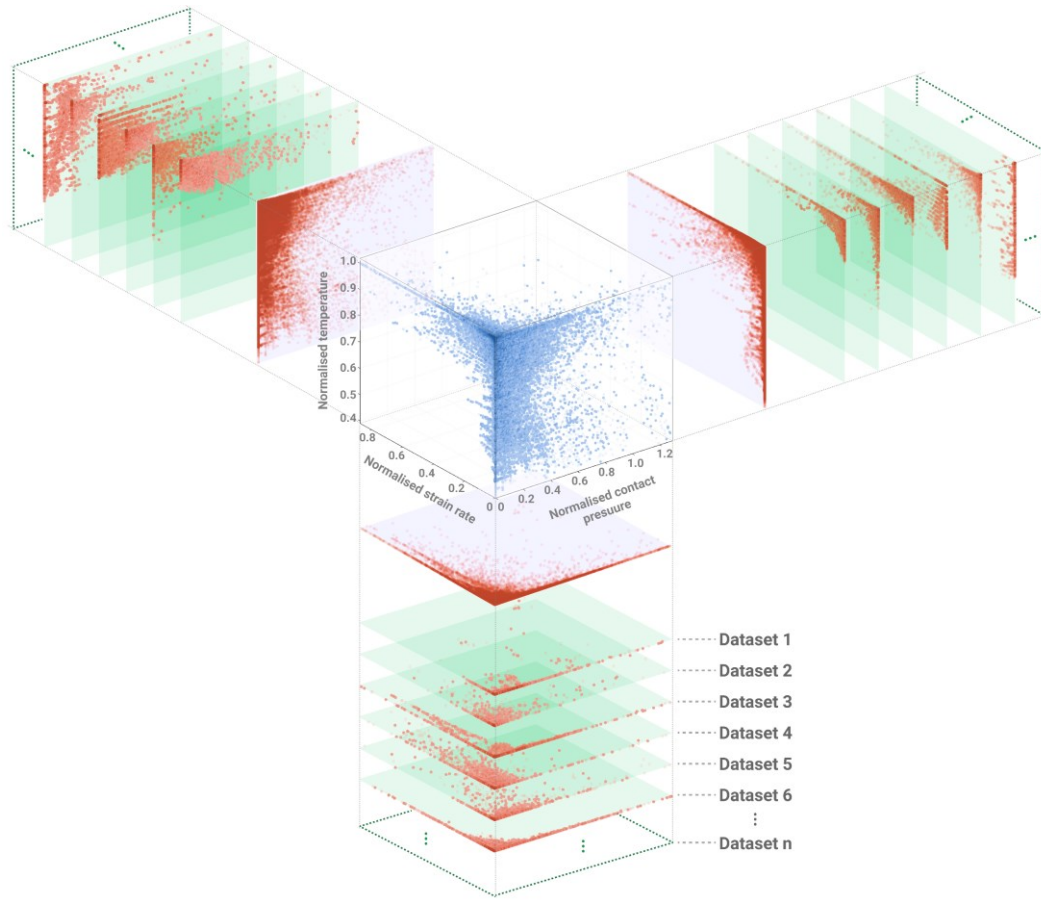


Figure 2.3 | Mapping the dataset from a specific metal forming process, hot stamping process, for automotive components production¹⁰⁶. Normalised temperature, contact pressure and strain rate are mapped for voluminous hot stamping datasets.

Data visualisation can reveal insightful digital information. The global flow of steels⁴ and aluminium⁵ were mapped based on big data, which provides comprehensive image on the entire material supply chain cycle from the raw materials to end-use goods. Big data was collected from the manufacturing processes enabling the development of Digital Characteristics (DC) to map the manufacturing processes from the perspective of metadata³, where our understanding remains incomplete. The DC incorporates essential information spanning the design, manufacturing and application stages of the manufactured products³. Fig. 2.4 shows the DC developed based on the hot stamping contact condition data (contact pressure, temperature and sliding speed) in different key regions, i.e., short-stroke region (region 1), long-stroke region (region 2) and hybrid region (region 3)³. Region 1 features with short sliding distance (normalised, <0.1) and a large range of contact pressure (up to 200 MPa). In contrast, region 2

demonstrates a large sliding distance (normalised, up to 1) with low contact pressure (lower than 20 MPa). Region 3 is the tribologically harsh region with high contact pressure and sliding speed. Significant deviations of contact pressure, sliding speed and interfacial temperature can be observed in different key regions, which vastly affect the tribological behaviours in hot stamping process.

It is the fact that the never-before-seen surge in the big data availability brings promising opportunities, while at the same time, brings tremendous challenges in data management and data processing as well¹⁰⁷, not to mention manage such a vast volume of data under the guidance of the FAIR data principles. In addition, since the data privacy or protection policies are regarded as the top priority in manufacturing sector³⁷, the collaborations, such as big data sharing and exchange within I-CPS or I-IoT systems, among different factories or institutions can be hindered. To process metal forming big data, the AI methods, especially the ML algorithms, are widely used nowadays. However, big challenges of achieving generalised prediction and high interpretability, and applying appropriate data pre-processing methods before using the ML algorithms remain. Moreover, due to the restrictions on the data collection methods and data privacy in automotive industry, most of the collected metal forming data would lack critical information of the formed products and metal forming process itself. This leads to unstable and inaccurate predictions while applying the ML algorithms since the available training data is insufficient.

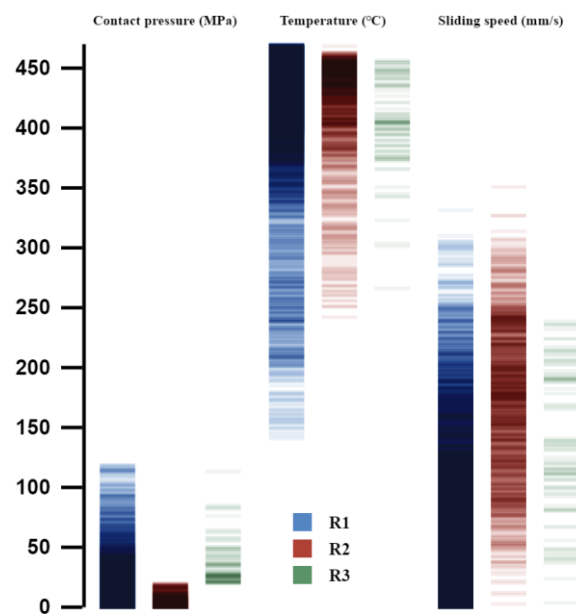


Figure 2.4 | Distribution of hot stamping contact condition metadata in key regions. Region 1 (R1), region 2 (R2) and region 3 (R3)³.

2.1.5 Cloud computing (CC)

Cloud-based computing resources, enabling distributed and dynamic collaborative manufacturing operations, have drawn increasing interests. Cloud computing (CC) is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction¹⁰⁸. The key for CC is to provide geographically distributed manufacturers with centralised computation services. For metal forming industry, a CC service was scheduled for establishing the cloud-based production system¹⁰⁹. Therein, a genetic algorithm-based planning and scheduling application was developed to provide cost-efficiency, flexibility and scalability solutions. The application case demonstrates that the proposed scheduling system utilised the CC technology to provide ‘close to real-time’ analysis and planning according to the dynamic requirements and inputs for multiple factories. In addition, the incremental metal forming process was adapted into CC for providing flexible manufacturing service to production networks³³. The tool path control was optimised by developing an adaptive control algorithm with variable forming depth at a process level for bypassing the fracturing of sheets due to the localised thinning. The potential of selecting incremental sheet forming service providers was highlighted based on the material database.

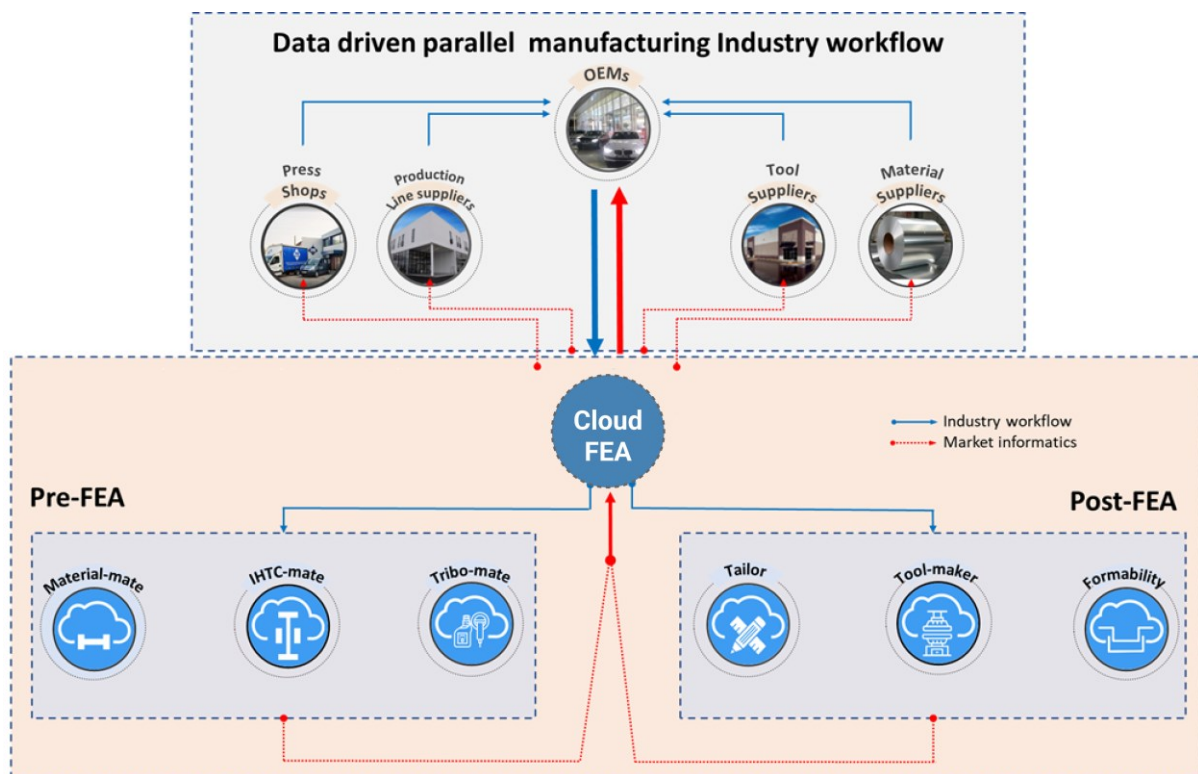


Figure 2.5 | The MaaS (Model-as-a-Service) configuration of the cloud FEA platform⁹⁴. This platform incorporates pre-FEA modules including Material-mate, IHTC-mate and Tribo-mate, and post-FEA modules including Tailor, Tool-maker and Formability.

Innovations are being made on configuring the cloud-based system for enhancing metal forming¹¹⁰. A group of researchers in Imperial College London have pioneered the cloud-based FEA technologies that enables advanced multi-objective FEA of metal forming processes to bridging the gap between fundamental research and industrial applications. In addition, commercial cloud based services such as the ESI cloud, AutoForm cloud, were developed to enhance the computational efficiency^{93,111,112}. Unlike the traditional CC or Software-as-a-Service (SaaS), this cloud-based platform is characterised by the framework of Model-as-a-Service (MaaS) for tackling the future digital challenges. The platform is decentralised and encourages users to share and exchange the frontier knowledge by generating ready-to-use models or applications. By using the AI technologies, the uploaded models and published publications can be converted into applications that are compatible with the platform for global users.

Specifically, this cloud-based FEA platform contains verified scientific data repository, pre-FEA modules, post-FEA modules, etc^{93,111}. Fig. 2.5 shows the configuration of this novel platform, where the stored data can be used for data sharing and analysis, leading to digitally enhanced research and development⁹⁴. The pre-FEA modules contain the ‘Material-mate’ module for enabling the generation of material cards to be used in forming tests, the ‘IHTC-mate’ module for creating interfacial heat transfer coefficient (IHTC) computing plug-ins for heat transfer models, and the ‘Tribo-mate’ module for enabling interactive friction models to be used and validated by forming tests. The post-FEA modules contains the ‘Tailor’ module for enabling the prediction of post-form strength, the ‘Tool-maker’ module for enabling the prediction of cold die quenching efficiency, and the ‘Formability’ module for enabling the prediction of formability. The effectiveness of these functional modules was successfully validated in peer-reviewed studies towards automotive applications^{36,93,111–116}. The cloud FEA can be further characterised into 3 layers, namely the resource layer, cloud platform layer and application layer. The resource providers and users can be world-wide academic institutions, material suppliers, and equipment, brand and design manufacturers.

2.2 Review on manufacturing data processing technologies

The volume of big metadata is rapidly growing through data collection from multi-source during daily manufacturing production and academic activities¹¹⁷. This unprecedented surging of the manufacturing metadata have profoundly influenced the research and development of

manufacturing technologies¹¹⁸. Fig. 2.6 shows the evolution of manufacturing metadata processing technologies¹¹⁸. In 1800s, the manufacturing data processing mostly relied on the experts' experiences ('handicraft age'); then through the 'machine age' to 'information age', the manufacturing data processing technologies, such as the computer aided design (CAD) and computer aided engineering (CAE), were widely applied to achieve the computer aided manufacturing. Currently, in the 'big data age', industrial 4.0 technologies are being extensively employed in manipulating the manufacturing big data, including the information systems data, smart equipment data, product data, user data and public data, with the support of internet and cloud-based technologies¹⁰⁷. As one of the most effective tools of big data analytics, the artificial intelligence (AI) is expected to enable the intelligent manufacturing and the digital transformation of the manufacturing sector with the fusion of other digital technologies used in the 'big data age'^{119,120}.

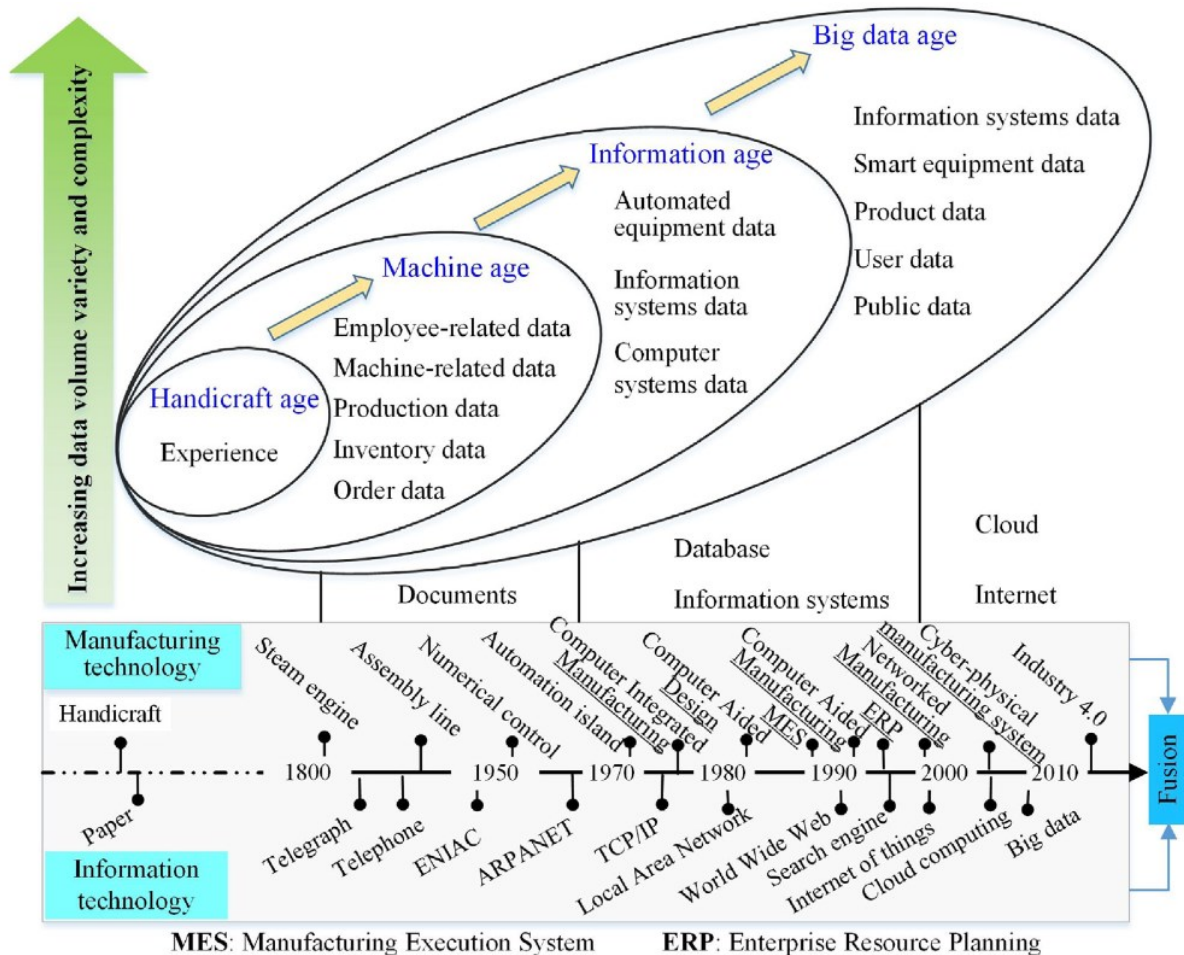


Figure 2.6 | The evolution of manufacturing metadata¹¹⁸. The manufacturing metadata evolution spanning over 'handicraft age', 'machine age', 'information age' and 'big data age'.

Therein, machine learning (ML) is the representative approach of the AI to drive the AI tendency focusing on developing ‘brain-like’ intelligence models and more interpretable algorithms¹¹⁹. The ML algorithms can be broadly categorised as three representative types, named the supervised ML algorithms, semi-supervised ML algorithms and unsupervised ML algorithms¹²¹. The supervised ML algorithms (e.g., the decision tree¹²², random forest¹²³, K-nearest neighbour¹²⁴ and multilayer perceptron¹²⁵) can be used when a large amount of labelled data (e.g., over 70% of the whole dataset) are available. The ‘label’ indicates that the specific class of each training data point was clearly marked. The unsupervised learning algorithms (e.g., cluster analysis¹²⁶) require no evaluation on the ‘labels’ and they are used to identify the key patterns of the unlabelled data¹²¹. The semi-supervised learning algorithms (e.g., label propagation¹²⁷), also called weak supervision, fall between supervised learning and unsupervised learning approaches where the unlabelled data are usually more sufficient than the labelled data to help improve the generalisation performance. The supervised ML is the dominant approach when conducting the big data analysis of manufacturing metadata due to its better interpretability compared to the unsupervised ML algorithm⁴³. However, it is challenging to obtain sufficient labelled data for training the supervised ML models due to enormous efforts spent on the labelling work. For instance, as one of the most widely used labelling approach, outsourcing labelling is very expensive and time-consuming, and the labelling accuracy is questionable when labelling the patterns or features that requires high expertise.

The manufacturing data processing technologies and the aforementioned industry 4.0 digital technologies are not isolated, as proved by the recent research focusing on the digital-twin-driven supervised ML¹²⁸, big data-driven and IoT-based ML approaches for real-time data processing¹²⁹, and cloud computing-enhanced ML approaches^{130,131}. In addition, the physical-informed neural networks (PINNs), first introduced by Raissi et al. for studying the hidden fluid mechanics¹³², are attracting wider attentions by integrating physical knowledge to the ML algorithms to enable more accurate and interpretable data processing, especially in material¹³³ and manufacturing fields¹³⁴. Due to the voluminous manufacturing metadata captured using sensing networks, manufacturing big data processing systems have been developing over the past decades for more compact data processing^{128,135}. This indicates that the realisation of efficient, accurate and intelligent manufacturing metadata processing requires emergent research on different disciplines and various digital technologies.

2.3 Summary

This chapter reviewed the recent development and implementations of the representative key digital technologies in Industry 4.0 used in the manufacturing sector, together with the recent development of representative data processing technologies used in the manufacturing sector, especially the metal forming industry. The digital technologies, including a variety of manufacturing data processing and characterisation technologies, are not isolated. The increasingly sophisticated manufacturing operations requires the emergent research on industrial cyber-physical system, industrial internet of things, digital twin, big data analytics, cloud computing technologies, artificial intelligence and physical-informed digital technologies. Advances in mechanical engineering, material engineering, communication engineering, electronic and information engineering, computer science, control science and engineering, data science, etc., also support to widen the scope of these technologies. These are highly expected to boost the creation of new digital technologies and new emerging subjects focusing on the digital transformation of metal forming technologies. The AI approaches, represented by the machine learning (ML) algorithms, are widely used for processing the manufacturing metadata. However, the generalisation performance when tackling a new or an unlabelled dataset is necessary to be improved. This is extremely challenging regarding to the long-standing issue that most of the manufacturing metadata are lacking information, which makes it very challenging to obtain sufficient labelled data for the ML training. This indicates that a physical-based data processing technique is necessary for tackling the manufacturing metadata that lacking essential information.

Chapter 3. Guidance on digital characteristics (DC) development

The understanding of the capabilities and strategic implications to extract the insightful values from manufacturing metadata remains incomplete¹³⁶. To enable the characterisation of the manufacturing processes from the perspective of metadata, this thesis introduced a novel concept named the digital characteristics (DC), for visualising the manufacturing metadata incorporating the essential information spanning the design, manufacturing and application stages of the manufactured products³. Fig. 3.1 shows the overall guidance on the development of the DC of the manufacturing processes following the FAIR data principles, including the essential stages named manufacturing metadata collection that leads to the development of a cloud-based data repository, data processing consists of data pre-processing and information absent data processing that leads to the development of a physical-based Evolutionary Binary (EB) algorithm, and data characterisation that leads to the development of DC. The applications of the DC was demonstrated in Chapter 6.

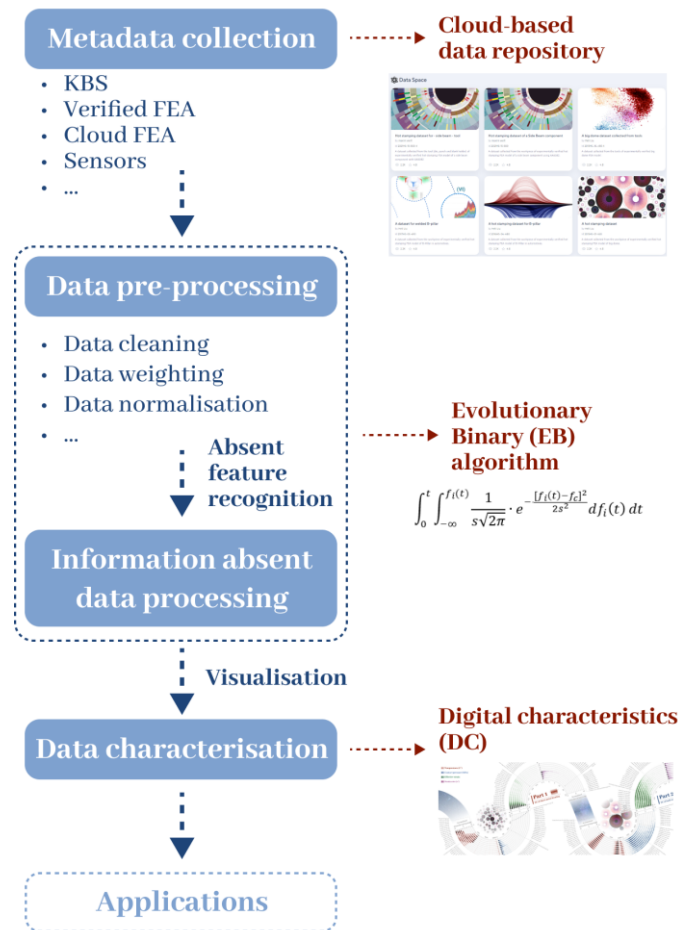


Figure 3.1 | The guidance on the digital characteristics (DC) development. Essential stages of developing the DC includes the metadata collection, data pre-processing and information absent data processing, and data characterisation.

3.1 Metadata collection leads to the establishment of cloud-based data repository and data pre-processing

In this thesis, the manufacturing metadata were obtained from a cloud-based data repository, which is hosted on a knowledge sharing platform, the SmartForming^{®93,111,137,138}, which focuses on the translation and wider sharing across different manufacturing sectors based on patented, experimentally verified and published frontier research. This platform has a monthly information traffic of 2.5 TB, including experimentally verified manufacturing metadata stored in the data repository, which are continuously contributed by world-leading academic institutions and industries located in over 35 countries over the past decade for research and development purposes^{111,114}. With the joint efforts of these contributors, the manufacturing metadata used in this research were collected from multiple sources including the experimentally verified knowledge-based systems, finite element (FE) models, cloud-FE models and Industry 4.0 technologies. The metadata were strictly controlled so that only experimentally verified metadata were included.

More specifically, the manufacturing data repository currently consists of large amounts of datasets filed in terms of different manufacturing processes characterised by the evolutions of over 20 types of thermo-mechanical data across the end-to-end manufacturing stages of the products. This further leads to the development of 201 functional data modules, consisting of the dataset file, verification reports, and corresponding data description and explanation, hosted in the data repository as open access resources. Each data module is available as an open access resource by referring to its unique ID number (Fig. 3.5), and the packed dataset is downloadable by the scientific community to augment the data-driven research efforts in manufacturing sciences, and furthermore, revolutionise the understanding in the era of digital manufacturing.

The metal forming metadata used in this thesis can be obtained by visiting the cloud-based data repository via the link: <https://app.smartforming.com/store/modules/all?categoryId=18>. The instructional video on how to get access to the data repository can be seen via : <https://youtu.be/Y0ibUrkuXXs>. Of these, two example data modules containing hot stamping datasets are available for free download for reproducing the main part of the current study: <https://app.smartforming.com/store/modules/407>; <https://app.smartforming.com/store/modules/408>.

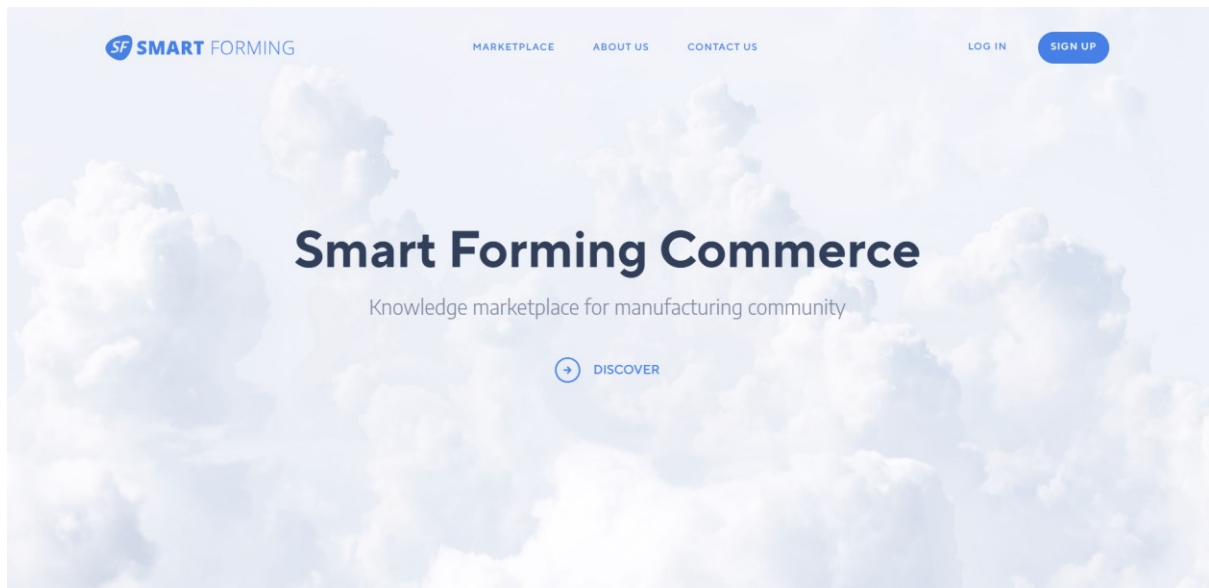


Figure 3.2 | Home page of the SmartForming® platform.



Figure 3.3 | A list of categories on the marketplace (including 'Data Space').

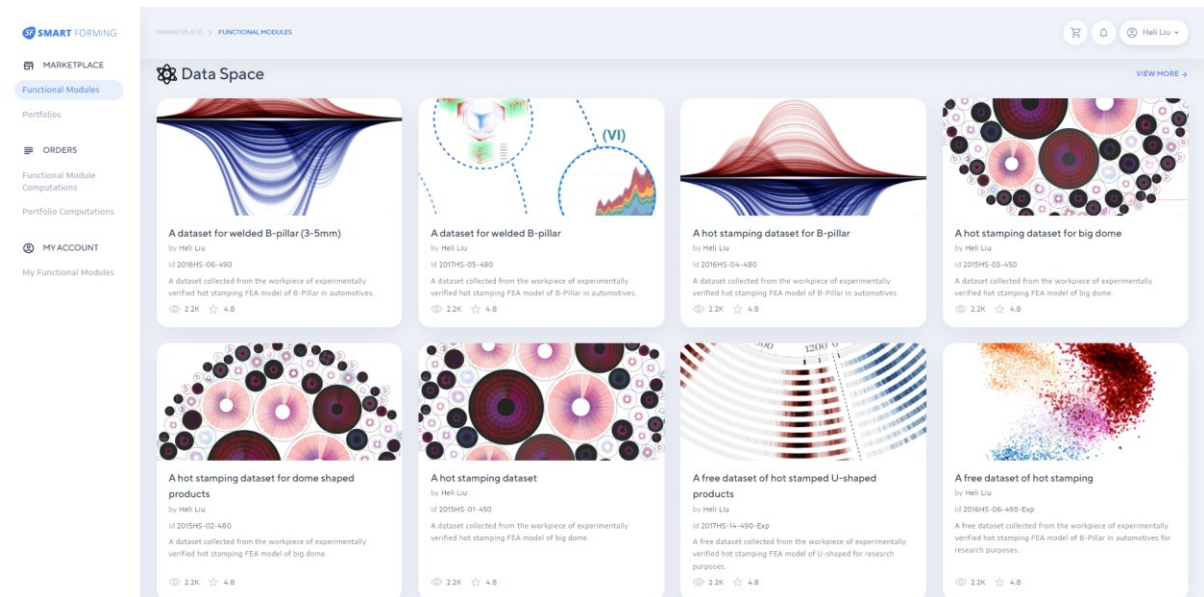


Figure 3.4 | Functional data modules of manufacturing processes under ‘Data Space’.

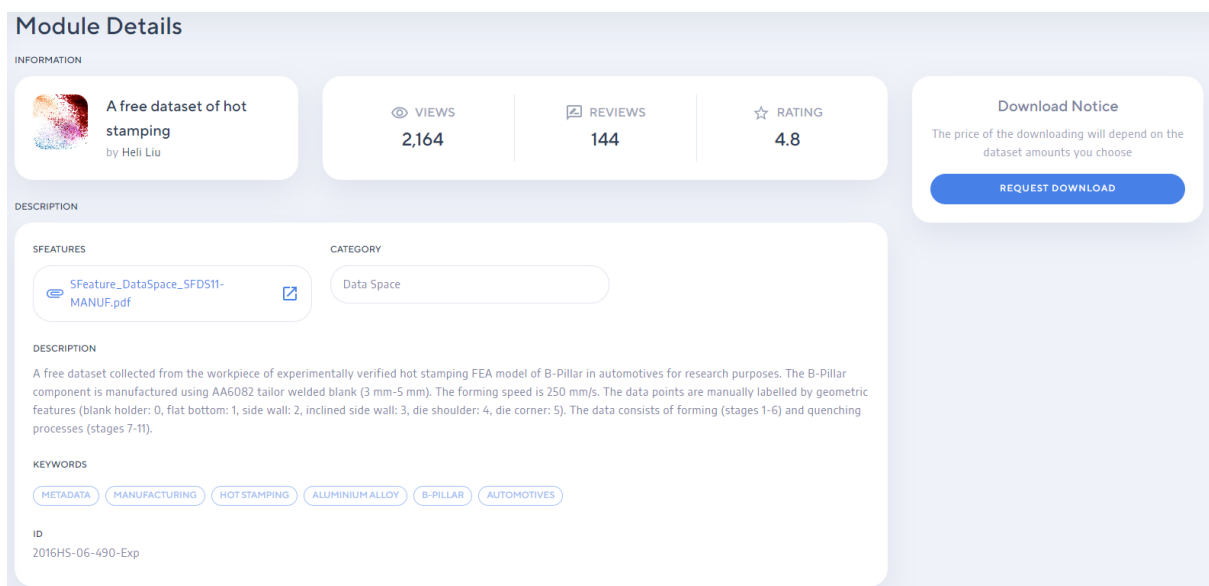


Figure 3.5 | Module details.

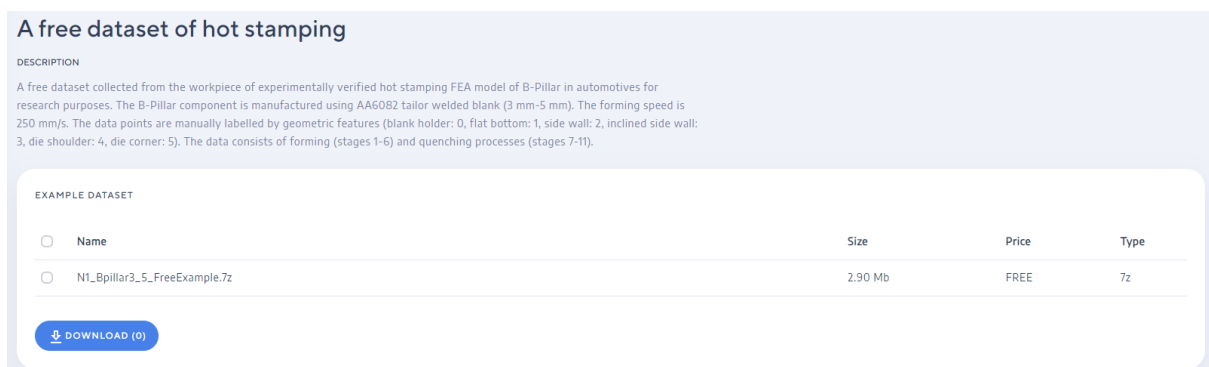


Figure 3.6 | Downloading area of a free data module.

In the data repository, large volumes of manufacturing metadata were collected from various sources in addition to the data collected from sensors, such as individuals (handcraft knowledge), knowledge-based systems (KBS, established in 1970s for metal forming industry)¹³⁹, FEA (established in 1990s for metal forming industry)¹⁴⁰, cloud-based FEA (established in 2020s)^{93,138}. Tab. 3.1 shows a breakdown in sources of manufacturing metadata collection in the current research over the past 15 years. The data collected from numerical sources were validated by the experimental data (collected by sensors). All metadata were collected with the joint contribution from the world-wide academic institutions and industries, and these metadata were used in the present work for research purposes.

Table 3.1 | Sources of data in the current study. The manufacturing data used in the present research were collected from various sources including the KBS, FEA, cloud-based FEA and sensing networks. The proportion of data and properties of each data collection method are listed.

Source	Volume	Verification	Comprehensiveness
KBS	6.64%	Yes	★★
FEA	75.73%	Yes	★★★★
Cloud-based FEA	16.63%	Yes	★★★
Sensing networks	1.0%	\	★

* *Comprehensiveness: ★★★★★: Comprehensive (contains essential information for scientific research needs); ★★★★★: High; ★★: Medium; ★: Fragmental (contains extremely scarce information).*

Fig. 3.7 further demonstrates the sources of metadata collection in this work. Therein:

1. In Fig. 3.7a, 75.73% (Tab. 3.1) of the manufacturing data were collected from the experimentally verified FEA models, where comprehensive information can be captured, including the diverse thermo-mechanical data such as stress and strain rate data, that are hard to be measured during the manufacturing operations. Of these, essential information, such as material cards, can be obtained from the KBS systems.
2. In Fig. 3.7b, 16.63% (Tab. 3.1) of the data (information absent for geometric features) were collected from the cloud-based (pre and post) FEA. These cloud-based technologies were jointly developed with the joint efforts with world-leading manufacturers for the analysis and optimisation of sheet metal forming processes with significant savings in R&D costs and efficient take-up of frontier knowledge. Furthermore, advanced FE simulations were carried out by running post-FEA analysis modules, including the prediction of ‘formability’, ‘quenching efficiency’ and ‘post-form strength’.
3. In Fig. 3.7c, the volume of data collected using sensing networks during experiments and manufacturing operations is 1.0% (Tab. 3.1). The data collected from sensors include (a)

temperature data collected by using thermo-couples or pyrometers¹⁴¹; (b) load-displacement data collected by using load cells and displacement sensors¹⁴² and (c) surface strain distribution data collected by using a digital image correlation (DIC) techniques (ARAMIS or ARGUS)^{143,144}. These data collected by sensors are essential to the validation of the data collected by other approaches.

4. Fig. 3.7d shows the experimental validation process conducted by industry partners by forming the side beam panel components. Therein, the temperature (Fig. 3.7e) were captured using sensors (thermo-camera) during the entire forming process. The measured temperature data before and after forming were used to validate FE simulation results. An example of the captured temperature dataset is shown in Fig. 3.7f.

At the present, all the metadata stored in this data repository have world-leading industrial collaborators involved via supporting on metal forming technology development and experiment conduction, and 76.1% of the data were contributed from collaborated industries^{9,10,18,145,146}; where 30.1% of the data were focused on sheet metal forming processes (such as stamping, tube gas forming and hydroforming, and incremental forming), and 62.9% of the data focused on bulk metal forming processes (such as forging and cross-wedge rolling). The remaining data were collected from machining processes. For sheet metal forming processes, 47.1% of the data were contributed from the hot stamping technology, and 29.8% of the collected metadata were produced using aluminium alloy (including AA2xxx, AA5xxx, AA6xxx and AA7xxx series) as the workpiece material with the remainder being steel grades. These manufacturing datasets contains the information of operating conditions, tool and workpiece materials, experimental and modelling parameters, and the data that contains the information of diverse evolutionary thermo-mechanical metadata including the temperature, contact pressure, strain and strain rate.

3.2 Information absent metadata processing

A long-standing challenge has been found that most of the manufacturing metadata are information absent or fragmental due to the limitations of data collection abilities, and further restricted by ubiquitous policies or rules fostered in today's manufacturing sector that require data privacy and protection^{46,47}.

The 'information absent data' is a counterpart of 'rich data' explained in FAIR data principles. To ensure the data are findable, accessible, interoperable and reusable, the rich data should be generous and extensive. Ideally, rich data allow computers to automatically accomplish routine and tedious sorting, and prioritising tasks that currently demand a lot of attention from engineers and researchers. Information absent data refer to data that lack information for a single or several data points, or a specific dataset or database, including critical information regarding the description, quality or condition, or essential features of the data, such as, physical or geometric features of the products or the underlying thermo-mechanical metadata. The absence of such information significantly depreciates the essential data values, hinders the progress of knowledge management, reuse and movement, and further deteriorating the long-standing challenge regarding the shortage of labelled data, which leads to tremendous challenges for data manipulation, in-depth analysis, characterisation and visualisation following the well-known FAIR data principles^{48,49}.

The collected metal forming metadata are information absent. For example, it was found that 99.9% of these metal forming metadata lack the information of geometric features (a sample information absent dataset used in this thesis is shown in Fig. 3.8a and also Fig. 3.9, where the geometric features are absent). For example, In this thesis, an information absent dataset of the hot stamping process, which covers a wide range of hot stamped products, is used in Chapter 4 as a study case for information absent data processing and DC development, (Fig. 3.8a). This leads to the identification of three representative geometric features of the hot stamping products, i.e., the blank holder (BH), flat bottom (FB) and side wall (SW) features (Fig. 3.8c) by developing the data processing methods for information absent metadata. Here, a representative hot stamped product containing these three features is shown in Fig. 3.8c: the BH feature contains all the data points remaining within the blank holder regions at the final forming stage, the FB feature contains all the data points between the flat parallel die surfaces at the final forming stage, and the SW feature contains all the data points entrapped in the die wall regions at the final forming stage.

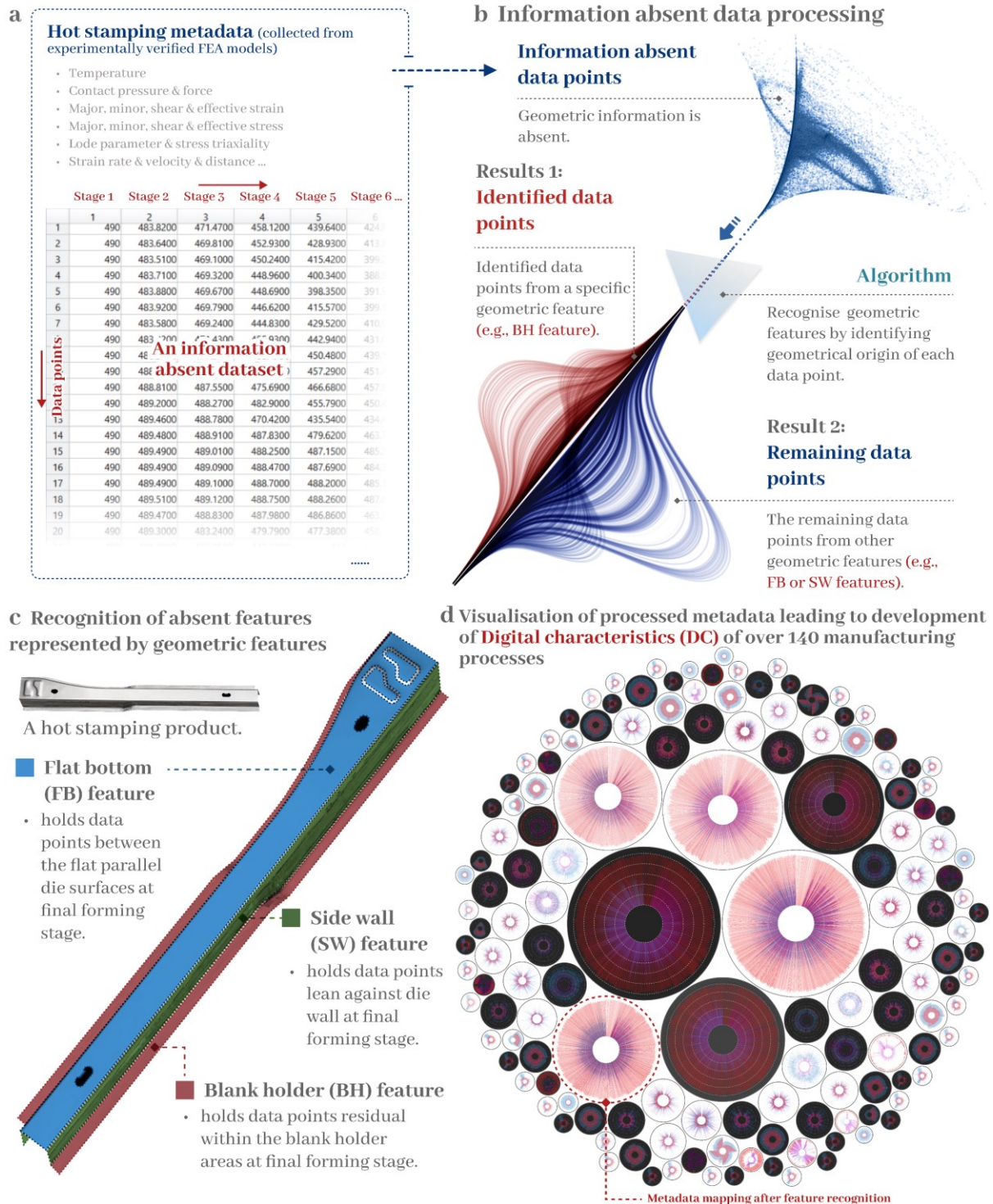


Figure 3.8 | Recognising geometric features from information absent data and mapping manufacturing processes via developing the digital characteristics (DC). **a**, An example of information absent metal forming metadata collected from experimentally verified hot stamping FEA models. **b**, Developing innovative algorithm enabling the recognition of the geometric features from the information absent data by identifying the geometric origins of the data points, aiming to identify **c**, representative geometric features of hot stamped products, i.e., the blank holder (BH), flat bottom (FB) and side wall (SW) features. A representative hot stamped automotive structural product, side beam, is shown as an example. These geometric information are absent in the hot stamping dataset. **d**, The digital characteristics (DC) of over 140 manufacturing processes visualised based on metadata processed by the proposed algorithm. Each ‘ring’ represents a dataset of a manufacturing process, the size of the ‘ring’ indicates the volume of this dataset.

Manufacturing stages												The geometric origin of each data point
	1	2	3	4	5	6	7	8	9	10	11	
1	1	0.8787	0.7697	0.6779	0.6097	0.5793	0.5710	0.5641	0.5168	0.4594	0.3757	NA
2	1	0.8801	0.7650	0.6719	0.5963	0.5567	0.5697	0.5636	0.5159	0.4582	0.3744	NA
3	1	0.8824	0.7654	0.6708	0.5915	0.5496	0.5679	0.5627	0.5145	0.4564	0.3724	NA
4	1	0.8809	0.7640	0.6695	0.5893	0.5473	0.5658	0.5614	0.5125	0.4539	0.3698	NA
5	1	0.8806	0.7634	0.6697	0.5896	0.5473	0.5636	0.5598	0.5099	0.4507	0.3664	NA
6	1	0.8842	0.7694	0.6760	0.5940	0.5484	0.5612	0.5576	0.5065	0.4465	0.3622	NA
7	1	0.8834	0.7696	0.6769	0.5952	0.5483	0.5589	0.5547	0.5021	0.4414	0.3572	NA
8	1	0.8788	0.7629	0.6714	0.5911	0.5468	0.5567	0.5509	0.4964	0.4351	0.3512	NA
9	1	0.8813	0.7671	0.6746	0.5931	0.5480	0.5544	0.5459	0.4894	0.4275	0.3442	NA
10	1	0.8851	0.7712	0.6788	0.5973	0.5507	0.5523	0.5393	0.4805	0.4182	0.3359	NA
11	1	0.8840	0.7680	0.6777	0.5973	0.5519	0.5500	0.5305	0.4694	0.4072	0.3263	NA
12	1	0.8822	0.7656	0.6768	0.5973	0.5528	0.5472	0.5188	0.4556	0.3938	0.3152	NA
13	1	0.8812	0.7646	0.6754	0.5991	0.5548	0.5423	0.5027	0.4381	0.3776	0.3019	NA
14	1	0.8836	0.7721	0.6853	0.6031	0.5580	0.5317	0.4807	0.4156	0.3575	0.2861	NA
15	1	0.8853	0.7721	0.6853	0.6058	0.5605	0.5098	0.4476	0.3845	0.3309	0.2655	NA
16	1	0.8836	0.7687	0.6845	0.6067	0.5620	0.4909	0.4227	0.3603	0.3099	0.2493	NA
17	1	0.8835	0.7719	0.6894	0.6104	0.5644	0.4733	0.4020	0.3401	0.2920	0.2366	NA
18	1	0.8841	0.7750	0.6934	0.6137	0.5673	0.4467	0.3699	0.3120	0.2687	0.2195	NA
19	1	0.8840	0.7722	0.6915	0.6142	0.5692	0.4281	0.3434	0.2892	0.2500	0.2047	NA
20	1	0.8865	0.7738	0.6940	0.6180	0.5719	0.4211	0.3272	0.2747	0.2376	0.1951	NA
21	1	0.8880	0.7757	0.6963	0.6202	0.5736	0.4184	0.3169	0.2651	0.2291	0.1884	NA
22	1	0.8883	0.7752	0.6958	0.6203	0.5736	0.4161	0.3084	0.2568	0.2216	0.1824	NA
23	1	0.8892	0.7804	0.7004	0.6239	0.5752	0.4141	0.3008	0.2493	0.2148	0.1769	NA
24	1	0.8872	0.7835	0.7053	0.6264	0.5782	0.4112	0.2932	0.2422	0.2083	0.1717	NA
25	1	0.8834	0.7777	0.7026	0.6252	0.5788	0.4040	0.2848	0.2353	0.2026	0.1673	NA
26	1	0.8824	0.7740	0.6987	0.6234	0.5771	0.3853	0.2739	0.2280	0.1970	0.1633	NA
27	1	0.8836	0.7761	0.6994	0.6240	0.5731	0.3612	0.2605	0.2195	0.1909	0.1592	NA
28	1	0.8822	0.7760	0.6988	0.6239	0.5692	0.3463	0.2491	0.2118	0.1852	0.1553	NA
29	1	0.8813	0.7747	0.6977	0.6225	0.5718	0.3407	0.2432	0.2076	0.1820	0.1529	NA
30	1	0.8803	0.7737	0.6972	0.6217	0.5754	0.3389	0.2400	0.2052	0.1800	0.1514	NA
31	1	0.8821	0.7789	0.7000	0.6229	0.5766	0.3372	0.2358	0.2016	0.1770	0.1490	NA
32	1	0.8859	0.7835	0.7025	0.6242	0.5770	0.3356	0.2310	0.1972	0.1734	0.1463	NA
33	1	0.8839	0.7784	0.6990	0.6225	0.5723	0.3342	0.2276	0.1942	0.1709	0.1444	NA
34	1	0.8810	0.7744	0.6961	0.6210	0.5679	0.3329	0.2256	0.1926	0.1696	0.1435	NA
35	1	0.8800	0.7737	0.6959	0.6205	0.5700	0.3304	0.2241	0.1917	0.1689	0.1430	NA
36	1	0.8800	0.7744	0.6964	0.6204	0.5728	0.3258	0.2223	0.1907	0.1683	0.1426	NA
37	1	0.8817	0.7772	0.6979	0.6218	0.5726	0.3200	0.2199	0.1896	0.1677	0.1422	NA
38	1	0.8821	0.7780	0.6977	0.6208	0.5641	0.3150	0.2174	0.1883	0.1669	0.1418	NA
39	1	0.8798	0.7751	0.6949	0.6174	0.5547	0.3127	0.2158	0.1874	0.1664	0.1415	NA

Figure 3.9 | A sample information absent dataset. The geometric features of the manufactured products are absent in the metadata.

As show in Fig. 3.8b, to reveal more insightful information from the information absent metal forming metadata, this thesis proposed a purely physical-based algorithm, named the Evolutionary Binary (EB) algorithm, following the thermo-mechanical principles, by exploring the information absent hot stamping metadata via developing and analysing the unique DC of the hot stamping process. The EB algorithm enables the recognition of the absent features via identifying the origin of each data point. The EB algorithm is led by a governing equation shown as follows:

$$\int_0^t \int_{-\infty}^{f_i(t)} \frac{1}{s\sqrt{2\pi}} \cdot e^{-\frac{[f_i(t)-f_c]^2}{2s^2}} df_i(t) dt = \begin{cases} 0, & \text{data point was identified} \\ 1, & \text{data point was not identified} \end{cases} \quad (3.1)$$

where ' $f_i(t) - f_c$ ' is the time-dependent thermo-mechanical filter (TMF) developed to identify the time-sensitive data points by discriminating the distinct evolutionary thermo-mechanical

characteristics against the critical value f_c , a thermo-mechanical based parameter. The TMF is the most important element embedded in the EB algorithm, which was developed to identify the data points with identical thermo-mechanical evolutionary characteristics, such as the data points with significant temperature reduction or sudden contact pressure variations during the production process (representing the characteristic of ‘Evolutionary’). Therein, $f_i(t)$ represents the thermo-mechanical data such as temperature data or contact pressure data; t is the time that represents which stage(s) of thermo-mechanical data should be considered; the subscript i refers to the i^{th} data point ($i=1, 2, 3, \dots, n$); s is the model parameter, which is calibrated in the calibration process, which makes the EB algorithm calculate two outcomes (representing the characteristic of ‘Binary’): the data point with a calculation result being ‘0’ is identified, whereas a calculation result of ‘1’ remains as unidentified.

3.3 Metadata visualisation leading to development of digital characteristics (DC)

To enable research of manufacturing processes from the perspective of metadata, this thesis introduced the concept of the digital characteristics (DC), which is the visualisation of the metadata incorporating the essential information spanning the design, manufacturing and application stages of the manufactured products³ (Fig. 3.8d). Unique characteristics of any specific manufacturing process can be digitally revealed, and insightful information can be highlighted and analysed via using appropriate DC based on the processed manufacturing metadata.

As shown in the Fig. 3.1, based on the verified manufacturing metadata (most of them are information absent), metadata pre-processing and processing (if the information of key features are absent) are applied to enable the DC development, which is a process of extraction of insightful characteristics from underlying scientific patterns. Then the DC are developed for specific features or manufacturing processes, and can be characterised by ‘3Us’, namely ‘Unified’, ‘Unique’ and ‘Useful’, based on FAIR data principles.

Unified: Diverse manufacturing processes can be comprehensively mapped by DC from the perspective of their metadata. All the manufacturing DC can be stored and retrieved in the cloud-based data repository with unified formats, rules for scientific data management and stewardship (e.g., FAIR data principles), and data privacy and protection policies, where the

data repository are updated with new manufacturing DC obtained by unified data collection, processing and characterisation methods.

Unique: DC are developed based on the unique evolutionary thermo-mechanical properties of each manufacturing process. This is the intrinsic condition of the identification of the metadata collected from any specific manufacturing process, and the recognition of any specific feature (e.g., dimensional or geometric features of the manufactured products) from the information absent manufacturing metadata (see Section 3.2). Furthermore, the DC can be assigned a globally unique and persistent identifier. Every specific manufacturing dataset, and its corresponding DC, can be referred via a unique identification number (see Fig. A), which makes each dataset or DC available as an open access resource, downloadable by the scientific community to augment the data-driven research and development efforts in manufacturing sciences.

Useful: As the mapping of the manufacturing processes, the DC enable insightful scientific research on the manufacturing processes from the perspective of metadata, and promotes the emerging research area of data sciences in manufacturing. Voluminous DC characterising different features of diverse manufacturing processes leads to the establishment of the digital characteristics space (DCS) of manufacturing processes (see Chapter 5).

In the present research, by using the proposed EB algorithm, the unique digital characteristics (DC) have been identified for a variety of manufacturing processes, leading to the establishment of the digital characteristics space (DCS) of manufacturing processes (see Chapter 5) that provides open access to the most up-to-date and information-rich cloud-based DC repository for diverse manufacturing technologies to accelerate and enhance the scientific research. Fig. 3.8d shows an overview of the DC for over 140 manufacturing processes by visualising the processed metadata including the temperature data, contact pressure data, strain data and strain rate data. Here, it is found the DC of each manufacturing process as a unique feature which carries its essential thermo-mechanical features.

3.4 Summary

This chapter presented a guidance on developing the digital characteristics (DC) for diverse manufacturing processes following the well-known FAIR (Findable, Accessible, Interoperable and Reusable) data principles. The guidance was illustrated with essential elements including

the manufacturing metadata collection leads to the development of a cloud-based data repository, metadata pre-processing and information absent data processing leads to the development of a physical-based Evolutionary Binary (EB) algorithm embedded with different types of thermo-mechanical filters, and the data characterisation leads to the development of the DC. The DC were characterised with three characteristics, namely the ‘3Us’, indicating ‘Unified’, ‘Unique’ and ‘Useful’, which supports the extraction of insightful characteristics from underlying scientific patterns, and then stimulates the future academic research and development.

Chapter 4. Unlocking digital characteristics (DC) of metal forming processes: a case study of hot stamping process

In this Chapter, the digital characteristics (DC) were developed for a representative metal forming process, the hot stamping process, following the guidance of DC development explained in Chapter 3. Fig. 4.1 shows the technical route of recognising the absent geometric features using the Evolutionary Binary (EB) algorithm. The metadata were pre-processed and were used for developing the thermo-mechanical filters (TMFs) following the thermo-mechanical principles. Embedded with the TFM, the EB algorithm was applied on a benchmark dataset that contains 20,000 hot stamping data points to recognise three representative but absent geometric features, namely, the blank holder (BH), flat bottom (FB) and side wall (SW) features.

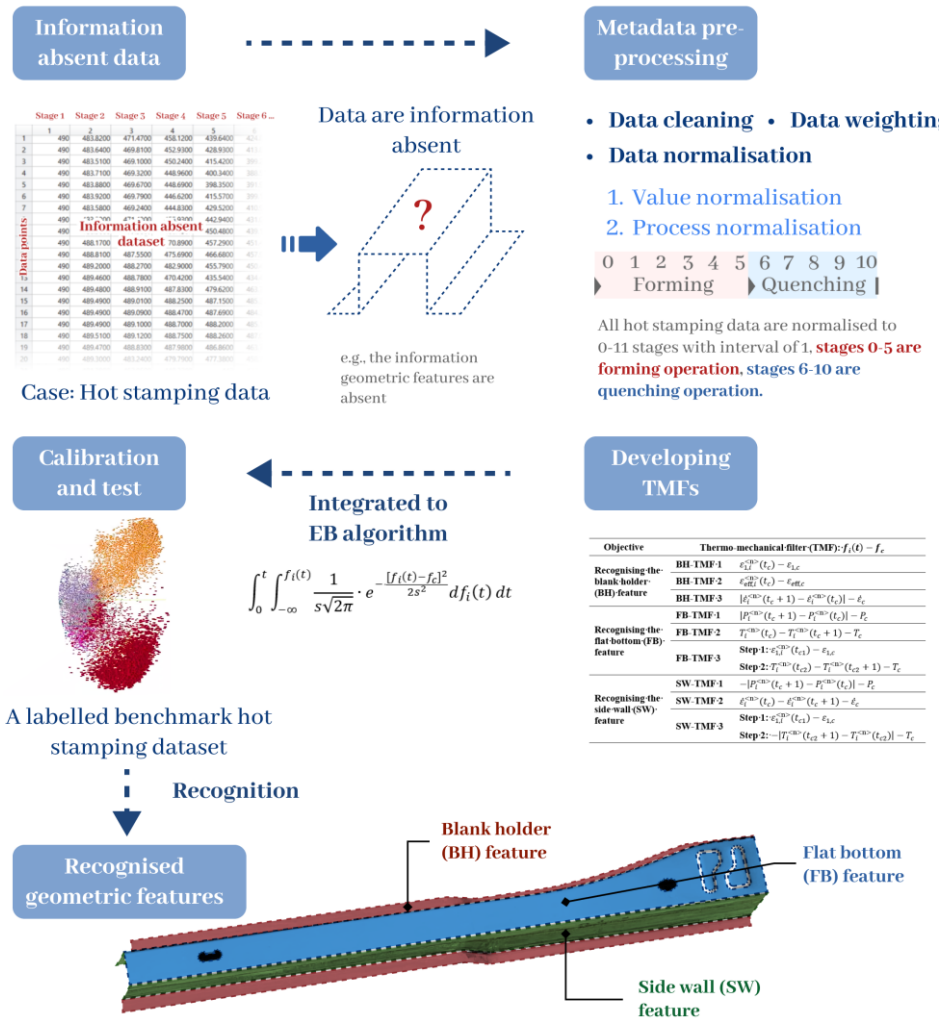


Figure 4.1 | Technical route of information absent data processing and development of the digital characteristics (DC).

4.1 Hot stamping process

Hot stamping is a hybrid metal forming process which combines forming and heat treatment in one process⁸. Advanced hot stamping technologies have been developed in the past decades to achieve the deformation of complex-shaped components and retain high post-formed strengths. For instance, Fig. 4.2 shows the schematic illustration of a representative advanced hot stamping technology, named the solution heat treatment, forming and indie quenching (HFQ[®]) technology, where the blank is first heated to its solution heat treatment (SHT) temperature, and transferred to a cold die, formed rapidly and then held in the cold dies to achieve a fast quenching to obtain the desirable microstructure that is critical for post-form strength⁹. The HFQ technology is also the main technology that contributes to the hot stamping metadata generation in the current study.

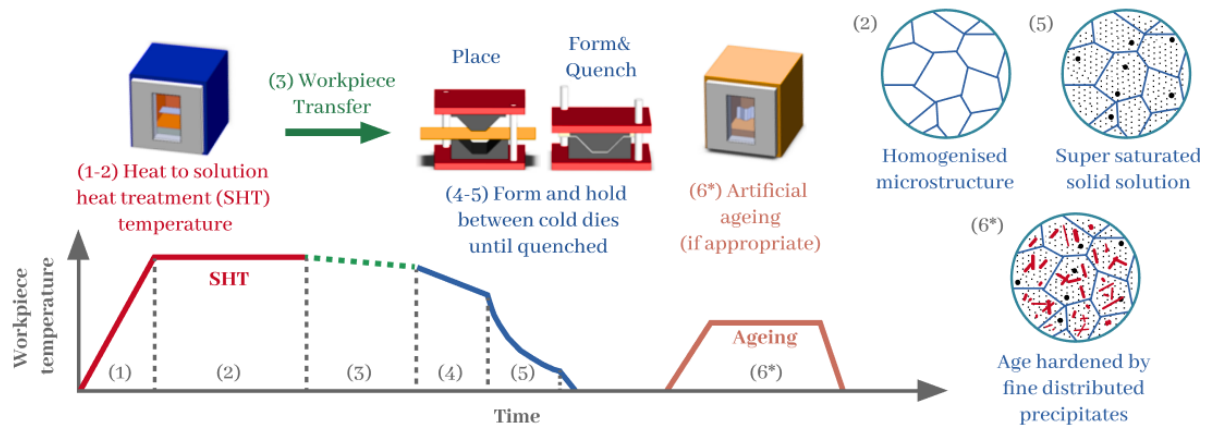


Figure 4.2 | Schematic diagram of the HFQ forming process.

For experimentally verified the hot stamping data collected from numerical sources, a series of experiments were conducted to verify the FEA models as the main data sources. Fig. 4.3 shows the experimental facilities of uniaxial tensile test (UATT) for material characterisation (Fig. 4.3 a), friction test for friction model verification (Fig. 4.3 b), and the interfacial heat transfer coefficient (IHTC) test for IHTC model verification (Fig. 4.3 c), and an experimentally verified FEA model established for the B-pillar test under the loading condition (Fig. 4.3 d). Subsequently, the metadata (characterised by various evolutionary thermo-mechanical properties including the temperature, strain and strain rate, contact pressure and stress data) were collected from the workpiece during the forming and quenching operations of the FEA models, yet the information of the BH, FB and SW features are absent.

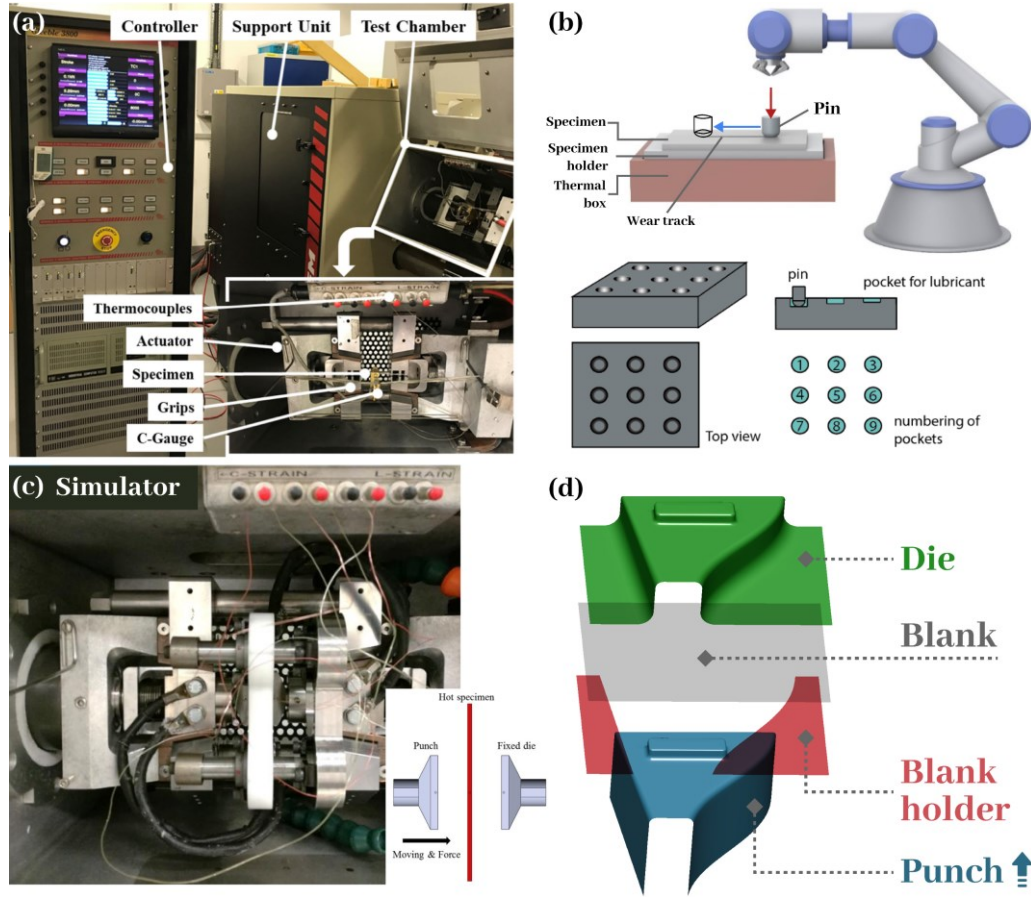


Figure 4.3 | Experimental and FEA setups. a, UATT test setup on the Gleeble 3800 simulator, **b**, friction test using Tribo-mate system³ including the operation robot and thermal box, and auto-lubrication rig, **c**, IHTC test setup on the Gleeble 3800 simulator and schematic diagram of the compression between the specimen and dies, and **d**, A verified FEA model of the B-pillar test under the loading condition.

4.2 Developing the thermo-mechanical filters embedded in the EB algorithm by exploring information absent hot stamping data

In Fig. 4.4, a schematic illustration of the temperature evolution is presented, which is a unique characteristic of the hot stamping process. The workpiece is heated (operation 1) to an elevated temperature and then soaked (operation 2) for a specified time period. Then, the hot/warm workpiece is rapidly transferred (operation 3) to a press and formed (operation 4) between a set of cold dies. Subsequently, the formed workpiece is held in the cold dies to achieve a rapid in-die quenching (operation 5). This unique processing window has led to the development of the unique DC by visualising the hot stamping metadata collected from the forming and quenching operations (operations 4 and 5), which carry the essential information of the temperature data (Fig. 4.4b), contact pressure data (Fig. 4.4c), major strain data (Fig. 4.3d), effective strain data (Fig. 4.4e), and strain rate data (Fig. 4.4f).

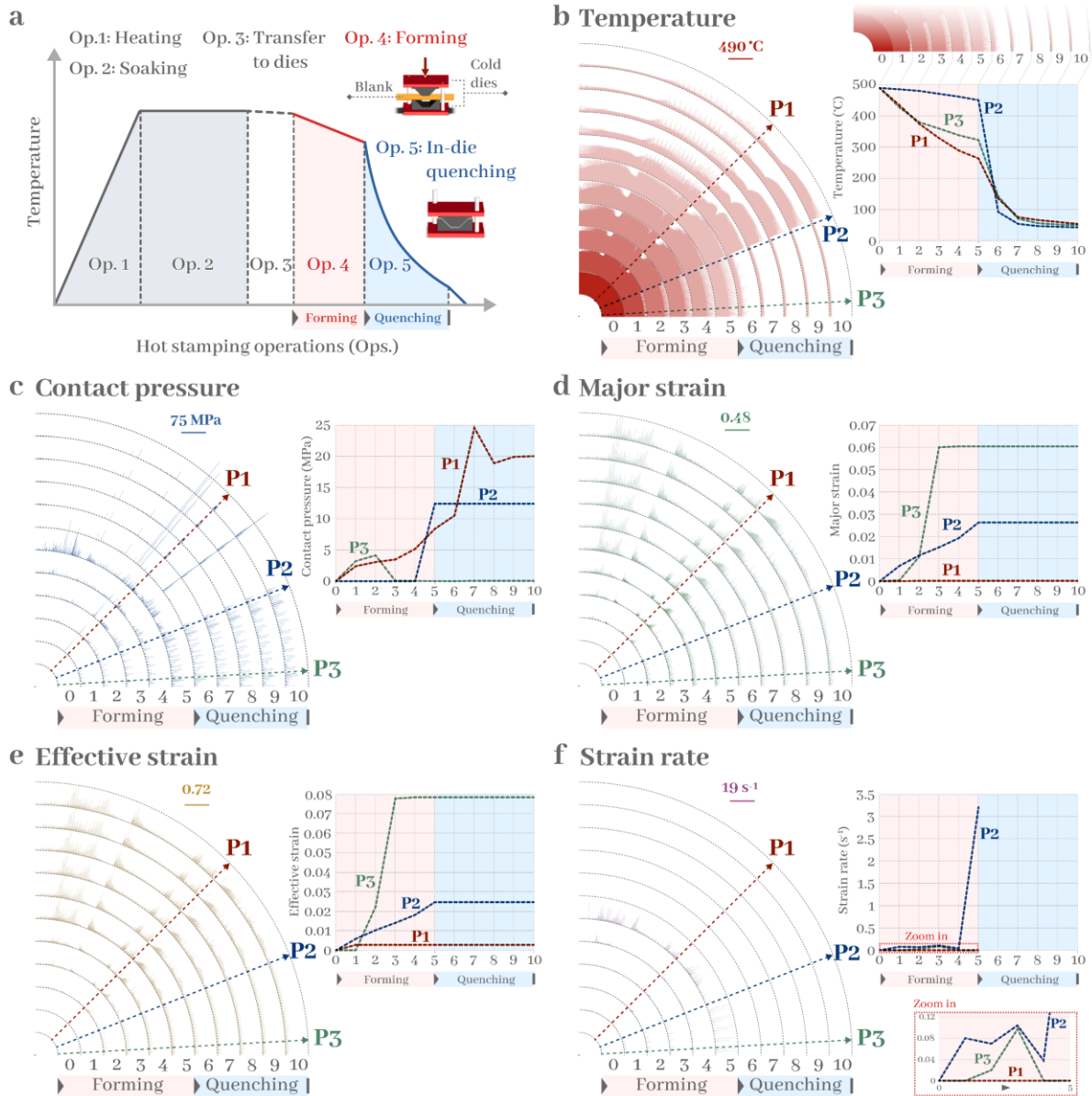


Figure 4.3 | Hot stamping process and the DC presenting its unique evolutionary thermo-mechanical characteristics. a, Schematic illustration of the hot stamping process via presenting its temperature evolution characteristics. The DC of the hot stamping process are presented by visualising the thermo-mechanical data of b, temperature, c, contact pressure, d, major strain, e, effective strain and f, strain rate data of the forming (normalised stages 0-5) and quenching (normalised stages 6-10) operations. Three representative data points (P1, P2 & P3) are selected to reveal the unique thermo-mechanical features from the DC.

Developing TMF by analysing distinct temperature DC of the hot stamping process. As shown in Fig. 4.4b, the specific feature of temperature evolution can be clearly revealed by the temperature evolutions of three representative data points P1, P2 and P3, which were chosen from the blank holder (BH) feature, flat bottom (FB) feature and side wall (SW) feature, respectively, to highlight the difference among their thermo-mechanical evolutionary characteristics. The temperature of P1, P2 and P3 decreases by 105.8 °C, 28.9 °C and 57.6 °C

from stages 2 to 5. This indicates that the data points can be identified by considering their distinct temperature reduction characteristics. For instance, P1, which experiences the most significant temperature reduction throughout stages 2 to 5, can be identified by:

$$T_i(t) - T_i(t + 1) > T_c, \quad i = 1, 2, 3, \quad t = \{2, 3, 4\} \quad (4.1)$$

where $T_i(t)$ and $T_i(t + 1)$ are the temperature data of the i^{th} data point ($i=1, 2, 3$ in this case represents data points P1, P2 and P3) at normalised stage t (stages 2, 3, 4 in this case) and subsequent normalised stage $t + 1$ (stages 3, 4, 5 in this case); T_c is the critical value of the temperature reduction ($16.0 < T_c < 25.1$ °C in this case) enabling the identification of data points from a specific geometric region. The distinct temperature reduction characteristic are mainly caused by the unique loading conditions in different geometric regions. Thus, to recognise the geometric region containing data points like P1, the thermo-mechanical filter can be written as:

$$f_i(t) - f_c = T_i(t_c) - T_i(t_c + 1) - T_c, \quad i = 1, 2, 3, \dots, n \quad (4.2)$$

where t_c is the normalised stage and T_c (representing f_c) is the thermo-mechanical based model parameter regarding temperature reduction that should be calibrated.

Developing TMF by analysing distinct contact pressure DC. As shown in Fig. 4.4c, the contact pressure of P1 constantly increases from 0 to 11.11 MPa from stages 0 to 5, while that of P2 remains close to 0 until stage 4, followed by a sharp rise to 12.41 MPa at stage 5. The contact pressure of P3 increases to 4.14 MPa at stage 2, and then decreases to 0. This indicates that P2 can be identified by:

$$|P_i(t + 1) - P_i(t)| < P_c, \quad i = 1, 2, 3, \quad t = \{0, 1, 2, 3\} \quad (4.3)$$

where $P_i(t)$ and $P_i(t + 1)$ are the contact pressure data of the i^{th} data point ($i=1, 2, 3$) at normalised stage t (stages 0, 1, 2, 3 in this case) and subsequent normalised stage $t + 1$ (stages 1, 2, 3, 4 in this case); P_c is the critical value of the contact pressure change ($0 < P_c < 0.23$ MPa in this case). This indicates that to recognise the geometric region containing data points such as P2, the thermo-mechanical filter can be written as:

$$f_i(t) - f_c = |P_i(t_c + 1) - P_i(t_c)| - P_c, \quad i = 1, 2, 3, \dots, n \quad (4.4)$$

where P_c (representing f_c) should be calibrated.

Developing TMF by analysing distinct major and effective strains DC. As shown in Fig. 4.4d and 4.4e, during stages 0 to 5, the major strain and effective strain of P1 increases from 0

to 9.31×10^{-5} and from 0 to 0.017, respectively, which are much lower than that of P2 and P3. Thus, P1 can be identified by:

$$\varepsilon_{1,i}(t) < \varepsilon_{1,c} \quad \text{or} \quad \varepsilon_{\text{eff},i}(t) < \varepsilon_{\text{eff},c}, \quad i = 1, 2, 3, \quad t = \{0, 1, 2, 3, 4, 5\} \quad (4.5)$$

where $\varepsilon_{1,i}(t)$ and $\varepsilon_{\text{eff},i}(t)$ are the major strain and effective strain data of the i^{th} data point ($i=1, 2, 3$) at normalised stage t (stages 0, 1, 2, 3, 4, 5 in this case); $\varepsilon_{1,c}$ and $\varepsilon_{\text{eff},c}$ are the critical values of the strain growths ($2.71 \times 10^{-4} < \varepsilon_{1,c} < 0.026$, $0.017 < \varepsilon_{\text{eff},c} < 0.025$ in this case). Thus, to recognise the geometric region containing data points such as P1, the thermo-mechanical filter can be written as:

$$f_i(t) - f_c = \varepsilon_{1,i}(t_c) - \varepsilon_{1,c} \quad \text{or} \quad \varepsilon_{\text{eff},i}(t_c) - \varepsilon_{\text{eff},c}, \quad i = 1, 2, 3, \dots, n \quad (4.6)$$

where $\varepsilon_{1,c}$ and $\varepsilon_{\text{eff},c}$ (representing f_c) should be calibrated.

Developing TMF by analysing distinct strain rate DC. As shown in Fig. 4.4f, distinct discrepancies are observed among the strain rate evolutions of P1, P2 and P3. For instance, the strain rate change of P2 from stages 4 to 5 is 3.18 s^{-1} , which is the most significant among these three data points, and can lead to the identification of P2 by:

$$|\dot{\varepsilon}_i(t+1) - \dot{\varepsilon}_i(t)| > \dot{\varepsilon}_c \quad t = 4 \quad (4.7)$$

where $\dot{\varepsilon}_i(t)$ and $\dot{\varepsilon}_i(t+1)$ are the strain rate data of the i^{th} data point ($i=1, 2, 3$) at normalised stage t (stage 4 in this case) and subsequent normalised stage $t+1$ (stage 5 in this case); $\dot{\varepsilon}_c$ is the critical value of the strain rate change ($0 < \dot{\varepsilon}_c < 3.17 \text{ s}^{-1}$ in this case). Thus, to recognise the geometric region containing data points such as P2, the thermo-mechanical filter can be written as:

$$f_i(t) - f_c = |\dot{\varepsilon}_i(t_c+1) - \dot{\varepsilon}_i(t_c)| - \dot{\varepsilon}_c, \quad i = 1, 2, 3, \dots, n \quad (4.8)$$

where $\dot{\varepsilon}_c$ (representing f_c) should be calibrated.

4.3 Information absent data processing: Geometric features recognition of hot stamping process

Metadata pre-processing. Here, data cleaning was performed to exclude the unnecessary or irrelevant data points of the manufacturing metadata. For instance, data points collected from the tools were excluded from the hot stamping dataset since they were irrelevant to the task of

recognising the component's geometric features. Data weighting was performed to eliminate the bias among different manufacturing datasets by selecting equal data points from each dataset. To enable the recognition, normalisation was conducted on the manufacturing stages and thermo-mechanical data. The operation stages of each manufacturing process were normalised from 0 to 10 with an interval of 1. For instance, the temperature data were normalised against the initial temperature of the workpiece (Eq. 4.9); the contact pressure, major strain, effective strain and strain rate data were normalised against the range of their values (Eqs. 4.10-4.13):

$$T_{i,j}^{<n>}(t) = \frac{T_{i,j}(t)}{T_j(t_0)} \quad (4.9)$$

$$P_{i,j}^{<n>}(t) = \frac{P_{i,j}(t)}{\max(P_j) - \min(P_j)} \quad (4.10)$$

$$\varepsilon_{1,i,j}^{<n>}(t) = \frac{\varepsilon_{1,i,j}(t)}{\max(\varepsilon_{1,j}) - \min(\varepsilon_{1,j})} \quad (4.11)$$

$$\varepsilon_{\text{eff},i,j}^{<n>}(t) = \frac{\varepsilon_{\text{eff},i,j}(t)}{\max(\varepsilon_{\text{eff},j}) - \min(\varepsilon_{\text{eff},j})} \quad (4.12)$$

$$\dot{\varepsilon}_{i,j}^{<n>}(t) = \frac{\dot{\varepsilon}_{i,j}(t)}{\max(\dot{\varepsilon}_j) - \min(\dot{\varepsilon}_j)} \quad (4.13)$$

where $T_{i,j}^{<n>}(t)$, $P_{i,j}^{<n>}(t)$, $\varepsilon_{1,i,j}^{<n>}(t)$, $\varepsilon_{\text{eff},i,j}^{<n>}(t)$ and $\dot{\varepsilon}_{i,j}^{<n>}(t)$ are the normalised temperature, contact pressure, major strain, effective strain and strain rate of the i^{th} data point in the j^{th} manufacturing dataset at the normalised manufacturing stage t ; $T_j(t_0)$ represents the initial workpiece temperature of the j^{th} dataset at the beginning of manufacturing (t_0).

Thermo-mechanical filters. Using the proposed Evolutionary Binary (EB) algorithm (Eq. 3.1), the geometric features of the hot stamping component were recognised via identifying the origin of each data point. In Tab. 4.1, for respectively recognising the BH, FB and SW features, three TMFs of each case that provide the highest accuracies are presented. The development of the thermo-mechanical filters considers the evolutionary thermo-mechanical characteristics.

Therein, the superscript $<n>$ indicates that this thermo-mechanical data was normalised. Thus, $\varepsilon_{1,i}^{<n>}(t_c)$ is the normalised major strain at the normalised stage t_c ; $\varepsilon_{\text{eff},i}^{<n>}(t_c)$ is the normalised effective strain at stage t_c ; $\dot{\varepsilon}_i^{<n>}(t_c)$ and $\dot{\varepsilon}_i^{<n>}(t_c + 1)$ are the normalised strain rates at stage t_c and subsequent stage $t_c + 1$, respectively; $P_i^{<n>}(t_c)$ and $P_i^{<n>}(t_c + 1)$ are the

normalised contact pressures at stage t_c and subsequent stage $t_c + 1$, respectively; $T_i^{<n>}(t_c)$ and $T_i^{<n>}(t_c + 1)$ are the normalised temperatures at stage t_c and subsequent stage $t_c + 1$, respectively; model parameter, including the t_c , $\varepsilon_{1,c}$, $\varepsilon_{eff,c}$, $\dot{\varepsilon}_c$, P_c and T_c , need to be calibrated.

Table 4.1 | Thermo-mechanical filters (TMFs). This table lists three TMFs that provide the highest accuracies for respectively recognising the BH, FB and SW features.

Objective	Thermo-mechanical filter (TMF): $f_i(t) - f_c$	
Recognising the blank holder (BH) feature	BH-TMF 1	$\varepsilon_{1,i}^{<n>}(t_c) - \varepsilon_{1,c}$
	BH-TMF 2	$\varepsilon_{eff,i}^{<n>}(t_c) - \varepsilon_{eff,c}$
	BH-TMF 3	$ \dot{\varepsilon}_i^{<n>}(t_c + 1) - \dot{\varepsilon}_i^{<n>}(t_c) - \dot{\varepsilon}_c$
Recognising the flat bottom (FB) feature	FB-TMF 1	$ P_i^{<n>}(t_c + 1) - P_i^{<n>}(t_c) - P_c$
	FB-TMF 2	$T_i^{<n>}(t_c) - T_i^{<n>}(t_c + 1) - T_c$
	FB-TMF 3	Step 1: $\varepsilon_{1,i}^{<n>}(t_{c1}) - \varepsilon_{1,c}$
		Step 2: $T_i^{<n>}(t_{c2}) - T_i^{<n>}(t_{c2} + 1) - T_c$
Recognising the side wall (SW) feature	SW-TMF 1	$- P_i^{<n>}(t_c + 1) - P_i^{<n>}(t_c) - P_c$
	SW-TMF 2	$\dot{\varepsilon}_i^{<n>}(t_c) - \dot{\varepsilon}_i^{<n>}(t_c + 1) - \dot{\varepsilon}_c$
	SW-TMF 3	Step 1: $\varepsilon_{1,i}^{<n>}(t_{c1}) - \varepsilon_{1,c}$
		Step 2: $- T_i^{<n>}(t_{c2} + 1) - T_i^{<n>}(t_{c2}) - T_c$

Calibration and test of the EB algorithm. The performance of the EB algorithm was evaluated in terms of recognising the blank holder (BH), flat bottom (FB) and side wall (SW) features of the hot stamping products. To validate and evaluate the potential of the EB algorithm, 9 groups of calibration dataset sizes (CDSs) and test datasets sizes (TeDSs) were assigned within the 20,000 data points-benchmark dataset. The benchmark dataset was manually labelled with blank holder (BH), flat bottom (FB) and side wall (SW) features to facilitate the validation of the EB algorithm. To evaluate the performance of the EB algorithm with different amounts of labelled data, as listed in Tab. 4.2, nine groups of the calibration dataset sizes (CDSs) and test datasets sizes (TeDSs) were assigned within the benchmark dataset.

During the calibration process of each thermo-mechanical filter (TMF), the model parameters (f_c , t_c and s) were calibrated via identifying the permutation and combination that provide the best accuracy using the calibration dataset. Subsequently, the test was performed using the test dataset with the calibrated model parameters to evaluate the test accuracy and efficiency. The data in the test dataset were not used in the calibration process. The calibration and test processes were automated and integrated in one calculation process, and the calibration time, test accuracy and test time with different CDSs were recorded for comparison.

Table 4.2 | Assignment of calibration and test dataset sizes with 20,000 hot stamping data points. The calibration dataset was used in the EB algorithm to calibrate the model parameters. The test dataset was used for evaluating the recognition performance.

	CDSs	0.1%	0.5%	1%	5%	10%	25%	50%	75%	90%
Calibration dataset	Data points amount	20	100	200	1,000	2,000	5,000	10,000	15,000	18,000
	TeDSs	99.9%	99.5%	99%	95%	90%	75%	50%	25%	10%
Test dataset	Data points amount	19,980	19,900	19,800	19,000	18,000	15,000	10,000	5,000	2,000

Recognition performance. As shown in Fig. 4.5a, when recognising the BH feature, the accuracies of using the thermo-mechanical filters (TMFs) considering the characteristics of major strain data (BH-TMF 1), effective strain data (BH-TMF 2) and strain rate data (BH-TMF 3), remain at the same-level, which range from minimum 91.23% (CDS=75%) to maximum 96% (CDS=0.5%), 90.33% (CDS=75%) to 95.5% (CDS=1%), and 90.37% (CDS=75%) to 95% (CDS=0.1%), respectively. The maximum calibration time of BH-TMF 1 is 12.83 ± 0.064 s (CDS=90%), which is approximately 3-4 times as that of the BH-TMF 2 (3.49 ± 0.022 s, CDS=90%) and BH-TMF 3 (4.63 ± 0.078 s, CDS=90%).

As shown in Fig. 4.5b, the FB feature is identified by using the thermo-mechanical filters considering the contact pressure data (FB-TMF 1), temperature data (FB-TMF 2), and the major strain data (FB-TMF 3, Step 1) and contact pressure data (FB-TMF 3, Step 2). Therein, FB-TMF 2 provides the best accuracy ranging from minimum 92.68% (CDS=25%) to maximum 96.5% (CDS=1%). The accuracy of FB-TMF 1 and FB-TMF 3 ranges from 84.91% (CDS=75%) to 91% (CDS=0.5%), and from 89.1% (CDS=75%) to 92.31% (CDS=0.1%), respectively. Being a two-step recognition process, the maximum calibration time of FB-TMF 3 is 94.55 ± 3.31 s (CDS=90%), which is significantly larger than that of the FB-TMF 1 (4.61 ± 0.0092 s, CDS=90%) and FB-TMF 2 (4.57 ± 0.043 s, CDS=90%).

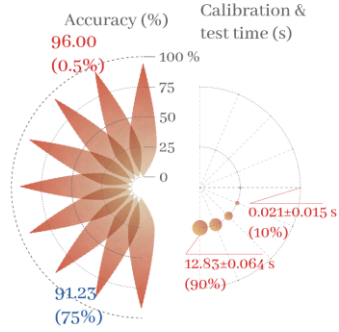
As shown in Fig. 4.5c, when recognising the SW feature, the accuracy ranges from minimum 78.55% (CDS=90%) to maximum 86% (CDS=0.5%) using the thermo-mechanical filters considering the contact pressure data (SW-TMF 1), 69% (CDS=1%) to 85% (CDS=0.1%) considering the strain rate data (SW-TMF 2), and 80.98% (CDS=50% & 75%) to 84.62% (CDS=0.1%) considering the major strain data (SW-TMF 3, Step 1) and temperature data (SW-TMF 3, Step 2). Being a two-step recognition process, the maximum calibration time of SW-TMF 3 is 101.56 ± 0.23 s (CDS=90%), which is significantly larger than that of the SW-TMF 1

(4.42 ± 0.068 s, CDS=90%) and SW-TMF 2 (4.42 ± 0.060 s, CDS=90%). The final calibrated model parameters of each TMF for geometric feature recognition can be found in Tab. 4.3.

Performance of EB algorithm for recognising:

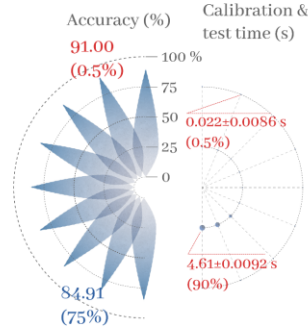
BH feature

a.1) BH-TMF 1



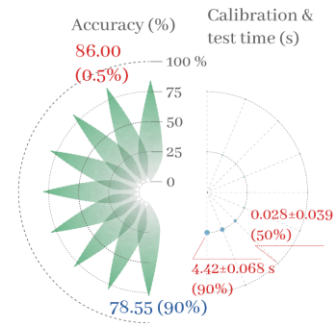
FB feature

b.1) FB-TMF 1

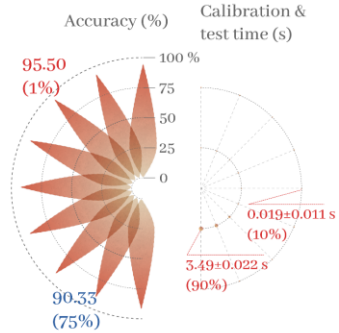


SW feature

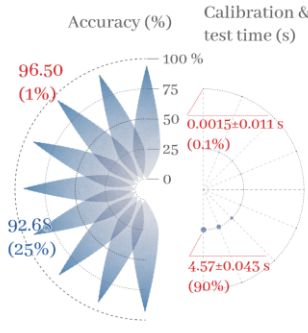
c.1) SW-TMF 1



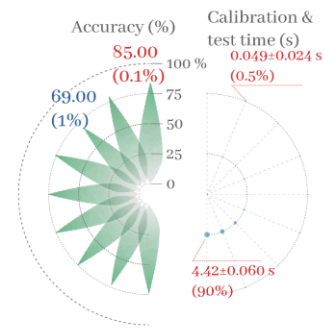
a.2) BH-TMF 2



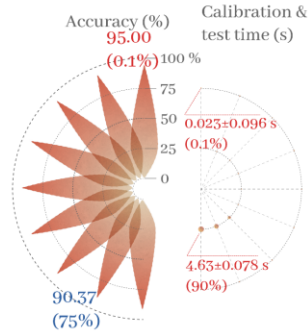
b.2) FB-TMF 2



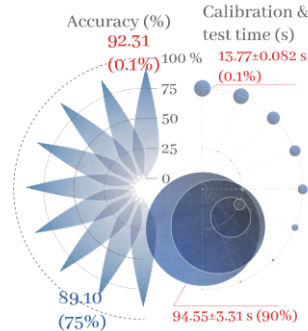
c.2) SW-TMF 2



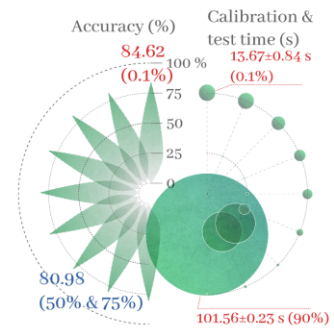
a.3) BH-TMF 3



b.3) FB-TMF 3

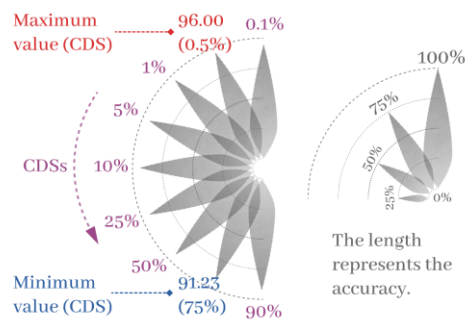


c.3) SW-TMF 3



Legend

Accuracy of tests (%)



Efficiency (s)

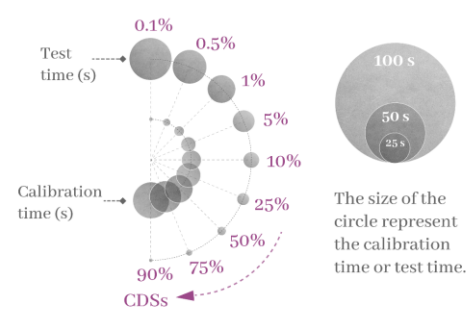


Figure 4.4 | Performance of the EB algorithm for recognising representative geometric features of hot stamped products. The accuracy and efficiency of the EB algorithm are evaluated in recognising the a.1-a.3,

BH feature, **b.1-b.3**, FB feature and **c.1-c.3**, SW feature under 9 groups of CDSs (0.1%, 0.5%, 1%, 5%, 10%, 25%, 50%, 75% and 90%) and TeDSs (correspondingly, 99.9%, 99.5%, 99%, 95%, 90%, 75%, 50%, 25% and 10%). The details of the calibrated model parameters (f_c , t_c and s) of each thermo-mechanical filter with different CDSs are listed in Tab. 4.3.

Table 4.3 | Model parameters of EB algorithm. The calibrated model parameters (f_c , t_c and s) were automatically calibrated via identifying the permutation and combination that provided the best accuracy while using different sizes of calibration dataset (CDSs: 0.1%, 0.5%, 1%, 5%, 10%, 25%, 50%, 75% and 90%). The recognised geometric features are shown in this table.

BH feature			FB feature			SW feature		
a.1) BH-TMF 1: $s=0.001$			b.1) FB-TMF 1: $s=0.001$			c.1) SW-TMF 1: $s=0.001$		
$\varepsilon_{1,i}^{<n>}(t_c) - \varepsilon_{1,c}$			$ P_i^{<n>}(t_c + 1) - P_i^{<n>}(t_c) - P_c$			$- P_i^{<n>}(t_c + 1) - P_i^{<n>}(t_c) - P_c$		
CDS	t_c	$\varepsilon_{1,c}$	CDS	t_c	P_c	CDS	t_c	P_c
0.1%	= {0, 1, 2, 3, 4, 5};	0.007	0.1%	= {0, 1, 2, 3, 4};	0.001	0.1%	$\in \{2\}$;	-0.01
0.5%	= {0, 1, 2, 3, 4, 5};	0.007	0.5%	= {0, 1, 2, 3, 4};	0.0001	0.5%	$\in \{0, 1, 2\}$;	-0.01
1%	= {0, 1, 2, 3, 4, 5};	0.007	1%	= {0, 1, 2, 3, 4};	0.0001	1%	$\in \{1, 2\}$;	-0.015
5%	= {0, 1, 2, 3, 4, 5};	0.0065	5%	= {0, 1, 2, 3, 4};	0.0001	5%	$\in \{1, 2\}$;	-0.015
10%	= {0, 1, 2, 3, 4, 5};	0.0065	10%	= {0, 1, 2, 3, 4};	5×10^{-5}	10%	$\in \{1, 2\}$;	-0.015
25%	= {4, 5};	0.0045	25%	= {0, 1, 2, 3, 4};	5×10^{-5}	25%	$\in \{1, 2\}$;	-0.015
50%	= {4, 5};	0.0045	50%	= {0, 1, 2, 3, 4};	5×10^{-5}	50%	$\in \{1, 2\}$;	-0.015
75%	= {4, 5};	0.0065	75%	= {0, 1, 2, 3, 4};	5×10^{-5}	75%	$\in \{1, 2\}$;	-0.005
90%	= {4, 5};	0.005	90%	= {0, 1, 2, 3, 4};	5×10^{-5}	90%	$\in \{1, 2\}$;	-0.01
a.2) BH-TMF 2: $s=0.001$			b.2) FB-TMF 2: $s=0.001$			c.2) SW-TMF 2: $s=0.001$		
$\varepsilon_{eff,i}^{<n>}(t_c) - \varepsilon_{eff,c}$			$T_i^{<n>}(t_c) - T_i^{<n>}(t_c + 1) - T_c$			$\dot{\varepsilon}_i^{<n>}(t_c) - \dot{\varepsilon}_i^{<n>}(t_c + 1) - \dot{\varepsilon}_c$		
CDS	t_c	$\varepsilon_{eff,c}$	CDS	t_c	T_c	CDS	t_c	$\dot{\varepsilon}_c$
0.1%	= {0, 1, 2, 3, 4, 5};	0.007	0.1%	= {0, 1, 2, 3, 4};	0.0095	0.1%	$\in \{0, 1, 2\}$;	-0.015
0.5%	= {0, 1, 2, 3, 4, 5};	0.007	0.5%	= {0, 1, 2, 3, 4};	0.0095	0.5%	$\in \{0, 1, 2\}$;	-0.01
1%	= {0, 1, 2, 3, 4, 5};	$f_c=0.007$	1%	= {0, 1, 2, 3, 4};	0.01	1%	$\in \{0, 1, 2\}$;	-0.005
5%	= {0, 1, 2, 3, 4, 5};	0.0065	5%	= {0, 1, 2, 3, 4};	0.01	5%	$\in \{1, 2\}$;	-0.005
10%	= {0, 1, 2, 3, 4, 5};	0.0065	10%	= {0, 1, 2, 3, 4};	0.01	10%	$\in \{1, 2\}$;	-0.005
25%	= {4, 5};	0.0045	25%	= {0, 1, 2, 3, 4};	0.01	25%	$\in \{1, 2\}$;	-0.005
50%	= {4, 5};	0.0045	50%	= {0, 1, 2, 3, 4};	0.01	50%	$\in \{1, 2\}$;	-0.005
75%	= {4, 5};	0.0065	75%	= {0, 1, 2, 3, 4};	0.01	75%	$\in \{1, 2\}$;	-0.005
90%	= {4, 5};	0.005	90%	= {0, 1, 2, 3, 4};	0.01	90%	$\in \{1, 2\}$;	-0.01
a.3) BH-TMF 3: $s=0.001$			b.3) FB-TMF 3: $s=0.001$			c.3) SW-TMF 3: $s=0.001$		
$ \dot{\varepsilon}_i^{<n>}(t_c + 1) - \dot{\varepsilon}_i^{<n>}(t_c) - \dot{\varepsilon}_c$			Step 1: $\varepsilon_{1,i}^{<n>}(t_{c1}) - \varepsilon_{1,c}$			Step 1: $\varepsilon_{1,i}^{<n>}(t_{c1}) - \varepsilon_{1,c}$		
CDS t_c $\dot{\varepsilon}_c$			Step 2: $T_i^{<n>}(t_{c2}) - T_i^{<n>}(t_{c2} + 1) - T_c$			Step 2: $- T_i^{<n>}(t_{c2} + 1) - T_i^{<n>}(t_{c2}) - T_c$		
CDS	t_c	$\dot{\varepsilon}_c$	CDS	t_{c1} t_{c2}	$\varepsilon_{1,c}$ T_c	CDS	t_{c1} t_{c2}	$\varepsilon_{1,c}$ T_c
0.1%	= {0, 1, 2, 3, 4};	0.002	0.1%	= {0, 1, 2, 3, 4, 5};	0.007	0.1%	= {0, 1, 2, 3, 4, 5};	0.007
0.5%	= {0, 1, 2, 3, 4};	0.0015		= {0, 1, 2};	0.002		$\in \{0\}$;	-0.02
1%	= {0, 1, 2, 3, 4};	0.0019		= {0, 1, 2, 3, 4, 5};	0.0065		= {0, 1, 2, 3, 4, 5};	0.0065
5%	= {0, 1, 2, 3, 4};	0.0015	0.5%	= {0, 1, 2};	0.003	0.5%	$\in \{0, 1, 2\}$;	-0.019
10%	= {0, 1, 2, 3, 4};	0.0015		= {4, 5};	0.0035		= {4, 5};	0.0035
25%	= {0, 1, 2, 3, 4};	0.0011		= {0, 1, 2, 3};	0.009		$\in \{0, 1, 2\}$;	-0.015
50%	= {1, 2, 3, 4};	0.0009	1%	= {4, 5};	0.0025	1%	= {4, 5};	0.0025
75%	= {0, 1, 2};	0.0004		= {0, 1, 2, 3};	0.007		$\in \{0, 1, 2\}$;	-0.015
90%	= {1, 2, 3, 4};	0.0012	5%	= {4, 5};	0.002	5%	= {4, 5};	0.002
				= {0, 1, 2, 3};	0.008		$\in \{0, 1, 2\}$;	-0.014
			10%	= {4, 5};	0.0015	10%	= {4, 5};	0.0015
				= {0, 1, 2, 3};	0.007		$\in \{0, 1, 2\}$;	-0.014
			25%	= {4, 5};	0.001	25%	= {4, 5};	0.001
				= {1, 2, 3};	0.007		$\in \{0, 1, 2\}$;	-0.013
			50%	= {0, 1, 2, 3, 4, 5};	0.0065	50%	= {0, 1, 2, 3, 4, 5};	0.0065
				= {1, 2, 3};	0.007		$\in \{0, 1, 2\}$;	-0.013
			75%	= {4, 5};	0.002	75%	= {4, 5};	0.002
				= {1, 2, 3};	$f_{c2}=0.007$		$\in \{0, 1, 2\}$;	-0.013

4.4 Performance comparison between the EB algorithm and classic machine learning algorithms

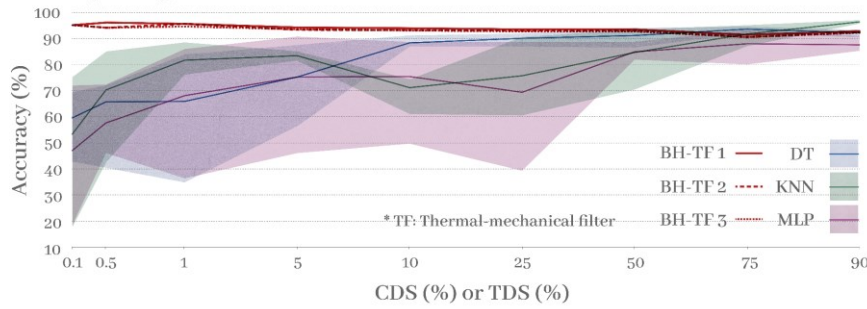
The performance of the EB algorithm was evaluated in terms of recognising the BH, FB and SW features under 9 groups of calibration dataset sizes (CDSs) and test datasets sizes (TeDSs) (Tab. 4.2). For comparative purposes, three classic machine learning (ML) algorithms, the Decision Tree (DT), K-Nearest Neighbour (KNN) and Multilayer Perceptron (MLP) algorithms, were trained by using nine groups of training datasets of the exact sizes as CDSs. While the sizes of CDSs and training dataset sizes (TDSs) were the same, the test dataset sizes (TeDSs) were also assigned to test the performance of ML algorithms and compared.

The ML algorithms enabled the recognition of all three geometrical features simultaneously. With CDSs of 0.1%, 0.5% and 1%, the EB algorithm yielded the accuracy of 94%-96% when recognising the BH feature, 88.5-96.5% when recognising the FB feature, and nearly 80-86% when recognising the SW feature (Fig. 4.5a-4.5c). Specifically, the accuracies of recognising the BH feature were 10.64%-60.23% (CDS=0.1%), 6.05%-76.88% (CDS=0.5%) and 8.71%-76.21% (CDS=1%) greater than that of the DT, KNN and MLP algorithms, respectively; and that for recognising the FB feature were 2.37%-80.84% (CDS=0.1%), 0-77.05% (CDS=0.5%) and 0-85.9% (CDS=1%), for recognising the SW feature were 0-41.06% (CDS=0.1%), 0-84.62% (CDS=0.5%) and 0-59.16% (CDS=1%). Meanwhile, the EB algorithm (maximum 0.16 s consumed in calibration) enabled an average 100-fold increase in the computational speed than these three ML algorithms due to their nonignorable training and validation time (see Fig. 4.5d). Nevertheless, there is a significant potential to improve the ML algorithms used in the present research by incorporating information on the physical nature of manufacturing processes^{133,147}.

With large-volume TDSs such as 50%, 75% and 90%, the EB algorithm yielded a same-level accuracy as the ML algorithms especially when recognising the BH and FB features (Fig. 4.5a and 4.5b). Meanwhile, the DT, KNN and MLP algorithms outperformed when recognising the SW feature, and yielded 4.52-17.74% (TDS=50%), 0.09-18.23% (TDS=75%) and 2-18.15% (TDS=90%) higher than that of the EB algorithm, respectively (Fig. 4.5c). However, as a consequence, the training and validation time surged accordingly with large-volume TDSs, which were on average 16-fold slower than the EB algorithm. This was particularly proved by the maximum training and validation time of 666.30 ± 143.70 s (TDS=90%) while using the

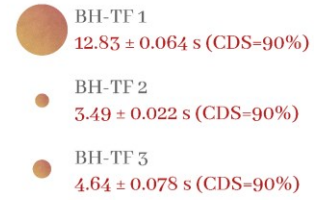
MLP algorithm (Fig. 4.5d). Therein, 566.07 ± 185.43 s was spent on the validation process. Meanwhile, the corresponding test time increased accordingly to 15.05 ± 1.89 s (TDS=90%).

a. Recognising BH feature

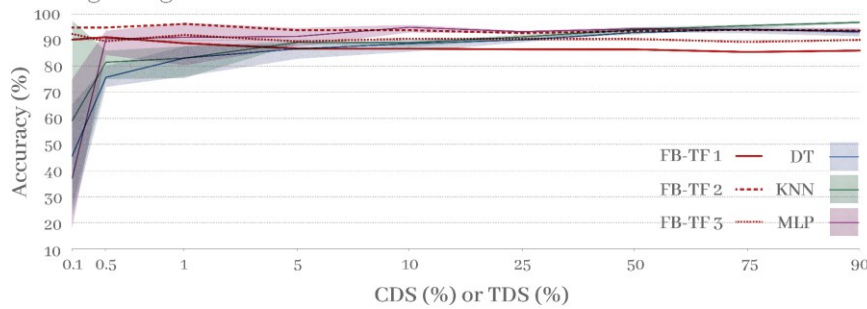


Efficiency

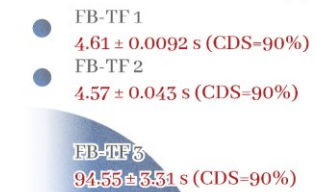
Maximum calibration time (s)



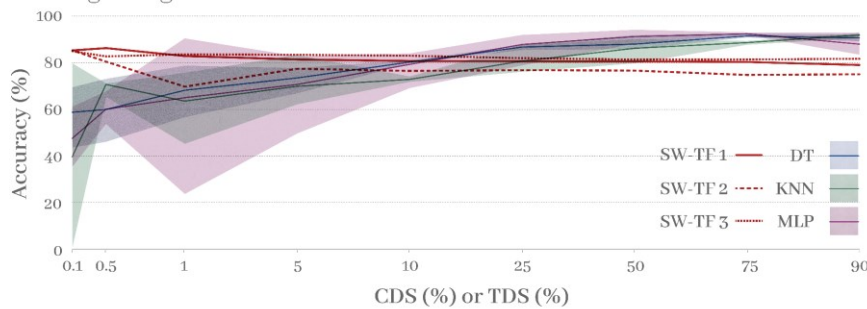
b. Recognising FB feature



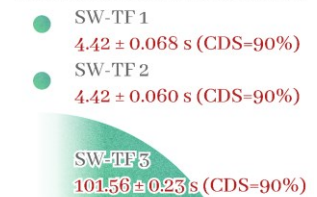
Maximum calibration time (s)



c. Recognising SW feature



Maximum calibration time (s)



d. Maximum training & validation time (s) of the ML algorithms

DT	KNN	MLP
298.70 ± 7.36 s (TDS=90%)	190.40 ± 16.60 s (TDS=90%)	666.30 ± 143.70 s (TDS=90%)

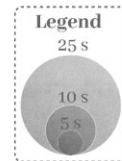


Figure 4.5 | Performance of the EB and ML algorithms for geometrical feature recognition. The accuracy and efficiency of the EB algorithm and ML algorithms (DT, KNN and MLP algorithms) were evaluated in recognising the **a**, BH feature, **b**, FB feature and **c**, SW feature. Therein, the time spent on the calibration process (automatic) of the EB algorithm, and the **d**, training and validation time of the ML algorithms were addressed.

4.5 Analysing DC of hot stamping process in terms of geometric features

By using the EB algorithm, the data points of the blank holder (BH) feature, flat bottom (FB) feature and side wall (SW) feature are accurately and efficiently recognised. The EB algorithm yields a highly efficient recognition of geometric features for a metal formed product with nearly 95% of overall accuracy with sparsely labelled data points ($\leq 1\%$). In this section, the unique DC of the hot stamping process in terms of the three geometric features are developed and analysed.

Hot stamping DC in terms of the BH feature. As for the BH feature, the temperature data cluster at the beginning of this manufacturing process with the same normalised initial temperature as 1.0 (Fig. 4.6a.1). As the forming process proceeds, the temperature data continuous to scatter (Fig. 4.6a.1), particularly demonstrating a clear temperature reduction at stage 6 (beginning of the quenching operation) to a minimum value of 0.14 (Fig. 4.6a.2). Subsequently, the minimum temperature value reduces from 0.14 (stage 6) to 0.057 (stage 10), while the median of temperature reduces from 0.24 to 0.11. In addition, the contact pressure data scatter within 0-0.5 during the forming operation (stages 0 to 5) (Fig. 4.6a.1). Most of the contact pressure data remain no more than 0.03 throughout the entire process (with the medians varying within 0-0.0056) (Fig. 4.6a.3).

The effective strain data of the BH feature scatter from 0 (Fig. 4.6b.1 and 4.7b.2), while remain at low values (<0.07) throughout the entire process due to the material flow restriction applied by the blank holders (Fig. 4.6b.2). The strain rate data initially cluster at 0, then remained at approximately 0.03 until stage 4 (Fig. 4.6b.1 and 4.7b.3). At stage 5, an increase of strain rate is observed with a maximum value of 0.10, which is caused by the sudden shaping applied by the tools. During stages 6-10, the strain rate values are all 0 since the forming process is completed.

Hot stamping DC in terms of the FB feature. The temperature reduction is insignificant at the beginning (Fig. 4.6a.1), as observed by all temperature data that are greater than 0.95 from stage 0 to 4, and greater than 0.91 at stage 5 (Fig. 4.6a.2). At stage 6, the minimum temperature rapidly reduces to approximately 0.17, and keeps declining to 0.07 at the end of in-die quenching. Meanwhile, the median temperature reduces from 0.59 to 0.09. The contact pressure data essentially concentrate to 0.10 until stage 4 (Fig. 4.6a.3). However, a significant pressure rising trend is observed at stage 5 (peak value of up to 0.98), which can also be demonstrated by the increasing temperature reduction rate (Fig. 4.6a.2). This is due to the die-

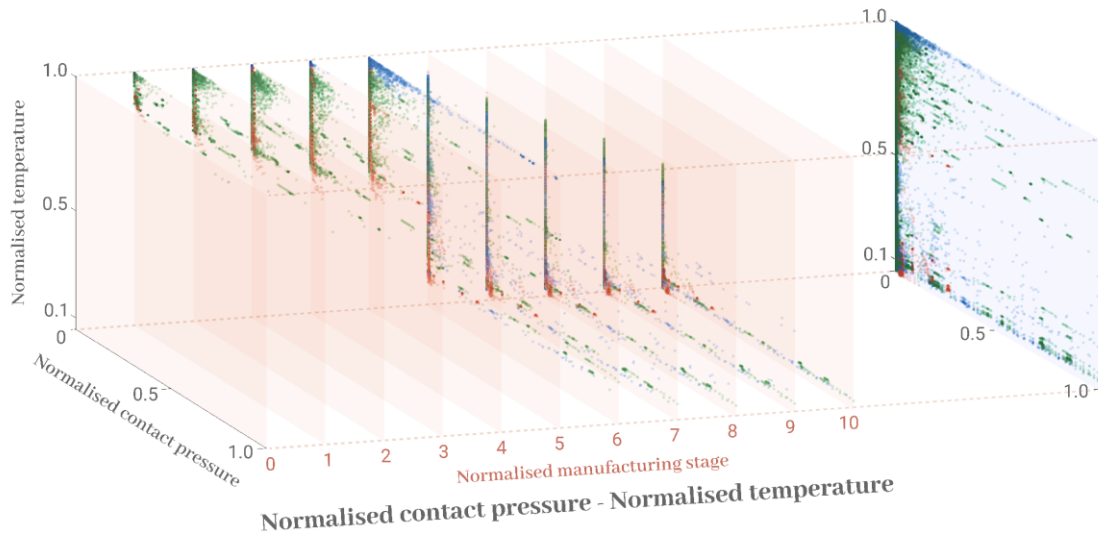
closing at the final stamping stage. Finally, the maximum contact pressure remains within the 0.96-1.0 range at stages 6-10, although with the medians all as 0, indicating that the contact between the workpiece and dies is imperfect (Fig. 4.6a.3).

The effective strain data at stage 0 are all 0 indicating no initial deformation occurs (Fig. 4.6b.1 and 4.7b.2). Subsequently the effective strain data begin to scatter, where the maximum value increases from 0 to 0.67, and the median increases from 0 to 0.07, respectively, from stages 0 to 5 (Fig. 4.6b.1 and 4.7b.2). The strain rate data are initially all 0, and lower than 0.1 until stage 4, where an abrupt strain rate increase is observed at stage 5, with a maximum strain rate of 1.0 due to the rapid shaping (Fig. 4.6b.3). The strain rates are all 0 during stages 6-10 since no deformation occurred within the region of FB.

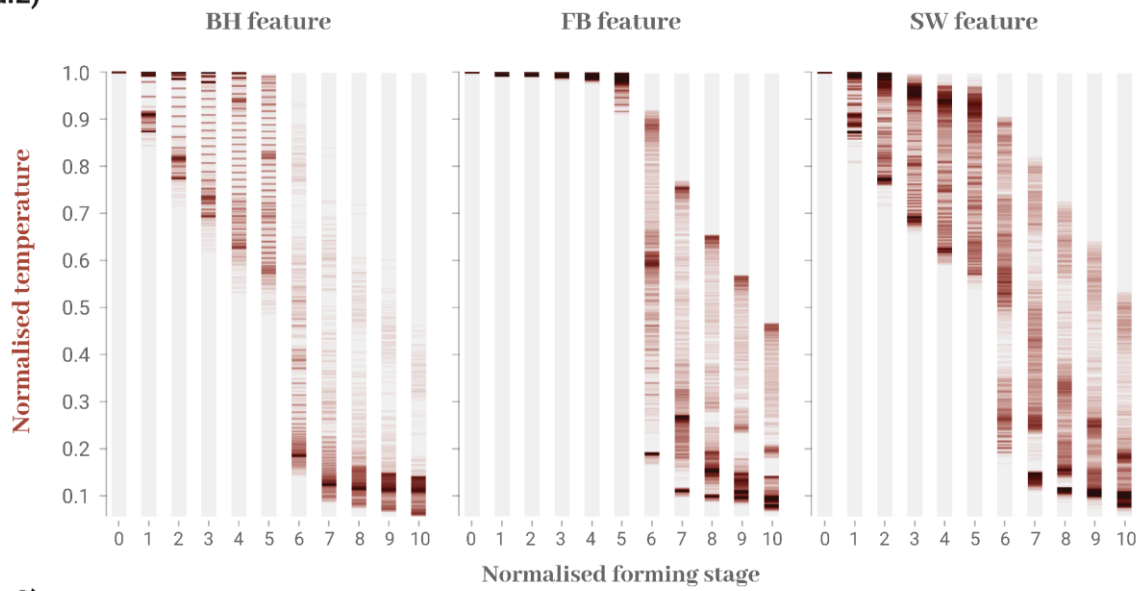
Hot stamping DC in terms of the SW feature. The temperature data cluster at the beginning with the same high initial normalised temperature of 1.0 (Fig. 4.6a.1), followed by the rapid heat transfer due to the contact between the hot workpiece and cold dies (Fig. 4.6a.2). A maximum temperature of 1.0007 is observed at stage 1 due to the inevitable frictional heat. Then, a significant temperature reduction is observed as the quenching commences, when the minimum temperature decreases from 0.17 to 0.06, with the median reducing from 0.58 to 0.10. The contact pressure scatter from 0 (Fig. 4.6a.1), where the peak contact pressure increases from 0 to 1.0 from stages 0 to 5 (forming operation), then at stages 6-10 (quenching operation), the distribution of the contact pressure data is maintained steady with insignificant variation, proved by the median contact pressure varying within 0-0.0078 (Fig. 4.6a.3).

The effective strain data are all 0 (Fig. 4.6b.1 and 4.7b.2), with subsequent scatter being more significant than the BH and FB features. The peak effective strain increases sharply from 0 to 1.0, and the median increases from 0 to 0.12 at stage 5 (Fig. 4.6b.2). This demonstrates that large plastic deformations for shaping the final components mainly occurs in the region of SW. Similar to the effective strain characteristics, the strain rates are much more significant at stage 5 (a peak value of 1.0) (Fig. 4.6b.3). The strain rates are all 0 during stages 6-10 since the forming operation is completed, which is also proved by the steady distribution of the effective strain data during this period (Fig. 4.6b.2).

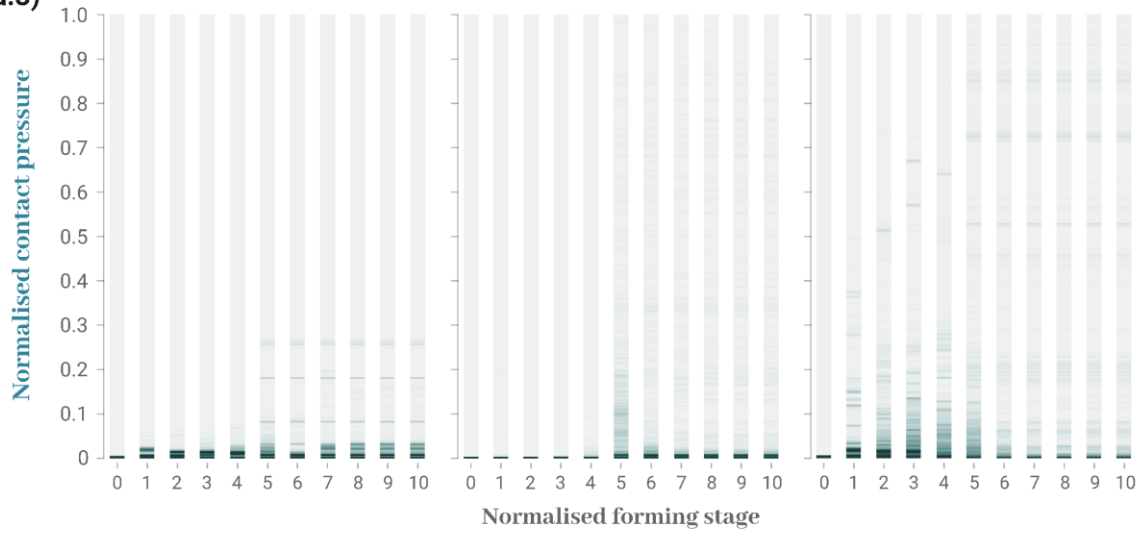
(a.1) ● BH feature ● FB feature ● SW feature



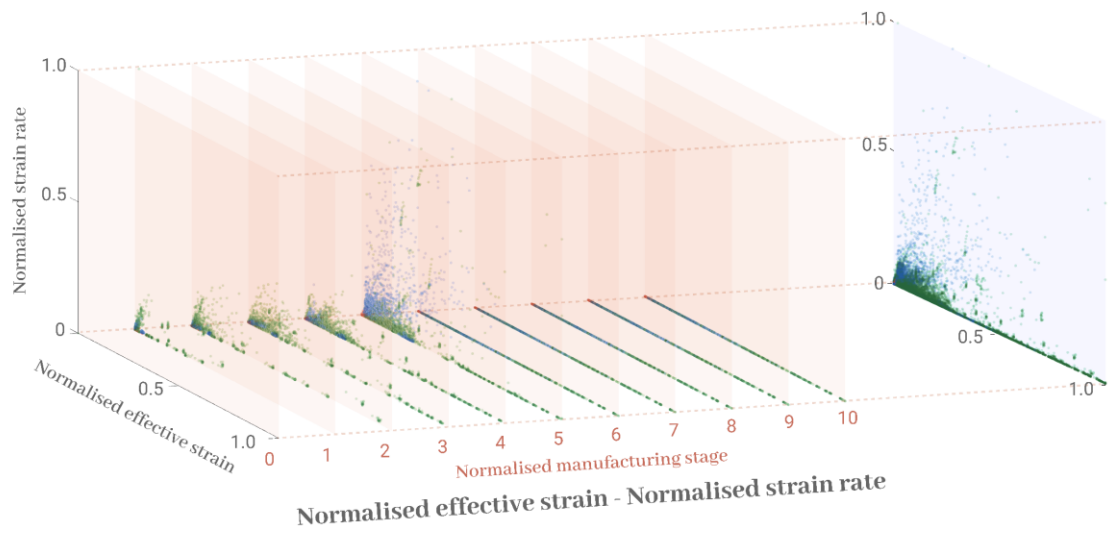
(a.2)



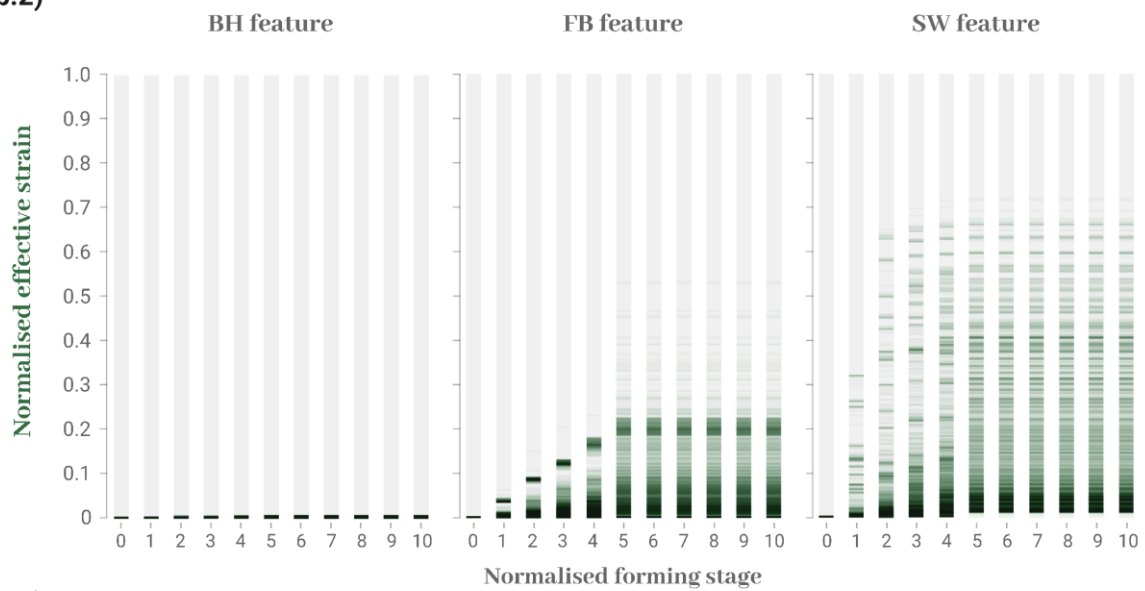
(a.3)



(b.1) ● BH feature ● FB feature ● SW feature



(b.2)



(b.3)

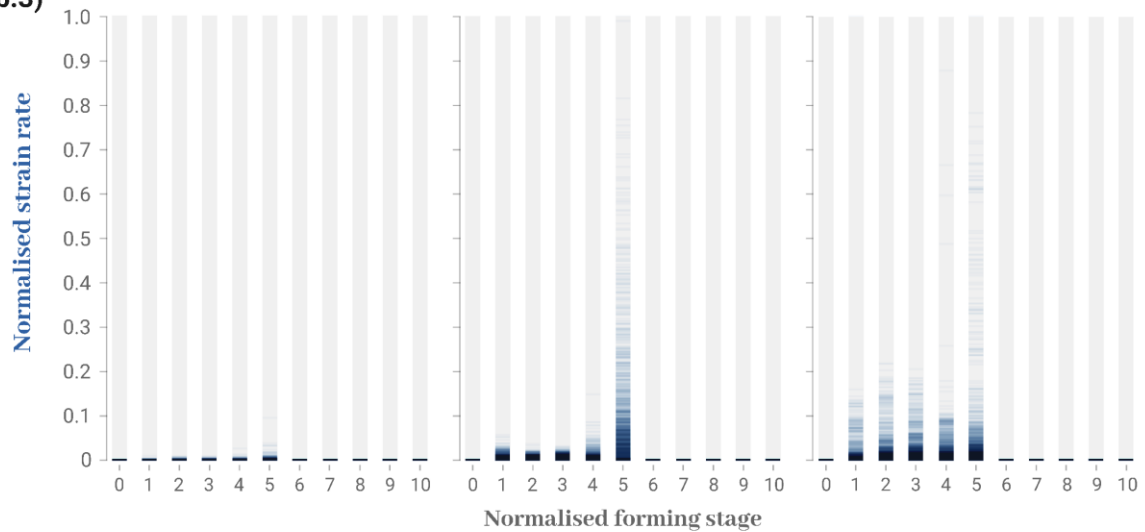


Figure 4.6 | Digital Characteristics (DC) of the hot stamping process in terms of geometric features. The information of the geometric features was recognised by the EB algorithm. **a.1-a.3**, DC by visualising the normalised contact pressure and normalised temperature, respectively, based on 3 geometrical features as a function of normalised forming stages from 0 to 10; **b.1-b.3**, DC by visualising the normalised effective strain and normalised strain rate, respectively, based on 3 regions as a function of normalised forming stages from 0 to 10; **c.1**, DC by visualising the unique normalised temperature of 3 representative geometric features as a function of normalised manufacturing stages from 0 to 10.

Unique temperature DC of hot stamping process. As the most representative thermo-mechanical characteristic of the hot stamping process, the evolutionary pattern of the hot stamping temperature data (normalised) was tracked and mapped as a function of normalised stages 0-10 (Fig. 4.7a-4.7c). The overall feature of the temperature data flow follows a ‘reverse-bias flow’ pattern, indicating the data mainly flows from high value zone into low value zone, for instance, the data flows from Zone IV into Zones II or III, or from Zone II to Zone I.

From stages 0 to 5 (the stamping operation), approximately 9.7-56.6%, 0.7-26.8% and 0.08-61.9% of the data in Zones I, II and III respectively flow from Zone IV to Zone III, and approximately 1.0-36.6% and 0.3-27.6% of the data in Zones I and III flow from Zone III to Zone II (Fig. 4.7a-4.7c). During this period, the temperature reduction in Zone II is very insignificant compared to that of other two regions, since all the temperature data remain within Zone IV and Zone III (Fig. 4.7b). Specifically, all the temperature data in Zone II remain over 0.9 from stages 0 to 5. Interestingly, 0.2% of the data are observed transiting from Zone III to Zone IV at stage 4 in Region II (Fig. 4.7b), and two flows with 0.04% and 0.13% data in Zone III are observed from Zone II to Zone III at stages 3 and 4 (Fig. 4.7c). These were likely caused by the rising frictional heat during the stamping operation.

From stages 6 to 10 (the quenching operation), the temperature reduction rate significantly increases. This indicates that an efficient cooling operation was likely applied on the workpiece. In Zone I, approximately 28.2% and 8.7% data flow from Zone III to Zone II and I, and 39.4% data flow from Zone II to Zone I at stage 5, where the cooling effect immediately appears (Fig. 4.7a). Meanwhile, in Zone II, 15.1% and 12.9% data flow from Zone IV to Zone III and II, and 51.0% and 13.6% data flow from Zone III to Zone II and I (Fig. 4.7b). In Zone III, 43.9% and 2.8% data flow from Zone III to Zone II and I, and 3.6% of the data flow from Zone II to Zone I at stage 5 (Fig. 4.7b). The continuous temperature reduction leads to the disappearance of Zone IV and Zone III from stage 8. At the end of this manufacturing process, 93.1%, 76.4% and 81.0% of the data remain within Zone I, which is the extremely low temperature regime (Fig. 4.7a-4.7c).

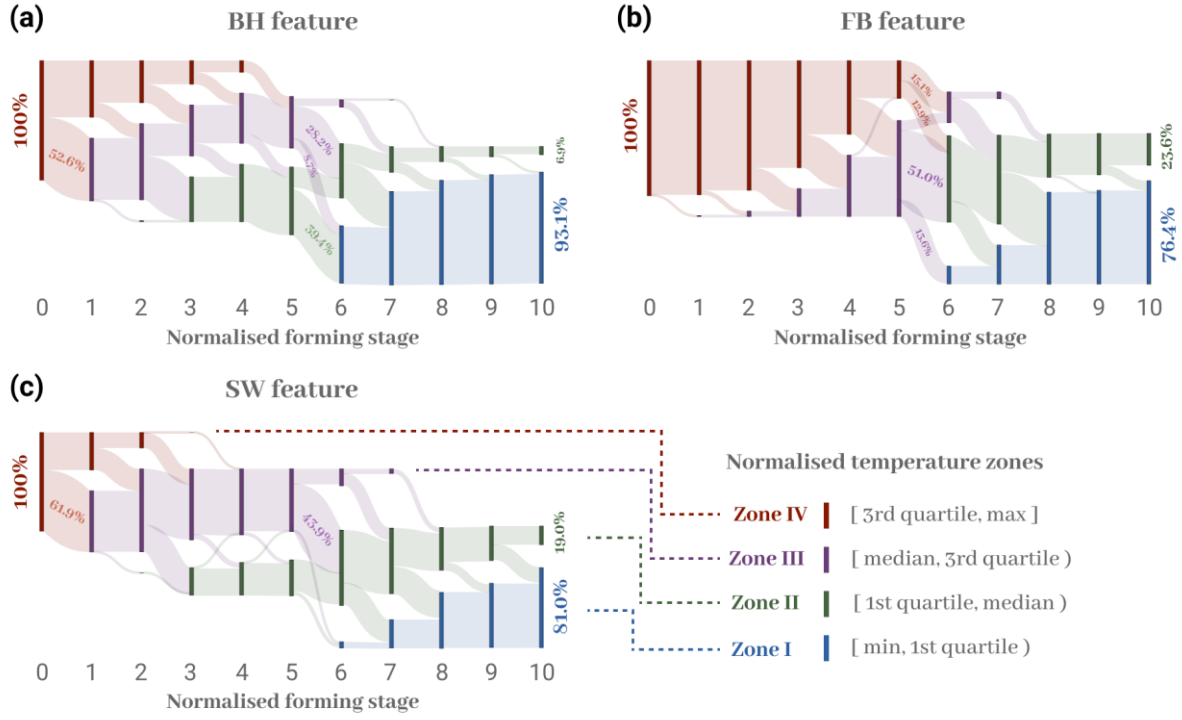


Figure 4.7 | Digital characteristics (DC) of the metal forming process featured by evolutionary temperature flow. DC by visualising the temperature data flow of the **a**, BH feature, **b**, FB feature and **c**, SW feature as a function of normalised stages 0-10 (stages 0-5: forming operation, stages 6-10: quenching operation). The data proportion (%) was calculated based on the total number of data points. The temperature data flow (100%) was split into four sequential ranges, i.e., Zone I, Zone II, Zone III and Zone IV, according to the minimum (0.057), first quartile (0.23), median (0.75), third quartile (0.99) and maximum (1.0007) of the collected temperature data. The width of the links between two adjacent forming stages is proportional to the data point flow.

4.6 Summary

This chapter presented the detailed development of the thermo-mechanical filters integrated in the physical-based Evolutionary Binary (EB) algorithm. This was realised by developing and analysing the unique temperature DC, strain DC, contact pressure DC and strain rate DC of a manufacturing process (hot stamping process in this case). Using a hot stamping benchmark dataset that contains 20,000 data points with manually labelled BH, FB and SW features, the recognition performance of EB algorithm was evaluated in terms of the recognition accuracy and efficiency. Results demonstrate that the EB algorithm achieved an overall accuracy of over 95% when identifying the data points from the BH, FB and SW features. High efficiency was achieved since the maximum calculation time was estimated less than 13 s. The recognition performance was compared to that of three classic machining learning (ML) algorithms. With small volume of labelled data (e.g., $\leq 1\%$), the EB algorithm is much more accurate than that of the ML algorithms. When the labelled dataset size increases to 75%, the ML algorithms

outperformed the EB algorithm with more accurate results, especially when recognising the SW features. However, the calculation time of the ML algorithms significantly increased, as proved by the maximum calibration time of over 666 s for the MLP algorithm. Then, the unique digital characteristics (DC) of the hot stamping process was developed and analysed in terms of the recognised geometric features. Particularly, the DC of temperature, one of the most important and unique thermo-mechanical characteristics of the hot stamping process, was developed and analysed.

Chapter 5. Establishing digital characteristics space (DCS) of manufacturing processes

5.1 DCS of manufacturing processes

The proposed Evolutionary Binary (EB) algorithm enables the recognition of the missing features from information absent manufacturing data, which enables the mining of insightful digital informatics and in-depth understanding of manufacturing technologies. Taking advantage of the surging volume of manufacturing metadata and its fidelity towards diverse manufacturing processes, the implementation of the EB algorithm enables the establishment of the digital characteristics space (DCS) of manufacturing processes, which is a novel cloud-based DC repository with most information-rich and up-to-date DC of over 140 manufacturing processes including a variety of sheet and bulk metal forming processes (Fig. 5.1).

Therein, the DCS is shown using the DC of one of the most representative thermo-mechanical characteristics, namely the forming/manufacturing temperature, of diverse manufacturing processes, including the stamping, cross wedge rolling, forging, rolling, extrusion, creep age forming, tube hydro/gas forming and incremental forming processes, spanning over representative sheet and bulk metal forming technologies. Key markers in the manufacturing data can be used as anchors to classify the shared data from ancestral manufacturing processes, and the DC of any size of the fragmental data is constructed and is precisely located in this manufacturing DCS. For instance, each manufacturing process can be precisely located via calibrated ‘angles’ (e.g., as shown in Fig. 5.1, the forging process is identified with angle range of 21.97° - 37.66° based on the unique DC distribution) or normalised values (e.g., the forging process is identified with value range of 0.24-0.42 based on the unique DC distribution) visualised in this DCS of manufacturing processes. These types of characteristics enable the potential applications of the DCS, such as the pairing of fragmental data (dataset that contains few data points of extremely sparse information) by comparing to the existing DC stored in the DCS.

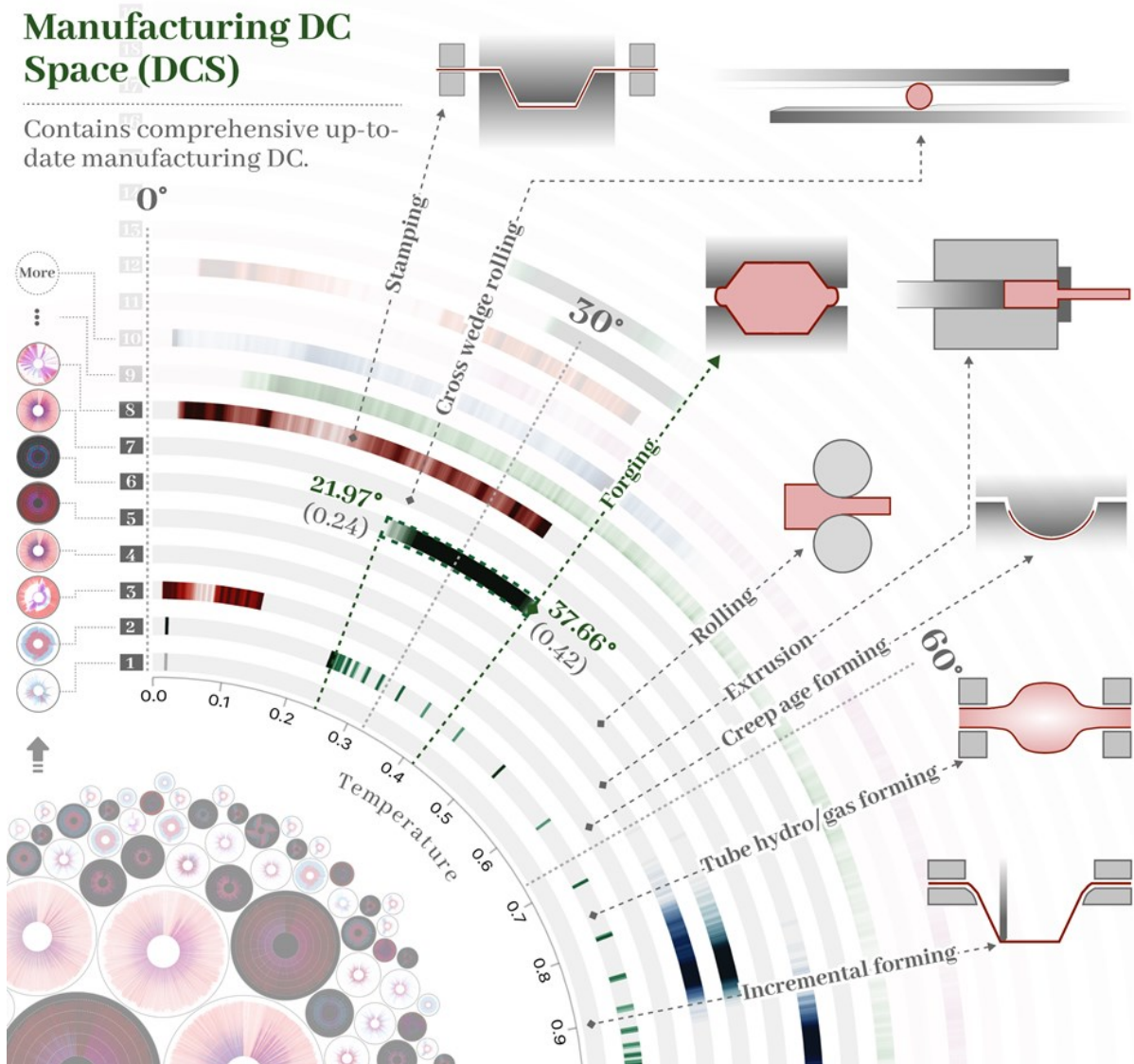


Figure 5.1 | The manufacturing DC space (DCS). The DCS is designed to contain the most comprehensive and up-to-date DC visualised for diverse manufacturing processes.

The purpose of the DCS is to provide access for scientific and industrial communities to the most up-to-date and information-rich DC of diverse manufacturing technologies. Experimentally verified manufacturing metadata is contributed to this cloud repository from world-leading academic laboratories and industrial institutions (Fig. 5.1), and can be lacking critical identification information including thermo-mechanical and geometric features. Sequencing through this data, the EB algorithm distinguishes each manufacturing process via its unique DC (e.g., DC visualised based on normalised temperature during a process as shown in Fig. 5.1) by identifying any inherited features from similar data of other manufacturing processes. The DCS enables easy searching and browsing of the data with unique identification numbers (Fig. 5.2), and each dataset is available as an open access resource, downloadable via

its globally unique and permanent ID by the scientific community to augment the data-driven research and development efforts in manufacturing sciences.

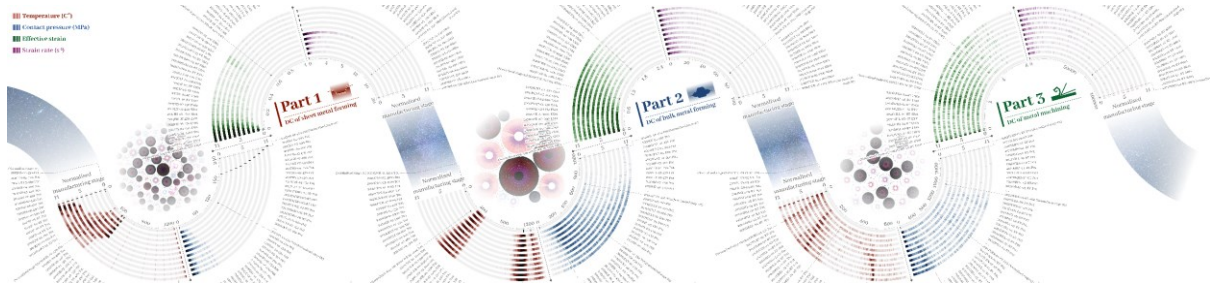


Figure 5.2 / Figure A (shown in the beginning of the thesis) | DCS of manufacturing processes showing 201 open access manufacturing datasets processed by the EB algorithm. By using the EB algorithm proposed in this study, the data in DCS are characterised by the DC of over 140 manufacturing processes including the sheet metal forming and bulk metal forming technologies.

Representative thermo-mechanical data, each with a unique identification number, from different metal forming processes are mapped in the DCS (Fig. 5.2). The data is available as open access to promote collaboration as a contributory resource for the advancement of manufacturing data sciences. As can be seen in Part I of Fig. 5.2, at present, the DC of the sheet metal forming processes show that across the end-to-end manufacturing stages, the temperature data values range from room temperature to 1267.0 °C, contact pressure data values range from 0 to 243.3 MPa, effective strain data values range from 0 to 0.95, and strain rate data values range from 0 to 18.8 s⁻¹. In Part 2 of the DCS, at present, the DC of the bulk metal forming processes show that the temperature data values of bulk metal forming processes range from 306.2 °C to 1254.3 °C, contact pressure data values range from 0 to 1000.0 MPa, effective strain data values range from 0 to 2.5, and strain rate data values range from 0 to 99.9 s⁻¹. In the Part 3 of the DCS, at present, the DC of the machining processes show that the temperature data values range from room temperature to 642.6 °C, contact pressure data values range from 0 to 2,258.3 MPa, effective strain data values range from 0 to 5.94, and strain rate data values range from 0 to 10,000 s⁻¹. The DCS enables the searching and browsing of the data with unique identification numbers, and each dataset or data fragment is available as an open access resource, downloadable by the scientific community to augment the data-driven research and development efforts in manufacturing sciences.

The DCS of manufacturing processes is a cutting-edge digital technology enabling the scientific community to gain access to the comprehensive manufacturing information, which is based on experimentally verified data and employs the key enabling approaches in terms of information absent data processing techniques (e.g., the EB algorithm) and data

characterisation techniques (e.g., the development of DC). Empowered by these technologies, the DCS can enable significant scientific impact by uncovering the esoteric values from any information absent manufacturing data, or fragmental data that contains extremely scarce information. For instance, to identify the origins of a random data or fragmental data, through the comparison with the manufacturing DC stored in the DCS, end-to-end global recognition of the fragmental data is expected to be achieved based on the extracted digital informatics (e.g., DC) and characteristic similarity to the incumbent manufacturing data.

5.2 Summary

This chapter introduced the establishment of the digital characteristics space (DCS) of manufacturing processes. The DCS was established by using the Evolutionary Binary (EB) algorithm for providing open access to scientific communities to the most comprehensive, up-to-date and information-rich DC of over 140 manufacturing processes. By using the data processing (e.g., EB algorithm) and characterisation technologies (DC), the DCS of manufacturing processes can enable significant scientific impacts by uncovering the esoteric values from any information absent manufacturing data, or fragmental data that contains extremely scarce information. This application is expected to augment the data-driven research and development efforts in manufacturing sciences. Potential applications, e.g., the fragmental data pairing, of the DCS were explained and studied in Chapter 6.

Chapter 6. Pairing unknown manufacturing fragmental data using digital characteristics space (DCS) as reference

This chapter introduced one of the applications of the digital characteristics space (DCS) of manufacturing processes. Using the DCS as the pairing reference, the esoteric values of any information absent manufacturing data, or even fragmental data (dataset that contains only a few of data points with extremely sparse information) that contains extremely scarce information. Figure 6.1 shows a flow chart of the pairing process, where the origins (e.g., which manufacturing process and stages) of a fragmental data can be identified using the DCS as a reference. The machine learning approach was applied in this thesis for pairing the fragmental data since after processing the information absent data using the EB algorithm, the DCS can be regarded as a labelled big database. Then the trained models can be used to predict the origins of any specific fragmental data.

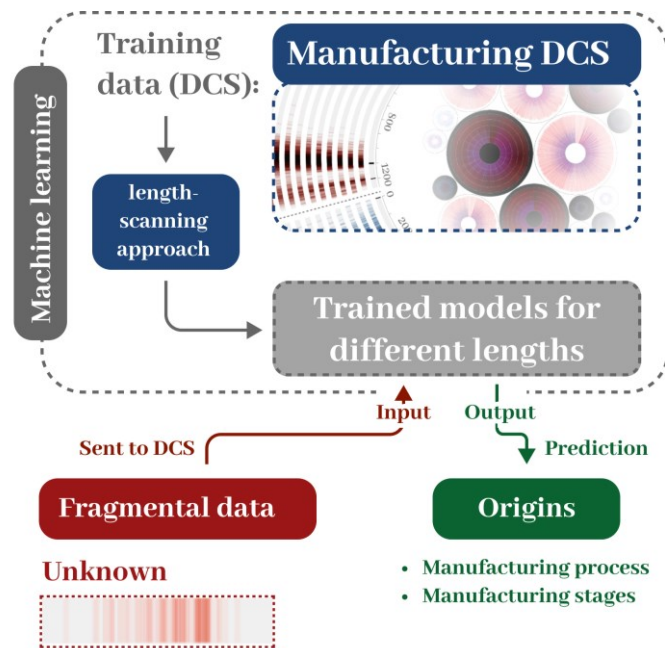


Figure 6.1 | The technical route of pairing an unknown fragmental data using the DCS as a reference.

6.1 Pairing model development and validation

Developing the pairing model using ML algorithm. The decision tree (DT) machine learning algorithm, one of the most classic machine learning algorithms, was employed in this thesis to recognise the manufacturing characteristics from fragmental data piece by comparing the thermo-mechanical characteristics with that of the DCS. The training process was conducted

inside the manufacturing DCS considering the thermo-mechanical characteristics of the entire manufacturing stages of different manufacturing processes. This indicates that the thermo-mechanical data (e.g., temperature data, one of the most distinct features in manufacturing processes) of each stage of each manufacturing process will be labelled as a distinct group respectively. After training (training dataset size assigned for each group: 90%), the temperature DC-based pairing model dedicated to different fragmental data sizes were established. A grid search was performed with stratified fivefold cross-validation in the training dataset for tuning the hyperparameters including the ‘criterion’ (the function to measure the quality of a split), ‘splitter’ (the strategy used to choose the split at each node), ‘max_depth’ (the maximum depth of the tree), ‘min_samples_split’ (the minimum number of samples required to split an internal node) and ‘min_samples_leaf’ (the minimum number of samples required to be at a leaf node).

By using a ‘length-scanning approach’, during the training of the temperature-based pairing model of length n , a ‘scanning window’ with a length of n was applied in each DC group for traversing throughout the entire length of the group, intending to capture each regional DC distribution characteristics within the ‘scanning window’ that varied significantly among different DC groups, so that the pairing model for length n can be trained using the captured DC distribution characteristics.

Subsequently, this pairing model was hyperparameter tuned and tested for evaluating the performance. The test dataset (size: 10% of whole data) was used for testing of the pairing models. The validated models can be utilised for recognising the origin of fragmental data without additional training or validation procedures during the prediction phase unless the temperature DC in the DCS is updated. Particularly, the overall accuracies on identifying which manufacturing process and manufacturing stage for different lengths of 100, 50, 40, 30, 20 and 10 were $81.27 \pm 0.16\%$, $80.05 \pm 0.14\%$, $79.51 \pm 0.10\%$, $77.97 \pm 0.15\%$, $75.97 \pm 0.19\%$ and $70.16 \pm 0.13\%$, respectively. Based on multiple trials, the time spent for establishing the pairing models of lengths of 100, 50, 40, 30, 20 and 10 are 148.9 ± 1.4 s, 95.7 ± 1.2 s, 84.4 ± 1.3 s, 76.8 ± 1.1 s, 65.4 ± 1.1 s and 53.6 ± 0.9 s, respectively.

After training and testing, the pairing model was established and ready for predicting the origins of fragmental data with a specific length n (each fragmental data length with a specific pairing model), indicating that the model can be used for identifying any fragmental data with

the same lengths as n without repetitive training unless the current DC in the DCS is being updated.

Validation of the pairing model. A hot stamping benchmark dataset contains 5,000 temperature data points (<https://app.smartforming.com/store/modules/408>) was used for validating the trained pairing model. In total, 18 fragmental data were randomly selected from this dataset with clear labels on manufacturing stages. The fragmental data were randomly assigned into six groups with various lengths, i.e., 100 temperature data points (L100-FD 1-3), 50 temperature data points (L50-FD 1-3), 40 temperature data points (L40-FD 1-3), 30 temperature data points (L30-FD 1-3), 20 temperature data points (L20-FD 1-3) and 10 temperature data points (L10-FD 1-3). In each group, three fragmental data pieces with the same lengths (e.g., L100-FD 1, L100-FD 2 and L100-FD 3) were prepared for comparison. Tab. 6.1 lists the validation results, where an overall accuracy 77.7% was achieved.

Table 6.1 | Validation of the trained pairing model using a benchmark hot stamping dataset. Therein, ‘HS-Sx’ means the xth manufacturing stage of hot stamping process.

Fragmental data	True labels	Predicted labels	Result
L100-FD 1	HS-S10	HS-S9	Incorrect
L100-FD 2	HS-S10	HS-S10	Correct
L100-FD 3	HS-S1	HS-S1	Correct
L50-FD 1	HS-S5	HS-S6	Incorrect
L50-FD 2	HS-S10	HS-S8	Incorrect
L50-FD 3	HS-S11	HS-S11	Correct
L40-FD 1	HS-S6	HS-S6	Correct
L40-FD 2	HS-S1	HS-S1	Correct
L40-FD 3	HS-S2	HS-S2	Correct
L30-FD 1	HS-S11	HS-S11	Correct
L30-FD 2	HS-S9	HS-S9	Correct
L30-FD 3	HS-S1	HS-S1	Correct
L20-FD 1	HS-S10	HS-S9	Incorrect
L20-FD 2	HS-S11	HS-S11	Correct
L20-FD 3	HS-S5	HS-S5	Correct
L10-FD 1	HS-S6	HS-S6	Correct
L10-FD 2	HS-S3	HS-S3	Correct
L10-FD 3	HS-S2	HS-S2	Correct
Overall accuracy:			77.7%

6.2 Pairing fragmental data against existing DC in DCS of manufacturing processes

Acquisition of fragmental data. A dataset of an unknown manufacturing process that contains 35,126 temperature data points was provided by a collaborative industry partner for research purposes. Therein, the temperature metadata were captured using infrared pyrometers and thermo-couples during forming trials or real production and have not been processed or analysed. In total, 18 fragmental data were randomly selected from this unknown temperature dataset, as shown in Fig. 6.2a, to enable a comparative study of the identification of the fragmental data pieces. The fragmental data were randomly assigned into six groups with various lengths, i.e., 100 temperature data points (0.29% of the whole unknown dataset, L100-FD 1-3), 50 temperature data points (0.15%, L50-FD 1-3), 40 temperature data points (0.12%, L40-FD 1-3), 30 temperature data points (0.087%, L30-FD 1-3), 20 temperature data points (0.058%, L20-FD 1-3) and 10 temperature data points (0.029%, L10-FD 1-3). In each group, three fragmental data pieces with the same lengths (e.g., L100-FD 1, L100-FD 2 and L100-FD 3) were prepared for comparison.

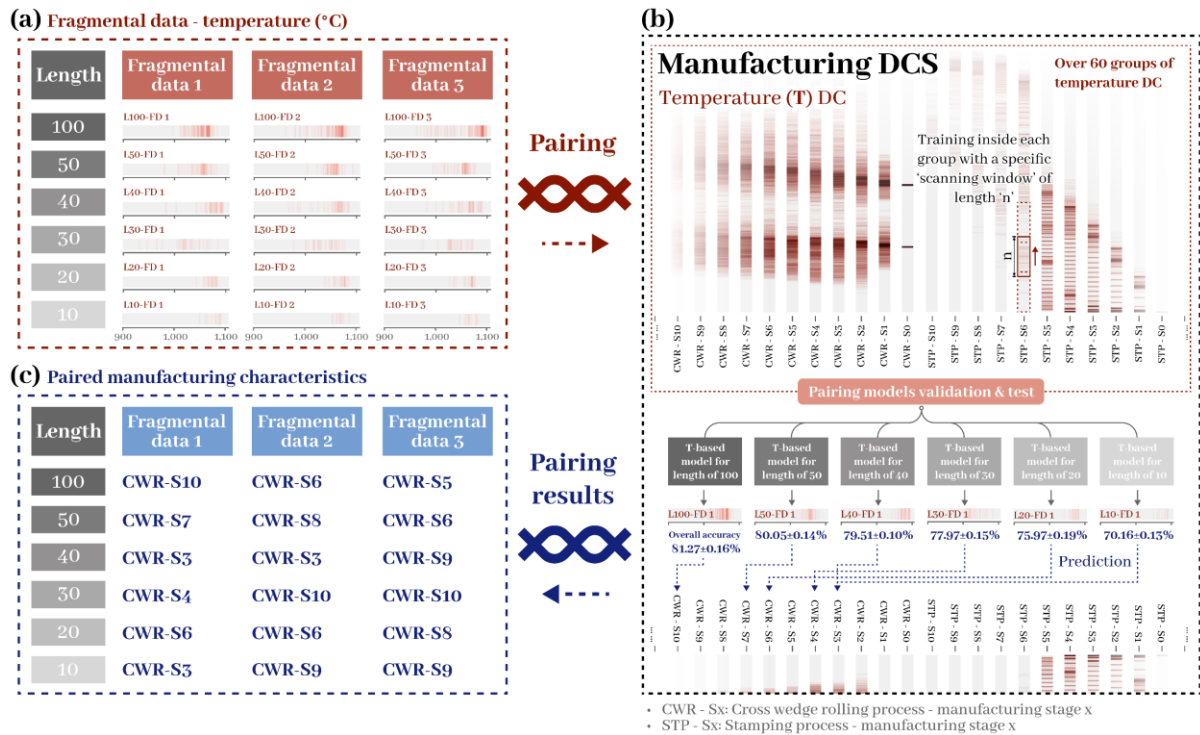


Figure 6.2 | Pairing fragmental temperature DC against the temperature DC in DCS. Six groups of randomly selected fragmental data with different lengths are paired with the most up-to-date temperature DC in the DCS (where 'L100-FD 1' means fragmental data 1 with a length of 100). DCS pairing models are trained, validated and tested using the existing temperature DC.

Pairing fragmental temperature data against the existing temperature DC in the DCS. In the present work, the fragmental temperature data are compared to the temperature DC stored in the DCS to identify the origin of this manufacturing dataset (Fig. 6.2b). Temperature DC-based pairing models were developed for identifying the origins of fragmental data with different lengths of 100, 50, 40, 30, 20 and 10, respectively. Regarding the temperature DC of each manufacturing stage of a specific manufacturing process (e.g., temperature DC at initial stage of stamping process) as a distinct DC group (over 60 groups in total), the DCS pairing model is trained using the existing temperature DC when identifying a given fragmental data with a specific length n (e.g., L100-FD 1).

Pairing results. The pairing results provide the manufacturing characteristics including the origins (e.g., ‘which manufacturing process’ and ‘which manufacturing stage’) of each fragmental data. As shown in Fig. 6.2c, using the temperature DC-based pairing models developed for 18 fragmental data lengths of 100 (L100-FD 1-3), 50 (L50-FD 1-3), 40 (L40-FD 1-3), 30 (L30-FD 1-3), 20 (L20-FD 1-3) and 10 (L10-FD 1-3), although these randomly selected fragmental data were identified with varying probabilities as originating from different manufacturing stages, they all stem from same manufacturing process - specifically, the cross wedge rolling (CWR) process (L100-FD 1: CWR-S10, L100-FD 2: CWR-S6, L100-FD 3: CWR-S5; L50-FD 1: CWR-S7, L50-FD 2: CWR-S8, L50-FD 3: CWR-S6; L40-FD 1: CWR-S3, L40-FD 2: CWR-S3, L40-FD 3: CWR-S9; L30-FD 1: CWR-S4, L30-FD 2: CWR-S10, L30-FD 3: CWR-S10; L20-FD 1: CWR-S6, L20-FD 2: CWR-S6, L20-FD 3: CWR-S8 and L10-FD 1: CWR-S3, L10-FD 2: CWR-S9, L10-FD 3: CWR-S9). The overall accuracies refer to the test accuracies when establishing the pairing model, which are $81.27 \pm 0.16\%$, $80.05 \pm 0.14\%$, $79.51 \pm 0.10\%$, $77.97 \pm 0.15\%$, $75.97 \pm 0.19\%$ and $70.16 \pm 0.13\%$ for different lengths of 100, 50, 40, 30, 20 and 10, respectively.

6.3 Cross wedge rolling (CWR) process

Cross wedge rolling process. Cross wedge rolling (CWR) is a metal forming process which plastically deforms a billet into an axisymmetrical shape by moving a pair of wedge-shaped tools tangentially towards each other^{148–150}. After decades of developments, the CWR has been designed and classified into five types based on the configuration of tools, including the flat type CWR (FT-CWR), multiple rolls CWR, concave wedge CWR, concave-roll CWR and flat wedge-roll CWR¹⁰⁰. Fig. 6.3 illustrates the schematic working principle of a representative

CWR process, namely the FT-CWR, and the typical shapes of the initial billets and deformation process, and the typical shapes of the final component^{151–154}. The billets are first rolled into cylindrical shape and then formed into final products by the tangentially sliding tools.

The CWR increasingly attracts attentions from industries due to significant advantages on high productivity, material utilisation, easy automation, less energy consumption and eco-friendliness^{153,155}. During the past few decades, most of the studies of CWR focus on revealing the failure mechanisms of the typical failure modes, including the improperly formed cross section of workpiece, the surface defects and the internal defects^{150,156–158}. While due to the fast development and optimisation throughout the CWR production, and non-destructive testing (NDT) technologies on internal crack detection, the internal crack failure has been almost eliminated. Currently, the most concern issue in the CWR production, is to further increase the material utilisation, especially through optimising the end forming quality towards to the near-net CWR forming^{159–161}.

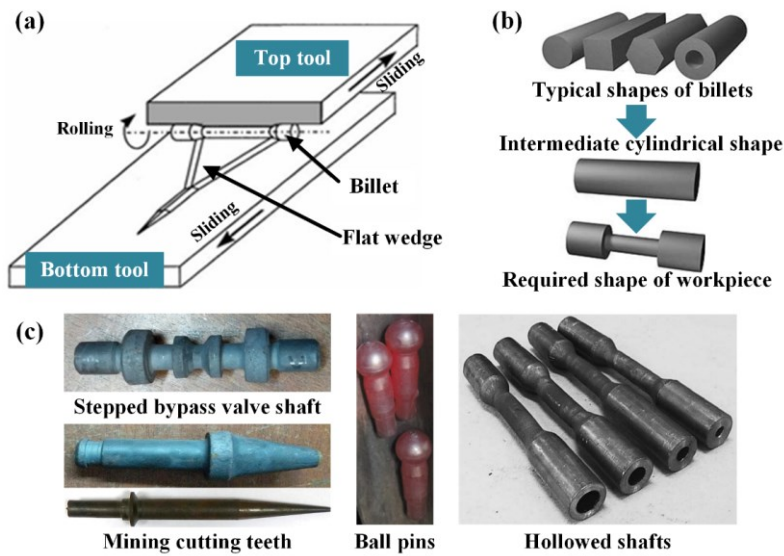


Figure 6.3 | Introduction of the CWR process. **a**, Schematic working principle of the CWR process (using flat type cross wedge rolling process as a case); **b**, typical shapes of the initial billets and deformation process and **c**, the typical shape of the final component^{151–154}.

The CWR process can be typically classified into four distinct stages¹⁵⁰. Fig. 6.4 schematically shows the typical stages of the CWR process (using FT-CWR for a clearer illustration):

Stage 1: Knifing stage. The tool wedge rapidly penetrates the billet surface and plastically deforms a V-shaped slot into the circumference of the workpiece. The depth of the slot reaches

the required rolling depth, Δr . The angle of the V-shaped slot is determined by the forming angle, α .

Stage 2: Guiding stage. The tool longitudinally enlarges the V-shaped slot obtained in the knifing stage into a uniform groove around the circumference of the workpiece. During the rolling process, this stage keeps the deformed part concentric with the undeformed regions.

Stage 3: Stretching stage. In this stage, the billet is further stretched along the longitudinal direction to the target length, and substantial plastic deformation takes place in this stage. The amounts of the plastic deformation and the elongation of the workpiece is determined by the stretching angle, β .

Stage 4: Sizing stage. This stage tunes the dimension tolerance and removes the profile irregularity remaining from the previous stages, leading to the improvement of surface quality. In addition, the trimming process is included or followed to cut off the end-waste from the workpiece.

The forming angle α and the stretching angle β are the key tool design parameters in CWR. In addition, the area reduction ratio (δ) can be calculated by the initial diameter of the billet (d_0) and the central diameter of the final workpiece (d), which is defined as $1 - (d/d_0)^2$. These geometrical parameters can significantly affect the rolling quality, stability and failure modes of CWR^{162,163}.

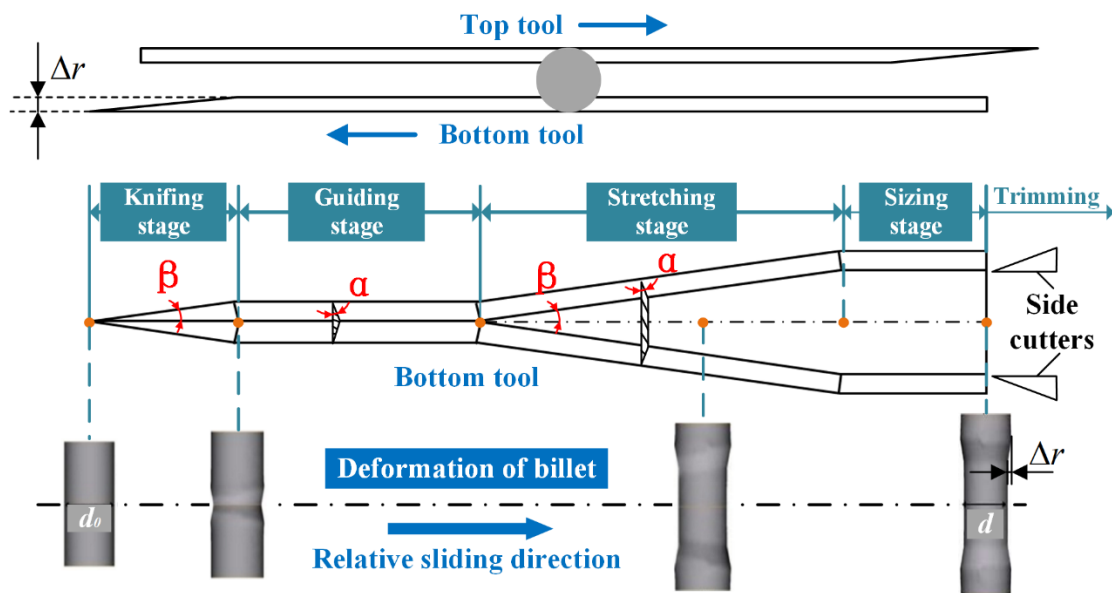


Figure 6.4 | Typical segments of tools in CWR. The knifing stage, guiding stage, stretching stage and sizing stage are schematically illustrated.

Experimental setup. The experiments were carried out in the FT-CWR machines of an industrial collaborator that focuses on the CWR production. The experimental data were collection during the forming and were used to validate the data collection from the FEA models. The top and bottom tools in the FT-CWR machines are driven by hydraulic loadings and move over each other at the same linear speed to form the billets (Fig. 6.5a). The rolling force and temperature were obtained and used for the verifications on FT-CWR FEA models. As shown in Tab. 6.2, the tools are made of DIN-1.2343 steel, while the workpiece is made of DIN-1.7034 steel.

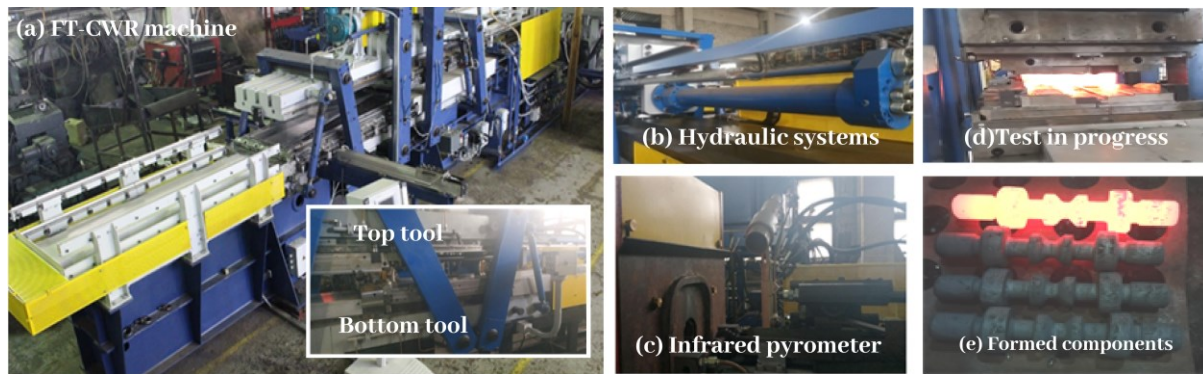


Figure 6.5 | Experimental setup. a, FT-CWR machine; b, Contact pressure recoding and monitoring system; c, Infrared pyrometer monitoring temperature variation; d, Forming test in progress; e, Formed components (BM 88).

Table 6.2 | Chemical compositions of tool (DIN-1.2343) and workpiece (DIN-1.7034) materials (wt %).

	C (%)	Si (%)	Mn (%)	P (%)	S (%)	Cr (%)	Mo (%)	V (%)	Fe (%)
DIN-1.2343	0.33-0.41	0.8-1.2	0.25-0.5	≤0.03	≤0.02	4.8-5.5	1.1-1.5	0.3-0.5	Bal.
DIN-1.7034	0.34-0.41	≤0.4	0.6-0.9	≤0.025	≤0.035	0.9-1.2	-	-	Bal.

The rolling force data were converted from the pressure data measured from the pressure recording system connecting with tools (Fig. 6.5b). The rolling and returning strokes of the top and bottom tools are controlled by the installed hydraulic oil pumps. The programmable logic controller (PLC) was applied to record and display the pressure variation curves via pressure sensors installed in the pumps. The sensors recorded the pressure data according to the deformation amount of the workpiece during rolling. The rolling force-displacement curves can be further developed for the verifications of the FEA simulated rolling force evolutions, and its mechanism can be seen in Fig. 6.6.

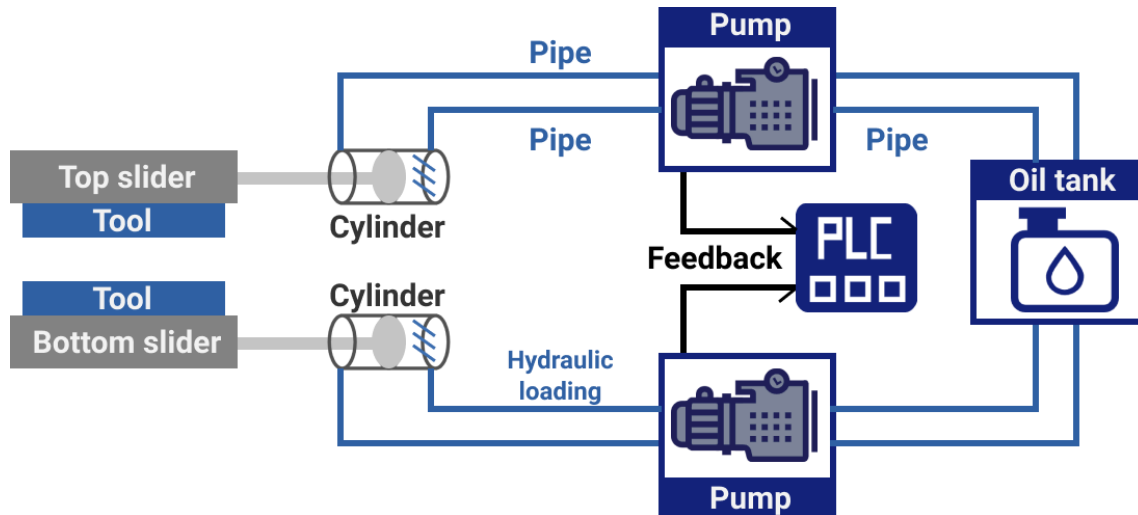


Figure 6.6 | Mechanisms of tool sliding and pressure recording system.

Finite element analyse (FEA) modelling setup. The DCS contains the CWR data obtained from a large number of models spanning seven different types of components, including a bypass valve shaft (product ID: BM 88, Fig. 6.7a), a trunnion ball part (BM 236, Fig. 6.7b), a connecting pipe (BM 244, Fig. 6.7c), two types of mining cutter bodies (BM 250 and BM 337, Fig. 6.7d and Fig. 6.7g) and two types of hydraulic power steering components (BM 253 and BM 257, Fig. 6.7e and Fig. 6.7f). The geometric and dimensional parameters of the components and tools, as well as the essential operating parameters, were provided by the industrial collaborator (Tab. 6.3).

Table 6.3 | Geometric and operating information. The detailed dimensional parameters of the billets and tools are listed, together with the essential operating parameters.

Product ID	BM 88	BM 236	BM 244	BM 250	BM 253	BM 257	BM 337
Billet length (mm)	86±0.5	90±0.5	53±0.5	105±0.5	124±0.5	120±0.5	150±0.5
Billet Diameter (mm)	32±0.5	32±0.5	32±0.5	48±0.5	42±0.5	42±0.5	40±0.5
Tool length (mm)	900±0.5	700±0.5	900±0.5	900±0.5	900±0.5	900±0.5	1048±0.5
Tool width (mm)	170±0.5	320±0.5	198±0.5	270±0.5	259±0.5	276±0.5	274.5±0.5
Initial temperature (°C)	1194	1100	1100	1095	1100	1100	1096
Forming time (s)	1.5	5.1	5.1	5.1	5.1	5.1	5

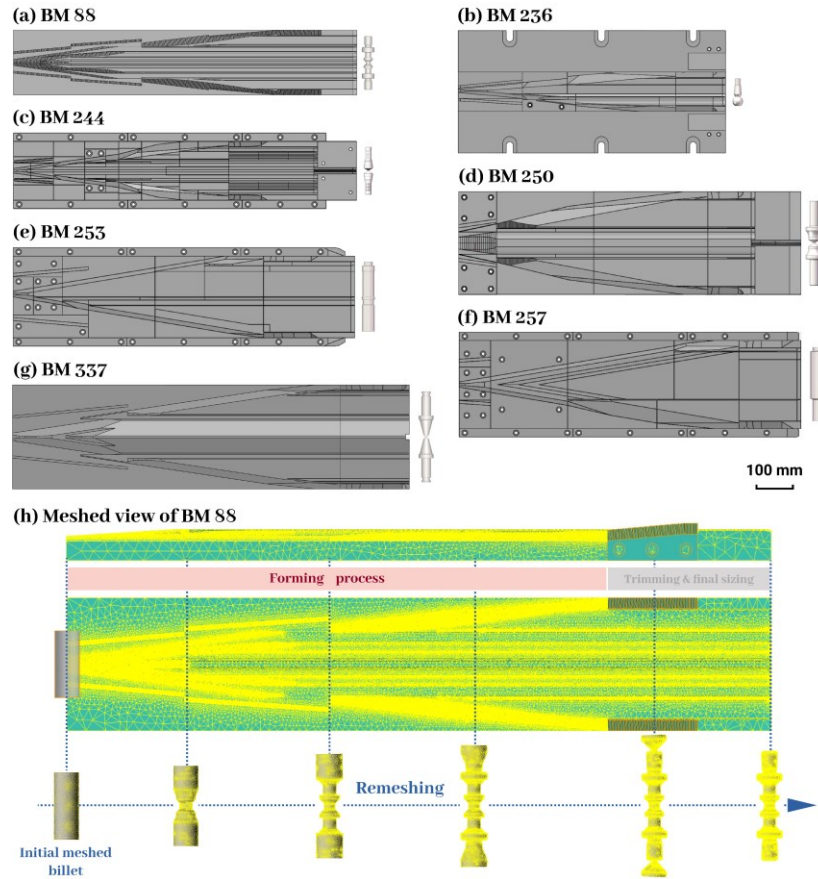


Figure 6.7 | CWR CAD components and designs of tool wedges. Seven components, namely **a**, BM 88, **b**, BM 236, **c**, BM 244, **d**, BM 250, **e**, BM 253, **f**, BM 257, and **g**, BM 337, and their tool designs are presented. **h**, Example of meshed view based on BM 88 modelling.

The FEA models of the CWR process were created using QForm. Enhanced by the dual mesh feature, QForm is a computationally efficient and highly robust tool used in simulating and analysing metal forming processes, especially bulk metal forming processes such as rolling, forging and extrusion¹⁵⁶. Geometry models of the billets and tool parts generated in CAD software were imported into the FE codes. As confirmed by the industrial collaborator, the tool material is specified as DIN-1.2343 tool steel which is appropriate for producing highly stressed structural parts, and the billet material is specified as DIN-1.7034 alloy steel which is ideal for parts that require high strength, toughness and ductility. The tool part was assigned a very high stiffness to prevent it from deforming. The dimensions of the billets and tools are the same as those used in the experiments, and the positions of the billets on the bottom tool were kept consistent with the corresponding experiments. 3D simulations were selected, and based on the dual mesh feature, the remeshing function was turned on due to the complex shape of the formed components (Fig. 6.7h). An explicit solver was selected due to its robustness in handling a frictional contact issue compared to the implicit solver¹⁶⁴. The FEA results were

verified by comparing the rolling force-displacement and temperature-displacement evolutions during forming with the corresponding experimental results conducted in the industrial collaborator's production plant.

Experimental verification of FE models via rolling force-displacement curves. Fig. 6.8 shows the rolling force evolutions from FEA and experiment of BM 88 component. The FEA simulated and experimental results both present the same 'double-rolling-force-peak' features. The rolling force of FEA constantly increases until the first peak of the simulated result appears with a rolling force of around 3.57 tons at 0.213 s. Compared to the experimental data with a rolling force of 3.80 tons at around 0.15 s, a close agreement of the peak values was obtained with an error less than 7 %. This peak represents the billet was penetrated in by the tool wedges, where large rolling force was required for initial cutting. As the rolling proceeds, the rolling force of FEA continues to drop till a valley of 0.81 tons appears, which is slightly lower than the experimental valley value (approximately 1.36 tons). Subsequently, the rolling force of FEA increases because the plastic deformations occur on both sides of the workpiece, where a second peak of FEA (4.43 tons) occurs at around 0.960 s. A close agreement between the FEA and experimental measurement (4.44 tons) was observed with an error less than 0.3 %. Then the rolling force remains a decreasing trend, where a sudden increase in the rolling force occurs due to the trimming of end waste.

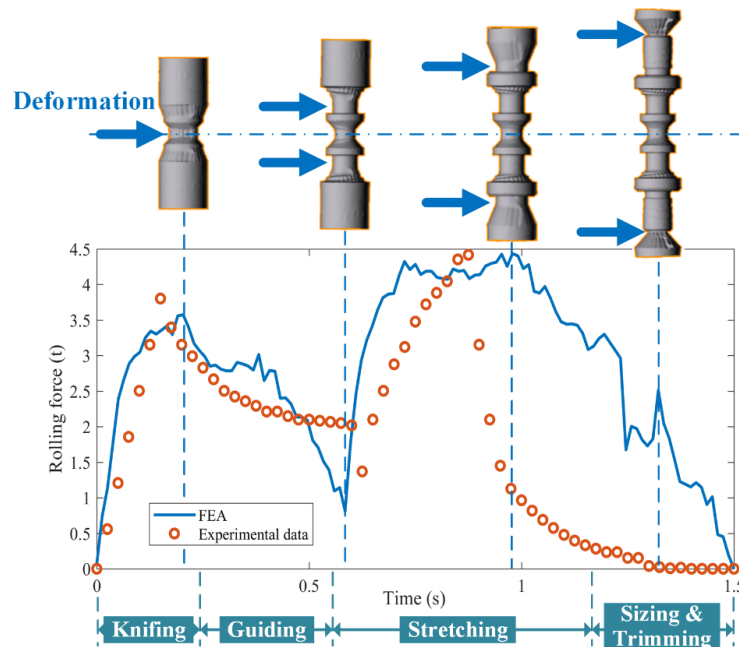


Figure 6.8 | Verification of FEA models for the BM 88 component using rolling force-displacement curves.

Experimental verification of FE models via temperature-displacement curves. The operation temperature data were recorded by the infrared pyrometer installed in the FT-CWR machines (Fig. 6.5c). The measuring position was at the side surfaces of the initial workpiece and the final formed component. The pyrometer precision is within approximately ± 0.5 °C for the target temperatures ranging from 700 °C to 1,300 °C. Consequently, the temperature-displacement curves can be developed for the experimental verifications on FEA temperature variations. Fig. 6.9 shows the temperature evolutions during cross wedge rolling of BM 88 component. The temperature evolution of the side face of the workpiece from FEA was captured for the experimental verification. The initial temperature of FEA is 1,200 °C, then it decreases till the termination of rolling, from the knifing stage to the sizing and trimming stage. The FEA temperature of the formed workpiece after rolling is 1,141 °C. Compared to the final workpiece temperature measured in the experiment (1,148 °C), a close agreement was obtained with an error of 0.6 %.

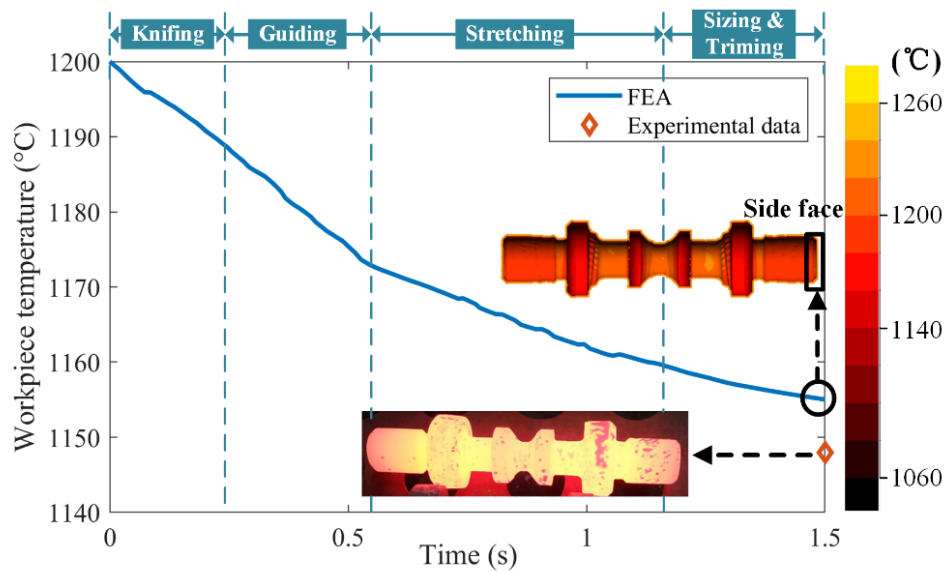


Figure 6.9 | Verification of FEA models for the BM 88 component using temperature-displacement curves.

Fig. 6.10 shows the temperature evolutions during cross wedge rolling of BM 250 and 337 components. The temperature evolutions of the side face of the workpieces from FEA were captured for the experimental verifications. The initial temperatures of both components are 1,100 °C for the FEA simulation, and the decreasing trends of the temperature evolutions from the knifing stage to the sizing and trimming stage are observed. The final temperatures of FEA simulation of the BM 250 and BM 337 components are 1,047 °C and 1,068 °C. The measured temperatures of the formed BM 250 and BM 337 components are 1,041 °C and 1,063 °C. Thus,

close agreements between the FEA and experimental measurements of BM 250 and BM 337 can be obtained with errors of 0.6 % and 0.5 %, respectively.

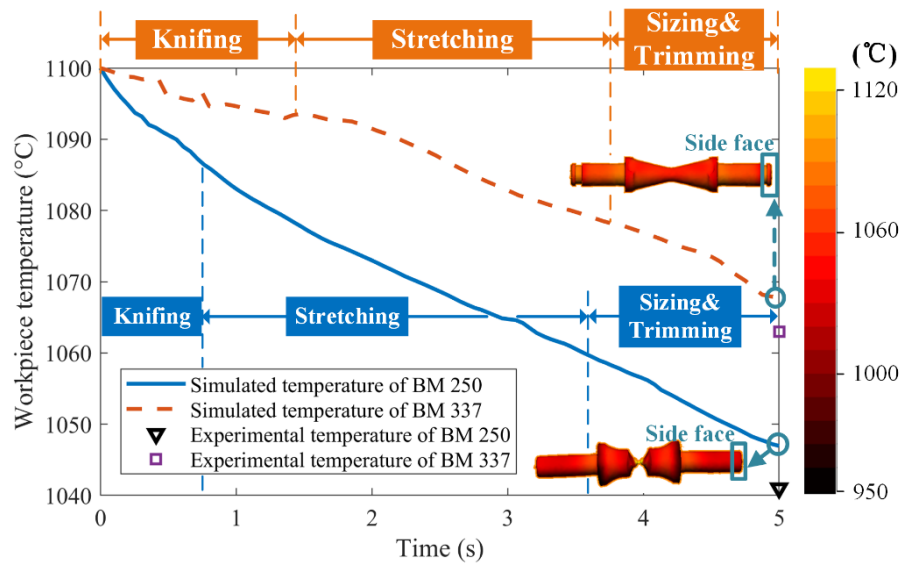


Figure 6.10 | Verification of FEA models for the BM 250 and BM 337 component using temperature-displacement curves.

6.4 Developing the unique DC for the CWR process

Here, diverse unique DC are analysed by mapping the unique thermo-mechanical metadata of over 1 million CWR data points stored in the data repository of manufacturing processes, including the essential thermo-mechanical metadata represented by temperature data, contact pressure data, effective strain data and strain rate data. The forming stages of each CWR process are normalised from 0 to 10 with an interval of 1 to enable the integrated analysis.

Analysing the unique temperature DC of the CWR process. Fig. 6.11a shows the unique DC of the CWR process mapping the forming temperature. Therein, in Fig. 6.11a-I, each circular layer contains the temperature of over 1 million CWR data points, and the overall trend is radially characterised through the 11 normalised forming stages from 0 to 10. The width of each circular layer represents the temperature value of 1,300 °C. The forming temperature of the CWR process ranges from 875.6 °C (observed in forming stage 3 as indicated by the region 3 of Fig. 6.11a-I) to 1,267.0 °C (observed in forming stage 2 as indicated by the region 2 of Fig. 6.11a-I) during the entire forming process. at the beginning of forming (stage 0), the billets are heated to their initial temperature values of 1,194 °C, 1,095 °C and 1,100 °C (observed in the initial stage as indicated by the region 1 of Fig. 6.11a-I), respectively, and are then placed between two parallel wedge-shaped tools and formed at room temperature. As the forming

process proceeds, the billets are then formed in a non-isothermal condition due to the cooling effect induced by heat transfer between hot billets and cold tools, and the heating effect induced by frictional heat and plastic deformation. Particularly, the mean temperature of different initial temperature 1,194 °C, 1,095 °C and 1,100 °C of each stage are 1,193.1 °C, 1,087.5 °C and 1,090.9 °C (stage 1), 1,200.8 °C, 1,075.0 °C and 1,088.7 °C (stage 2), 1,202.7 °C, 1,067.5 °C and 1,082.5 °C (stage 3), 1,203.4 °C, 1,059.2 °C and 1,080.0 °C (stage 4), 1,199.3 °C, 1,054.7 °C and 1,076.2 °C (stage 5), 1,196.4 °C, 1,053.6 °C and 1,071.4 °C (stage 6), 1,194.3 °C, 1,052.0 °C and 1,067.7 °C (stage 7), 1,190.1 °C, 1,043.0 °C and 1,062.2 °C (stage 8), 1,187.7 °C, 1,039.5 °C and 1,061.2 °C (stage 9), and 1,187.9 °C, 1,035.1 °C and 1,062.7 °C (stage 10), respectively. Although increasing mean temperature occurs due to the heating effect, an overall decreasing trend is observed during forming due to the more dominant cooling effect.

Fig. 6.11a-II shows the DC that maps the temperature distribution probability of over 1 million CWR data points through the 11 normalised forming stages from 0 to 10. The temperature rise can be attributed to the increasing frictional heat and substantial plastic deformation. Particularly, 29.43% (stage 1), 33.74% (stage 2), 34.48% (stage 3), 33.96% (stage 4), 28.61% (stage 5), 28.57% (stage 6), 26.26% (stage 7), 23.61% (stage 8), 22.17% (stage 9), and 22.39% (stage 10) of the data points have the temperature values greater than their corresponding initial forming temperatures at stage 0 (1,194 °C, 1,095 °C and 1,100 °C), respectively. However, overall, heat transfer between the hot billets and the cold tools leads to significant temperature reduction of the billets, as proved by the fact that there are 70.57% (stage 1), 66.26% (stage 2), 65.52% (stage 3), 66.04% (stage 4), 71.39% (stage 5), 71.43% (stage 6), 73.74% (stage 7), 76.39% (stage 8), 77.83% (stage 9), and 77.61% (stage 10) of the data points exhibit the temperature values smaller than their corresponding initial forming temperatures at stage 0 (1,194 °C, 1,095 °C and 1,100 °C), respectively. Of these, the probabilities of stages 2 to 4 (<70%) are smaller than others mainly due to the heat induced by friction and rapid penetration of the tools into the billet surface in the early forming stages.

Analysing the unique effective strain DC of the CWR process. Fig. 6.11b shows the unique DC of the CWR process mapping the effective strain through the 11 normalised forming stages from 0 to 10. The effective strain of the CWR process ranges from 0 (observed in forming stage 0 as indicated by the region 1 of Fig. 6.11b-I) to 2.95 (observed in forming stage 6 as indicated by the region 2 of Fig. 6.11b-I) during the entire forming process. At the beginning of forming, the effective strain data are all 0, then as the forming process proceeds, an overall increasing trend can be observed until the end of forming. Particularly, the mean and median of the

effective strain are 0.24 and 0.15 (stage 1), 0.43 and 0.39 (stage 2), 0.51 and 0.47 (stage 3), 0.58 and 0.55 (stage 4), 0.59 and 0.54 (stage 5), 0.60 and 0.54 (stage 6), 0.60 and 0.55 (stage 7), 0.62 and 0.59 (stage 8), 0.67 and 0.71 (stage 9), and 0.72 and 0.77 (stage 10), respectively. Obvious growths in the mean and median effective strain are observed from stages 0 to 4 and from stages 7 to 10, except stages 4 to 5, where the main region of the billets may go through the guiding stage without significant stretching deformation.

Fig. 6.11b-II shows the DC that maps the effective strain distribution probability through the 11 normalised forming stages from 0 to 10. Of these, there are 99.96% (stage 1), 88.22% (stage 2), 88.26% (stage 3), 78.22% (stage 4), 78.83% (stage 5), 79.87% (stage 6), 79.52% (stage 7), 79.61% (stage 8), 78.65% (stage 9), and 73.61% (stage 10) of the data points have the effective strain values smaller than 1.0, respectively. In addition, there are 84.57% (stage 1), 60.39% (stage 2), 52.57% (stage 3), 46.87% (stage 4), 46.78% (stage 5), 46.43% (stage 6), 46.43% (stage 7), 42.65% (stage 8), 35.22% (stage 9), and 30.30% (stage 10) of the data points have the effective strain values smaller than 0.5, respectively, indicating the overall effective strain increase that can be attributed to the effective cutting and stretching processes.

Analysing the unique strain rate DC of the CWR process. Fig. 6.11c shows the unique DC of the CWR process mapping the strain rate through the 11 normalised forming stages from 0 to 10. The strain rate of the CWR process ranges from 0 (observed in forming stage 0 as indicated by the region 1 of Fig. 6.11c-I) to 99.9 s^{-1} (observed in forming stage 8 as indicated by the region 2 of Fig. 6.11c-I) during the entire forming process. At the beginning of forming, the effective strain data are all 0, then as the forming process proceeds, the strain rate data suddenly increase, and the mean and median of the strain rate are 5.77 s^{-1} and 0.76 s^{-1} (stage 1, peak value 96.4 s^{-1}), 5.12 s^{-1} and 0.72 s^{-1} (stage 2, peak value 98.7 s^{-1}), 4.43 s^{-1} and 0.25 s^{-1} (stage 3, peak value 97.4 s^{-1}), 3.54 s^{-1} and 0.06 s^{-1} (stage 4, peak value 99.5 s^{-1}), 2.46 s^{-1} and 0.091 s^{-1} (stage 5, peak value 90.4 s^{-1}), 2.74 s^{-1} and 0.052 s^{-1} (stage 6, peak value 97.6 s^{-1}), 2.45 s^{-1} and 0.022 s^{-1} (stage 7, peak value 98.0 s^{-1}), 2.47 s^{-1} and 0.037 s^{-1} (stage 8, peak value 99.9 s^{-1}), 2.46 s^{-1} and 0.049 s^{-1} (stage 9, peak value 91.2 s^{-1}), and 1.87 s^{-1} and 0.033 s^{-1} (stage 10, peak value 91.9 s^{-1}), respectively. Therein, an overall decreasing trend can be observed in the variation of strain rate data, where larger mean and median strain rate are observed in the first few stages since during the knifing stage, the tool wedge rapidly penetrates the billet surface and plastically deforms a V-shaped slot into the circumference of the billets.

Fig. 6.11c-II shows the DC that maps the strain rate distribution probability through the 11 normalised forming stages from 0 to 10. Of these, there are 53.57% (stage 1), 54.39% (stage 2), 64.74% (stage 3), 73.70% (stage 4), 82.00% (stage 5), 81.00% (stage 6), 81.96% (stage 7), 79.61% (stage 8), 79.96% (stage 9), and 82.43% (stage 10) of the data points have the strain rate values smaller than 1.0 s^{-1} , respectively. Moreover, there are 45.30% (stage 1), 46.39% (stage 2), 57.96% (stage 3), 68.22% (stage 4), 73.83% (stage 5), 76.26% (stage 6), 77.30% (stage 7), 74.39% (stage 8), 75.87% (stage 9), and 76.30% (stage 10) of the data points have the strain rate values smaller than 0.5 s^{-1} , respectively. This indicates that the larger strain rate data are mainly attributed to the penetration of billets surface by wedged tools, while the large strain rate data in other operation stages (e.g., 99.9 s^{-1} observed in stage 8) are mainly due to the fast-stretching process of the billet surface.

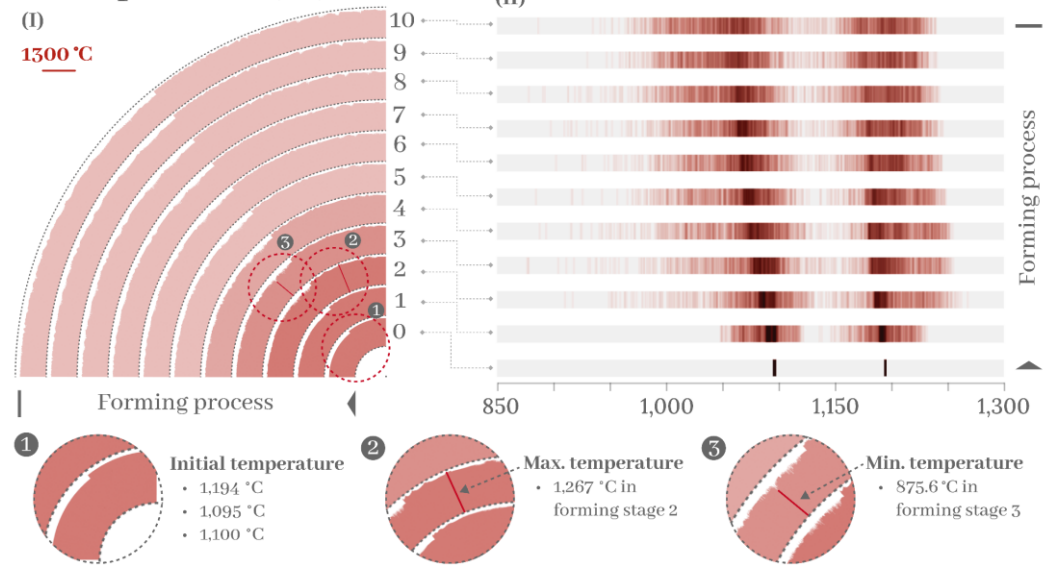
Analysing the unique contact pressure DC of the CWR process. Figs. 6.11d-6.11f show the unique DC of the CWR process mapping the contact pressure of X, Y and Z directions through the 11 normalised forming stages from 0 to 10, where the X direction is parallel to the axial direction of the billet, Y direction is the radial direction that is parallel to the rolling direction, and Z direction is the radial direction that is vertical to the tools. At the beginning stage 0, the contact pressure data values of X, Y and Z directions are all 0 before the forming commences (observed in forming stage 0 as indicated by the region 1 of Fig. 6.11d-I, Fig. 6.11e-I and Fig. 6.11f-I). As the forming operation proceeds, the maximum contact pressure values of X, Y and Z directions are 676.6 MPa (observed in forming stage 8 as indicated by the region 2 of Fig. 6.11d-I), 170.1 MPa (observed in forming stage 1 as indicated by the region 2 of Fig. 6.11e-I) and 726.0 MPa (observed in forming stage 3 as indicated by the region 2 of Fig. 6.11f-I), respectively. Then as the forming process proceeds, the contact pressure data suddenly increase.

In Fig. 6.11d-I, the mean of the contact pressure X are 0.8 MPa (stage 1, peak value 103.3 MPa), 1.6 MPa (stage 2, peak value 135.2 MPa), 1.6 MPa (stage 3, peak value 168.8 MPa), 1.6 MPa (stage 4, peak value 203.1 MPa), 1.5 MPa (stage 5, peak value 225.2 MPa), 2.2 MPa (stage 6, peak value 222.6 MPa), 1.5 MPa (stage 7, peak value 204.4 MPa), 2.2 MPa (stage 8, peak value 676.6 MPa), 2.0 MPa (stage 9, peak value 523.5 MPa), and 1.1 MPa (stage 10, peak value 242.6 MPa), respectively. In Fig. 6.11e-I, the mean of the contact pressure Y are 0.4 MPa (stage 1, peak value 170.1 MPa), 0.4 MPa (stage 2, peak value 119.3 MPa), 0.4 MPa (stage 3, peak value 81.0 MPa), 0.05 MPa (stage 4, peak value 45.0 MPa), 0.1 MPa (stage 5, peak value 35.4 MPa), 0.08 MPa (stage 6, peak value 41.4 MPa), 0.09 MPa (stage 7, peak value 39.7 MPa), 0.07 MPa (stage 8, peak value 43.6 MPa), 0.09 MPa (stage 9, peak value 47.4 MPa), and 0.06

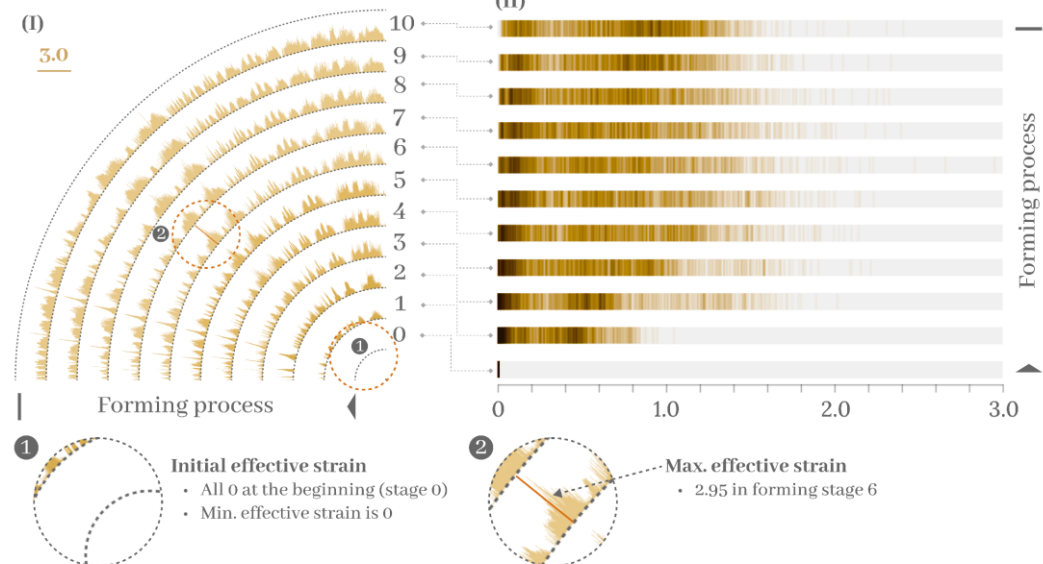
MPa (stage 10, peak value 47.5 MPa), respectively. In Fig. 6.11f-I, the mean of the contact pressure Z are 6.2 MPa (stage 1, peak value 377.4 MPa), 4.4 MPa (stage 2, peak value 299.3 MPa), 4.7 MPa (stage 3, peak value 726.0 MPa), 2.3 MPa (stage 4, peak value 286.1 MPa), 2.8 MPa (stage 5, peak value 299.2 MPa), 2.1 MPa (stage 6, peak value 282.5 MPa), 1.8 MPa (stage 7, peak value 313.1 MPa), 2.1 MPa (stage 8, peak value 676.6 MPa), 1.9 MPa (stage 9, peak value 357.7 MPa), and 1.0 MPa (stage 10, peak value 319.8 MPa), respectively. Overall, the contact pressure values of X and Z directions are significantly greater than that of the Y direction, since during forming the billet material is mainly stretched along the X direction and compressed along the Z direction, where significant plastic deformation occurs, while the contact pressure response along the Y direction is due to the material plastic deformation that is pushed by the tool wedges.

Fig. 6.11d-II, Fig. 6.11e-II and Fig. 6.11f-II show the DC that map the contact pressure distribution probability through the 11 normalised forming stages from 0 to 10. Overall, during the entire forming process, only 2.39%, 1.32% and 2.58% of the data points of the billets have contact pressure responses in X, Y and Z directions, respectively, since only two slim linear regions of the billet contacting with the tools have compressive or tensile contact pressure responses. In Fig. 6.11d-II, within the 2.39% of data points that have contact pressure X responses, there are 2.17% (stage 1), 3.53% (stage 2), 12.33% (stage 3), 24.07% (stage 4), 23.91% (stage 5), 45.59% (stage 6), 14.04% (stage 7), 19.72% (stage 8), 20.97% (stage 9), and 18.75% (stage 10) of the data points have the contact pressure larger than 100.0 MPa, respectively. In Fig. 6.11e-II, within the 1.32% of data points that have contact pressure Y responses, there are 36.36% (stage 1), 24.64% (stage 2), 53.36% (stage 3), 9.09% (stage 4), 37.02% (stage 5), 21.74% (stage 6), 38.10% (stage 7), 20.83% (stage 8), 31.82% (stage 9), and 21.05% (stage 10) of the data points have the contact pressure larger than 10.0 MPa, respectively. In Fig. 6.11f-II, within the 2.58% of data points that have contact pressure Z responses, there are 47.54% (stage 1), 48.51% (stage 2), 64.94% (stage 3), 42.00% (stage 4), 59.18% (stage 5), 43.48% (stage 6), 36.00% (stage 7), 31.37% (stage 8), 34.62% (stage 9), and 24.14% (stage 10) of the data points have the contact pressure larger than 100.0 MPa, respectively. More large contact pressure X data are observed from stages 4 to 7 where the main stretching activity occurs, and more large contact pressure Z data are observed from stages 1 to 5 where the main area reduction of the billets occurs.

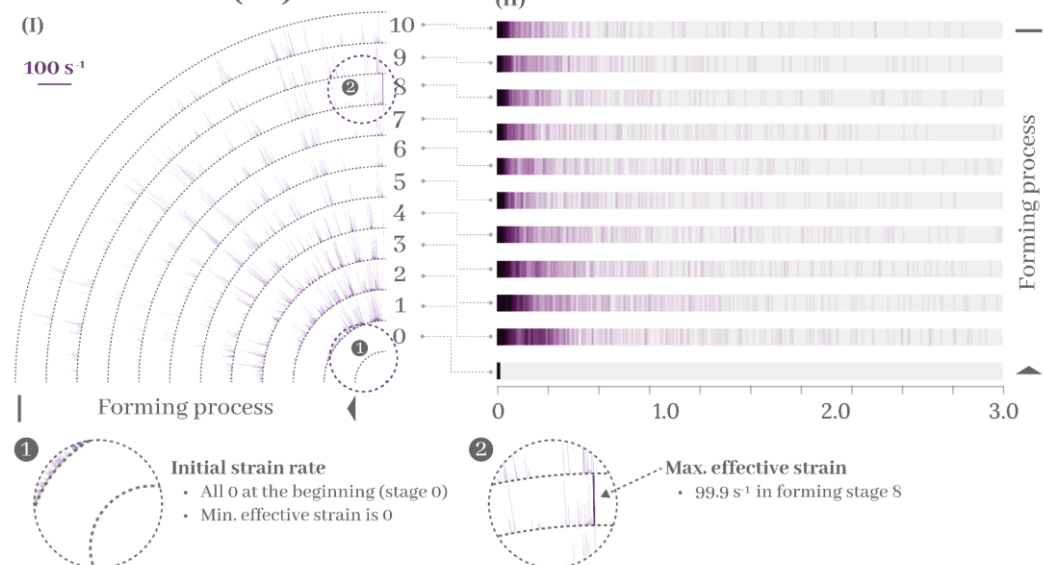
a Temperature ($^{\circ}\text{C}$)



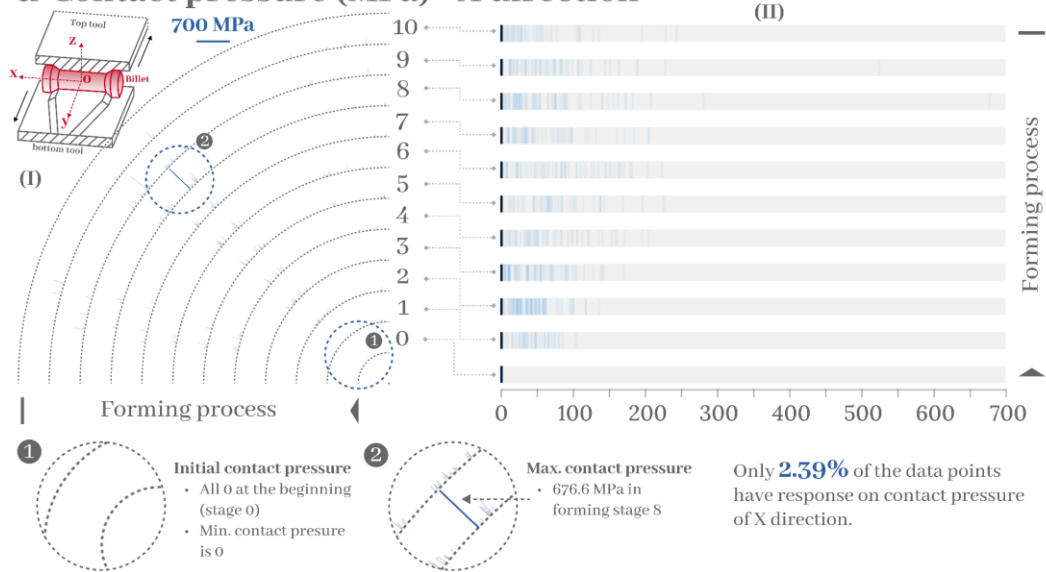
b Effective strain



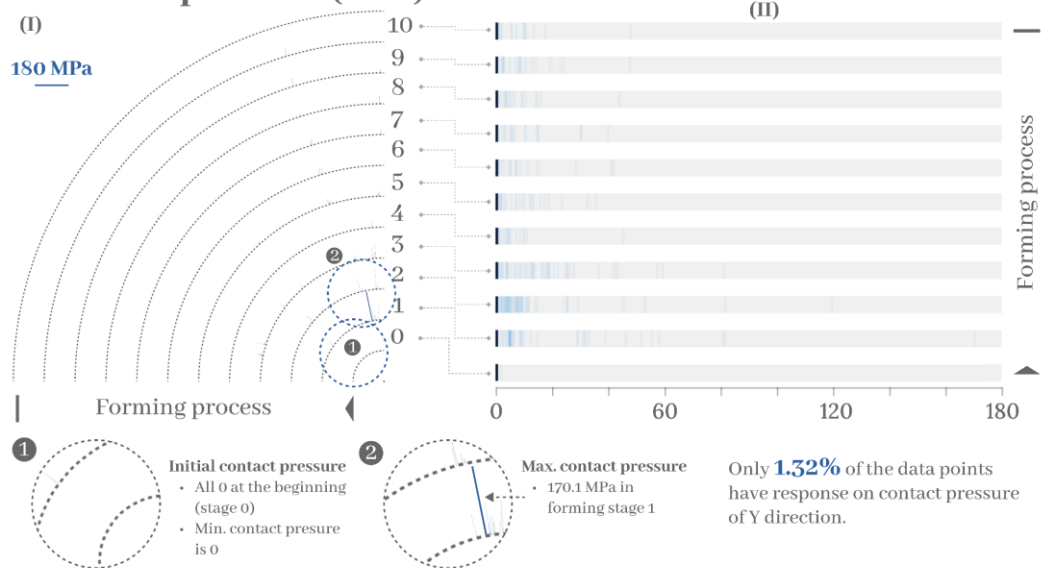
c Strain rate (s^{-1})



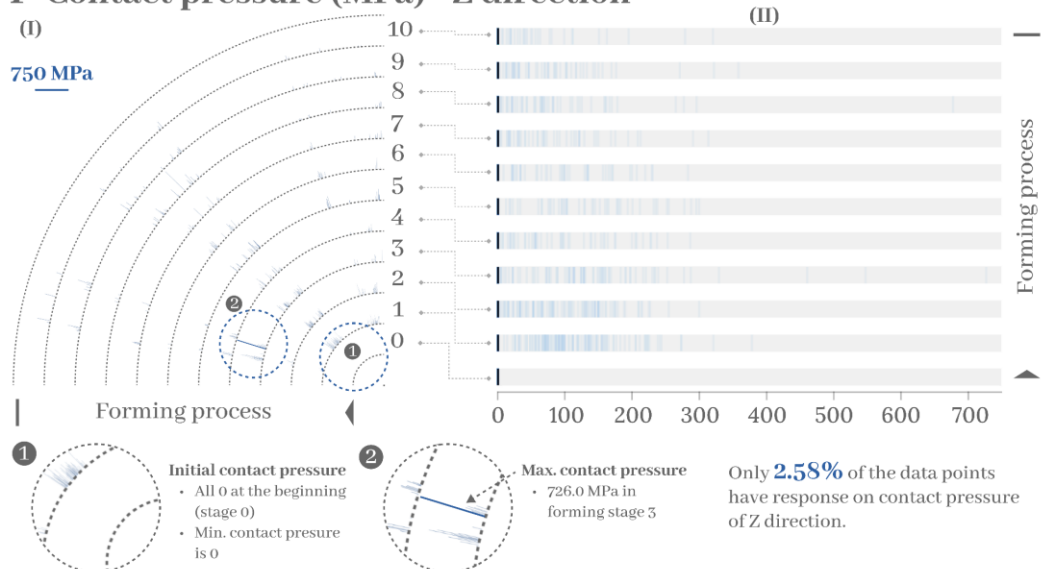
d Contact pressure (MPa) - X direction



e Contact pressure (MPa) - Y direction



f Contact pressure (MPa) - Z direction



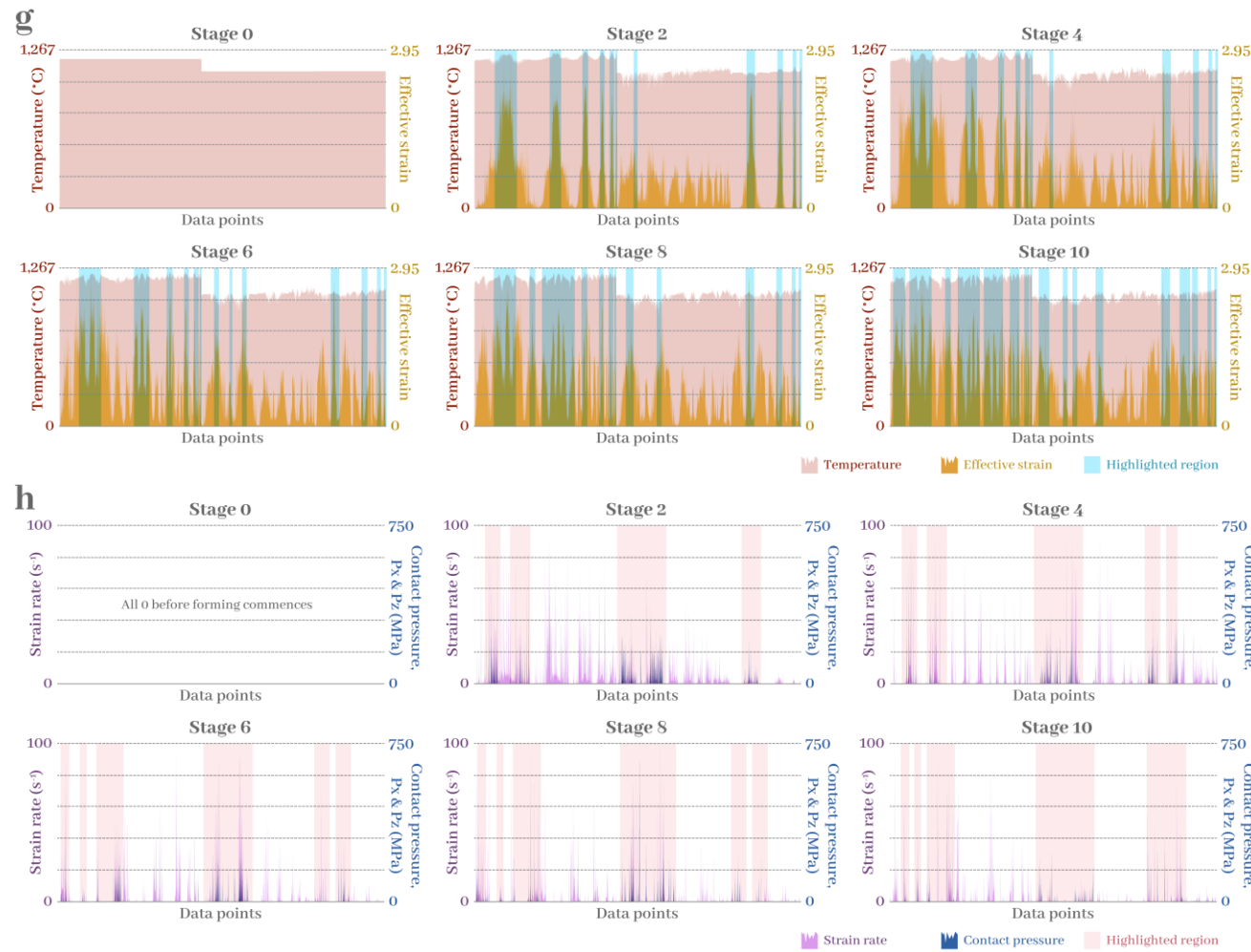


Figure 6.11 | Unique digital characteristics (DC) of CWR process. The DC of CWR process by mapping the evolutions of representative thermo-mechanical data including the **a**, temperature data, **b**, effective strain data, **c**, strain rate data, and contact pressure data of **d**, X direction, **e**, Y direction and **f**, Z direction. Each thermo-mechanical feature is characterised by two types of DC, (I) and (II), that address the trends and probability distributions of thermo-mechanical features. Critical regions in the DC (I) are zoomed in for clearer illustration. As the forming proceeds, **g**, relationship between the temperature and effective strain data and **h**, relationship between the strain rate and contact pressure data in forming stages 0, 2, 4, 6, 8 and 10 are highlighted and analysed.

Intriguingly, a positive relationship between the temperature data and effective strain data during forming is detected, as can be seen in Fig. 6.11g, where maps the DC of temperature and effective strain of stages 0, 2, 4, 6, 8 and 10. Larger effective strain values, indicating larger cross-section reduction and deformation ratio of the billets, usually result in higher temperature of the billets due to the friction and deformation, represented by knifing, radial compression and axial stretching (Fig. 6.11g). This ‘heating’ effect is much more significant and efficient than the heat transfer effect between the hot billets and cold tools, since there are over 20% of the data points in each stage possess temperature data values greater than 1,194 °C (the maximum initial temperature). Similarly, a positive relationship between the strain rate data and contact pressure data of data points that have contact pressure responses during forming is detected, as highlighted in Fig. 6.11h, where maps the corresponding DC of stages 0, 2, 4, 6, 8 and 10. Here, higher contact pressure spikes usually lead to higher strain rate responses especially in the regions where tool wedges rapidly penetrate the billet surface (Fig. 6.11h).

according to the DC of FT-CWR shown in Fig. 6.11a and 6.11c, this metal forming process requires the billet material maintaining high ductility and formability under extremely high forming temperature (maximum 1,267.0 °C) and high strain rate (maximum is 99.9 s⁻¹). In addition, it would be very challenged to apply the liquid-based and solid-based lubrication in FT-CWR operations due to such high forming temperature, while if necessary, coating techniques can be considered via using coating materials with high heat resistance to enhance the post-formed surface quality. The effective strain DC may inspire the FT-CWR product design since higher temperature can be induced by larger cross-section reduction and deformation ratio (Fig. 6.11g), leads to increasing failure risks such as surface cracks. Similarly, the strain rate DC may provide insights for tool design or operating parameters since high strain rate induced by sharp tool wedges or high forming speed can leads to high contact pressure responses (Fig. 6.11h).

6.5 Summary

In this chapter, as the most information-rich pairing reference, the DCS of manufacturing processes can make a significant scientific impact by revealing the esoteric values from any information absent manufacturing data, or fragmental data with extremely scarce information. The pairing model was validated by using a benchmark hot stamping temperature dataset with an overall accuracy of 77.7%. Using a serious of randomly selected fragmental data (with

different lengths of 100, 50, 40, 30, 20 and 10) of an unknown manufacturing process provided by the industrial partner, the origins (including the information of manufacturing process and manufacturing stages) of these unknown fragmental data were successfully recognised with an average accuracy of over 75% (i.e., $81.27 \pm 0.16\%$, $80.05 \pm 0.14\%$, $79.51 \pm 0.10\%$, $77.97 \pm 0.15\%$, $75.97 \pm 0.19\%$ and $70.16 \pm 0.13\%$, respectively, with the calculation time ranging from 50 s to 150 s). This was achieved by paring the representative thermo-mechanical feature (e.g., the forming temperature) of a series randomly selected fragmental data (with a smallest length of 10 data points) against the existing DC (e.g., temperature DC) within the DSC. The unique thermo-mechanical DC, represented by the temperature DC, effective strain DC, contact pressure DC and strain rate DC, of the paired manufacturing process, i.e., the CWR process, were developed and analysed in detail. Note that the ‘length-scanning approach’ can be achieved by applying various algorithms (e.g., machine learning algorithms), and there is a considerable potential for optimising the performance of ‘length-scanning approach’ developed in this particular research by integrating information pertaining to the physical characteristics inherent in manufacturing processes to the employed machine learning algorithms.

Chapter 7. Conclusions and future work

7.1 Thesis review and conclusions

This thesis focuses on the development of the digital characteristics (DC) for mapping metal forming processes, including the sheet and bulk metal forming processes, from the perspective of data towards the data science in manufacturing. Scientific guidance is provided for better understanding of this novel concept in manufacturing sector. To tackle the collected metadata that lack the essential information, this thesis developed the Evolutionary Binary (EB) algorithm following the thermo-mechanical principles to enable a highly accurate and efficient recognition of missing features from information absent data.

By using the EB algorithm, the DC of representative metal forming processes (i.e., the hot stamping) are developed and analysed in detail. These data processing and characterisation technologies enable the establishment of the digital characteristic space (DCS) of manufacturing processes, which provides access to the scientific communities with the most information-rich DC of manufacturing processes. The DCS enables the uncovering of manufacturing characteristics from fragmental data that contains extremely scarce information.

Overall, the key contribution of this thesis focuses on proposing the framework of data science in manufacturing. This framework was established by incorporating the four sectors, including the metadata collection addressed by the establishment of cloud-based data repository, information absent data processing addressed by the development of physical-based EB algorithm, data characterisation and analysis addressed by the development of DC and DCS of manufacturing processes, and digitally enhanced research and development using the fragment data recognition as a case. Main conclusions can be summarised as follows:

1. A cloud-based data repository was established on a knowledge sharing platform. This data repository contains 201 functional data modules incorporating with experimentally data files and essential information. Each data module was assigned a globally unique and permanent ID for providing access to the scientific communities with the most up-to-date manufacturing metadata.
2. The guidance of developing digital characteristics (DC) for manufacturing processes incorporates the essential stages of metadata collection (establishment of the cloud-based data repository), data pre-processing and information absent metadata processing (development of the EB algorithm), and metadata characterisation leading to the

development of DC. The DC can be characterised by ‘Unified’, ‘Unique’ and ‘Useful’ following the FAIR (Findable, Accessible, Interoperable, Reusable) data principles.

3. A physical-based Evolutionary Binary (EB) algorithm was developed by analysing the thermo-mechanical evolutionary characteristics of manufacturing processes to enable the information absent data processing. No training process is required since the embedded thermo-mechanical filters are developed following the thermo-mechanical principles. Using a hot stamping benchmark dataset, the EB algorithm enables approximately 95% of accuracy with good efficiency (maximum calculation time no more than 13 s) for recognising the representative geometric features of hot stamped products with extremely sparsely labelled data ($CDS \leq 1\%$). When the labelled dataset size increases to 75%, the machine learning (ML) algorithms can outperform the EB algorithm with more accurate results, especially when recognising the SW features. However, the calculation time of the ML algorithms significantly increase to a maximum calibration time of over 666 s.
4. The EB algorithm enables the development of the unique DC of the metal forming processes (e.g., the hot stamping process). The temperature DC, contact pressure DC, effective strain DC and strain rate DC were developed and analysed. The DC maps the metal forming processes from the perspective of data, assists in identifying the digital trends and underlying scientific patterns, supports the data-driven research and development by providing insightful information.
5. The DC of diverse manufacturing processes enable the development of digital characteristics space (DCS) of manufacturing processes. The DCS is a cutting-edge digital technology enabling the scientific community to gain access to the most comprehensive and information-rich manufacturing information, which is based on experimentally verified data and employs the key enabling approaches in terms of information absent data processing techniques (e.g., the EB algorithm) and data characterisation techniques (e.g., the development of DC).
6. The DCS of manufacturing processes can enable significant scientific impact by uncovering the esoteric values from any fragmental data that contains extremely scarce information. In this thesis, using the DCS as a pairing reference, the origins (including the manufacturing processes and manufacturing stages) of a series of randomly selected unknown fragmental data were successfully identified with an average accuracy of over 75% (calculation time ranging from 50 s to 150 s) with a minimum length of 10 data points. The unique DC, represented by the temperature DC, contact pressure DC, effective strain DC

and strain rate DC, of the identified manufacturing process were developed and analysed, which can stimulate the data-driven research and development.

7.2 Future work

The cloud-based data repository and digital characteristics space (DCS) of manufacturing processes are being updated and enriched with new manufacturing datasets and DC. Thus, large efforts are required to manage the data repository and develop new manufacturing DC using the Evolutionary Binary (EB) algorithm. Dedicated thermo-mechanical or other physical-based filters for the EB algorithm will be developed according to the different objectives of information absent data processing. In addition, there is a considerable potential for optimising the performance (e.g., accuracy and efficiency) of identifying the fragment data pieces by using or developing more advanced physical-based approaches or machining learning algorithms, which can be enhanced by integrating information pertaining to the physical characteristics inherent in manufacturing, such as physics-informed neural networks (PINNs). To comprehensively understand the mechanism of fragmental data pairing and pairing time saving, purely physical-based pairing approach is highly recommended to reveal the relationship between the fragmental data to that of the existing DC stored in the DCS.

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