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RESEARCH ARTICLE

Predictive models in digital manufacturing: research, applications, and future outlook

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ABSTRACT
Data has become a high-value commodity in manufacturing. There is a growing realisation that the data-driven applications could become strong differentiators of manufacturing enterprises. To guide the developments in digitisation, a widely accepted framework is needed. In the absence of the universal framework, the components making a digital enterprise are captured in an example framework that is introduced in the paper. The adoption of new technology and software solutions has increased complexity of manufacturing systems. In addition, new product introductions have become more frequent and the demand more variable. A digital space enables optimisation and simulation of decisions before their realisation in the physical space. Predictive modelling with its time dimension is a valuable actor in the digital space. Three challenges of predictive modelling such as model complexity, model interpretability, and model reuse are identified in this paper. The coverage of each challenge in the literature is illustrated with the recently published papers. The main aspects of these challenges and the synthesis of the developments in digital manufacturing are articulated in the form of eight observations that could guide the future research.

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digital manufacturing; predictive modelling; data science; smart manufacturing; digital twin

1. Introduction

The first usage of the term 'digital manufacturing' dates back around the year 2000, initially referenced in commercial magazines and conferences. The past two decades have produced a large volume of research content in digital manufacturing. There is a need to synthesise the developments and capture the main trends which is accomplished in this paper. To set the stage for accomplishing this goal, a brief review of the representative literature is presented next. Cheng and Webb (2006) published a collection of papers presented at the 4th International Conference on e-Engineering and Digital Enterprise Technology. The papers summarised the developments in digital manufacturing and enterprise technologies. Mahesh et al. (2007) presented a framework for distributed manufacturing using agents and included digital manufacturing in its title. Nylund and Andersson (2011) discussed a framework for extended digital manufacturing systems. Some aspects of the framework embracing modelling, simulation, analysis, and change management were illustrated with an industrial example. A methodology for estimation of costs in digital manufacturing was presented in Jin et al. (2012). A prototype tool estimating the cost of manufacturing and assembly operations was developed and illustrated with an industrial example. Mourtzis et al. (2015) discussed different applications of simulation in digital manufacturing. The applications in product design, process design, and enterprise resource planning were highlighted. In the special issue of the *International Journal of Production Research*, Chien et al. (2020) have assembled research papers on algorithms, applications, and case studies on applications of artificial intelligence in manufacturing and logistics systems. This special issue summarised the accomplishments and outlined future developments in digital manufacturing. A perspective on digital manufacturing as an agent integrating the functional areas of an enterprise was presented in Park, Woo, and Choi (2020). Dictionaries and ontologies serve as enablers of digitisation. An extended version of the previously developed ontology of functionally graded materials was presented in Ali et al. (2021). A data schema for small manufacturing enterprises was developed and implemented. The speed of data processing is a key factor impacting the latency in digital twins. Talwar et al. (2021) published a systematic literature review on big data in

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operations and supply chain management. Besides identifying trends and areas of future research, a new framework to benefit production managers was developed. Dolgui and Ivanov (2022) discussed implications of 5G technologies in digital supply chains and operations management. The recently published paper by Zhou et al. (2022) summarised the developments in intelligent manufacturing in the 2005–2020 period with the focus on value creation, resource configuration, capacity and production planning, scheduling, and logistics. The paper by Balfaqih (2023) offers insights into applications where artificial intelligence integrated them with supply chain management. The concepts presented are intended for logistics and supply chain managers. Manufacturing has experimented with different forms of modelling and data since its early beginnings (Kuo and Kusiak 2019). Models ranging from simple analysis of a handful of data points and operations research to real-time simulation and virtual reality have been used. The confluence of multiple factors, including progress in manufacturing technology and artificial intelligence, has raised a bar for digitisation in manufacturing. Some of the new concepts that have been developed are highlighted next.

Of all concepts covered in the digital manufacturing literature, digital twin has received most attention. It is to serve as a digital replica of the physical manufacturing space. The requirements for the design of a digital twin reference model for fault diagnosis of rotating machinery were presented in Wang et al. (2019). Zheng, Lu, and Kiritsis (2021) elaborated on the concept of cognitive digital twin versed in ontology and knowledge graphs. Reference architectures and integration of mission-specific digital twins were discussed. A digital twin of a rotor was developed and demonstrated in diagnosis and adaptive degradation applications. Liu, Ong, and Nee (2022) offered a comprehensive survey of digital twin implementations based on analysis of 121 published papers. The Internet of Things and Services (IoTS) is closely aligned with the digital twin concept. Haghnegahdar, Joshi, and Dahotre (2022) surveyed 93 papers in the IoTS domain. Applications of artificial intelligence technologies in machining such as predictive modelling, parameter optimisation and control, chatter stability, tool wear, and energy conservation were discussed in Chuo et al. (2022). The challenges of Artificial Intelligence (AI) technologies, such as data quality, knowledge transfer, and eXplainable AI were also addressed.

The best recognition of the level of interest in digital manufacturing is the recently released draft of the 'Digital Engineering Measurement Framework' (DEMF 2022) developed by experts from different industries, government, and academia. Though many frameworks and reference models exist, this framework is recent, and it recognises that the industry is undergoing a transformation where the traditional engineering requirements, design, development, integration, and verification methods based on documents and artefacts are being replaced by digital models and cross-functional digital representations of system designs and end-to-end solutions. The framework covers a range of topics related to digital engineering, e.g. state of the practice, definitions of terms and concepts, mapping data to measurement specifications, measurement principles, and measurement concepts and specifications.

Though the framework (DEMF 2022) is focused on measurements, it touches on many aspects of digital enterprises. Of particular interest is the classification of digital processes presented in Figure 1.

The components of the framework in Figure 1 are defined next.

- Digital Infrastructure: Refers to computing assets and tools that support digital engineering. The digital infrastructure is to support company's information needs and related data. It could be programme or domain-specific and integrate tools from different domains.
- Life-cycle models: Various life-cycle models and the related data and information needed by these models.
- Process models: Models integrating products, people, and processes involved.
- Data and model ontology: This repository of artefacts is referred to as an Authoritative Source of Truth (ASoT) as all stakeholders use the same data and models. The data models define how the data is stored and accessed, while domain ontologies define generic concepts and relationships in the domain that enables sharing of data and knowledge. It is expected that maintenance of data and models will be automated. This way a change in one area of ASoT will propagate to other areas.
- Operational data and models: Models that capture relationships between individual models, define the operational use of the system that enables analysis of issues of interest, and manage the relationships between the individual models.
- System data and models: System models and supporting data that span multiple engineering and business domains.
- Discipline -specific data and models: A collection of models and data applicable to a narrow domain.

The classification presented in Figure 1 is an effort to systemise developments around digital engineering. The fact that it has been developed by consensus among experts representing industries, government, and

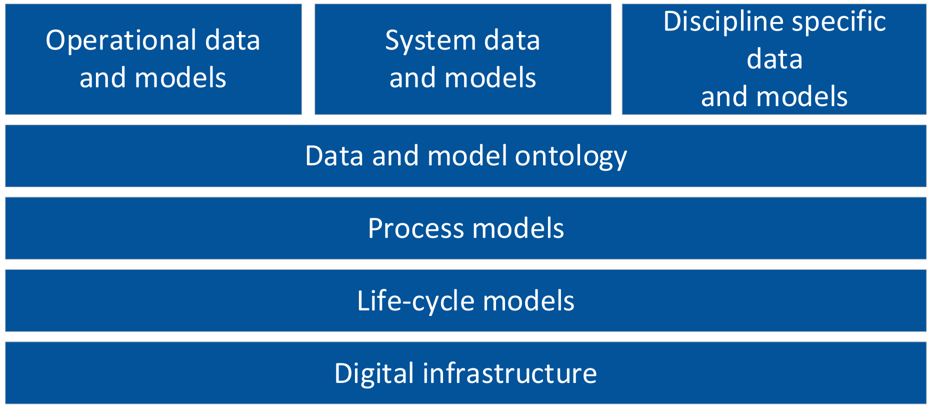

Figure 1. Classification of digital processes in manufacturing (DEMF 2022). A five-layer block diagram. The lower four layers starting from bottom up are: digital infrastructure, life-cycle models, process models, and data and model ontology. The top (fifth) layer contains three elements, operational data and models, system data and models, discipline-specific data and models.

academia in an asset. The full value of the proposed classification awaits demonstration which could be accomplished by providing relevant content (e.g. models and data) to the seven blocks in Figure 1. The next section of this paper is to assess the status of predictive models in digital manufacturing. Such models will gain prominence in any manufacturing framework, including the DEMF framework illustrated in Figure 1.

2. Predictive models in digital manufacturing

Predictive models are relatively new to manufacturing; however, the number of publications on their applications is growing at a high rate. The topical coverage of predictive modelling is not uniformly distributed, for example, the process control area has been most widely research. The origin of this distribution skewed towards some manufacturing areas is likely due to: (i) the nature of the application domain or (ii) the availability of historical data. It can be observed that many papers published to date trace back to the same public data sets. The public data is used for benchmarking algorithms and development of models. Some domains of manufacturing are either: (i) not naturally amenable for predictive modelling or (ii) could not be suitable at all for applications of such models. For example, the machine layout problem is usually considered deterministic and as such is not a natural candidate for predictive modelling. This does not exclude possibility of applying predictive modelling to some phases of the machine layout modelling, e.g. data generation.

To identify representative applications of predictive modelling in manufacturing, a comprehensive analysis of publications included in the following four digital libraries, Science Direct, Informa, Springer Link, and IEEE Xplore, has been performed. The four libraries are likely to include majority of the content relevant to the paper domain. Among many candidate areas considered, the eight application areas listed in Table 1 have been selected. These areas are of interest to manufacturing researchers and practitioners.

It has been decided that an application area with at least 3500 publications that appeared in 2021 across the four libraries be analysed. The one-year total of 2021 publications is a good representation of the papers published over longer time periods. It has been observed that the number of papers published on topics in any of the eight areas in Table 1 has been largely increasing every year. The search of the four digital libraries has been performed on the keywords included in the first column of Table 1 + prediction + manufacturing. For example, condition monitoring + prediction + manufacturing. For the two of the eight areas that include 'prediction' in their names, this keyword was not repeated. Digitisation of industry is progressing, and it offers data for predictive models in manufacturing. The eight applications areas are ranked in the last column of Table 1. Based on the search performed, the process control area of manufacturing has been the most widely researched (Rank 1) and the fault prediction area the least (Rank 8).

The eight applications of predictive modelling in manufacturing of Table 1 are illustrated with the recently published papers.

- Condition monitoring

Wang et al. (2019) discussed a deep heterogenous gated-recurrent-network for prediction of tool wear. Performance of the proposed approach was demonstrated in computational experiments. Trends in applications of

Table 1. The number of 2021 publications included in four digital libraries.

	Digital library					
Application area	Science Direct	Informa	Springer Link	IEEE Xplore	Total	Overall rank
Condition monitoring	5254	3663	2622	364	11,903	6
Fault prediction	1928	632	825	448	3833	8
Process control	16,779	9365	6334	1092	33,570	1
Quality prediction	12,305	7666	4999	883	18,187	2
Production demand prediction	5779	4728	1990	107	12,604	5
Decision making	4888	5883	2856	249	13,876	4
Planning	6104	4920	2722	381	14,127	3
Scheduling	2311	1625	876	213	5025	7

deep learning to machine health monitoring were presented. A methodology and model for identification of assembly stations of inferior performance was proposed in Verna et al. (2022). This in turn allowed quality engineers to determine root causes of the production problems.

- Fault prediction

A predictive maintenance model involving integration of generative adversarial and long-short-term memory networks was offered in Liu et al. (2021). This integration eliminated the problem of vanishing gradients of the long-short-term memory (LSTM) network and the mode collapse of the generative adversarial network, while enabling self-detection of data anomalies. A hybrid sparse convolutional neural network for prediction of defects in components produced in a laser-based powder bed fusion process was developed by Zhang and Zhao (2021). To improve the model performance, a generalised convolution operation was applied to a sparse matrix.

- Process control

Liu et al. (2022) discussed a model for prediction of production progress in a make-to-order environment. Performance of the developed neural-network model was validated against eight algorithms.

- Quality prediction

Machine learning offers a great potential in prediction of product quality. Tercan and Meisen (2022) reviewed the papers on predictive quality in manufacturing published in the 2012–2021 period. Challenges for predictive quality and future research were provided.

- Product demand prediction

A neural-network model to predict the demand of printed circuit boards was discussed in Hu (2022). The paper emphasised estimation of the demand intervals. Computational analysis has demonstrated favourable performance characteristics of the grey prediction model.

- Decision making

Data-driven technologies for decision-making in intelligent manufacturing were analysed in Li, Chen, and Shang (2022). An intelligent decision-making framework was proposed.

- Planning

Oluyisola et al. (2022) offered a methodology for design and development of smart production planning and control systems. The methodology applied machine learning and data analytics to data from different sources as well as utilised prior production planning knowledge. A case study was presented.

- Scheduling

Serrano-Ruiz, Mula, and Poler (2022) developed a model for smart manufacturing scheduling. The model utilised machine learning to increase flexibility, enhance rescheduling capability, and increase autonomy in manufacturing.

Figure 2 shows an example manufacturing system involving processes such as subtractive manufacturing, additive manufacturing, assembly, quality control, and production control and scheduling. The eight applications and their ranks from Table 1 are listed next to the corresponding processes in Figure 2.

The coverage of the predictive modelling in manufacturing is likely to grow in time.

For a more focused characterisation of the 2021 publications, an additional search of the four digital libraries considered in Table 1 has been performed. The first two keywords used in the search reported in Table 1 were retained, while the last keyword ‘manufacturing’ has been replaced with ‘digital manufacturing’. This search has reduced the number of publications, e.g. the search of the Science Direct library on ‘condition monitoring’ and

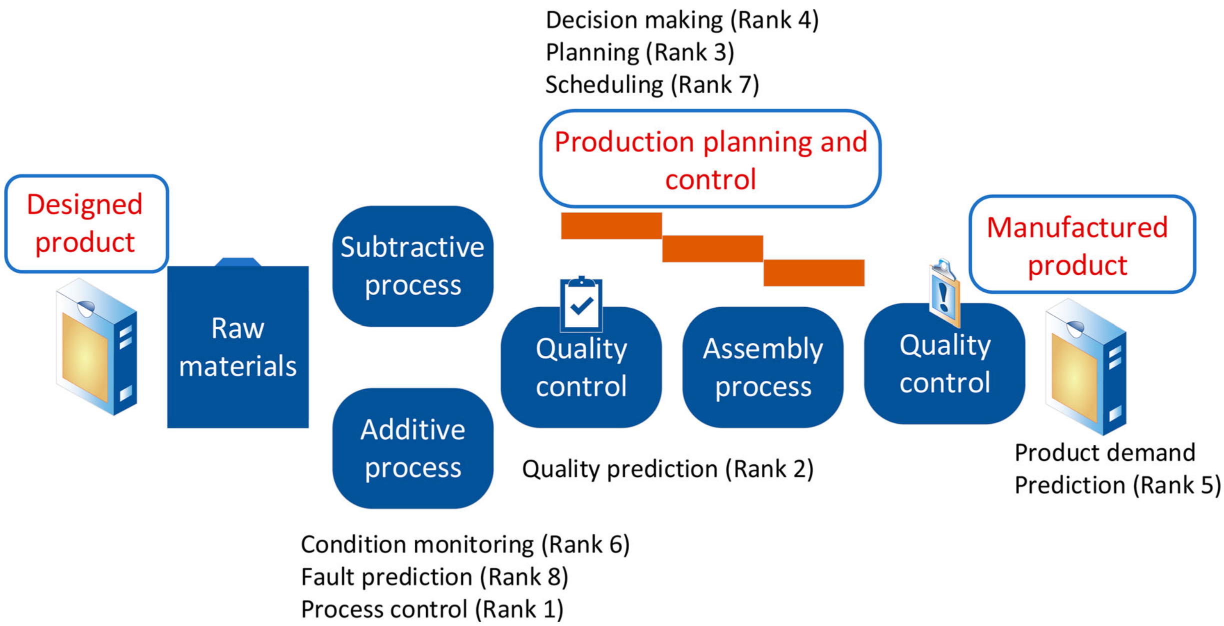

Figure 2. A manufacturing system with basic processes. A process like diagram that starts with design product as an input, followed by raw materials, then two parallel blocks (additive process and subtractive process), followed by quality control, assembly process, and another quality control block. The diagram ends with manufactured product.

'prediction' and 'digital manufacturing' has resulted in 1685 publications vs. 5254 publications in the original search reported in Table 1. The total of 1685 publications included 274 review articles, 1209 research articles, 18 encyclopaedia chapters, and 184 book chapters. All review papers identified in the search of the four digital libraries have captured the progress and identified challenges in the eight application areas of Table 1 usually in the period of 5–10 years. A deep analysis of the 2021 review papers on predictive modelling in digital manufacturing across the eight application areas of Table 1 has been conducted. The detailed content analysis has resulted in eight observations and three challenges discussed next. These observations offer two benefits: (i) assess the past developments in digital manufacturing and (ii) serve as an inspiration for future research.

Observation 1: The research on predictive models in manufacturing is limited in scope and unevenly distributed.

Comment: The scope of modelling is largely dictated by the data available for research. The totals in Table 1 vary across different application areas.

Observation 2: Predictive modelling in manufacturing is fragmented.

Comment: The predictive models are usually developed in silos. It is seldom that integration of these models with other predictive models and application environments is discussed. The assignment of unrelated application areas to different process in Figure 2 supports this observation. Models integrating any of the eight different applications areas could not be identified in the literature surveyed.

Observation 3: The use of industry-collected data in the published research is limited, given the total number of papers published.

Comment: Papers tend to use the previously published public data sets. While applying benchmark data sets for comparative analysis is welcome, the use of the same data sets at the outset of many different research projects is not likely to support creativity of manufacturing research in predictive modelling.

Observation 4: The diversity of data available to the manufacturing research community is limited.

Comment: Based on the origin of data sets, the research papers fall into the following four categories: (i) public data sets, (ii) secondary use of industrial data sets supplemented with public data, (iii) data generated from designed experiments, and (iv) industrial data sets only. It is seldom that the published research utilises industrial data from large-scale experiments specific to the data science project. The use of data generated for purposes other than modelling (secondary use of data) prevails in the manufacturing literature.

Observation 5: High-impact industrial use cases in predictive modelling have limited visibility in the literature.

Comment: This is a complex issue as the research community has a limited control over industry-generated data and applications. Any progress in this domain would likely enhance research and accelerate development of new applications.

The analysis of the literature has revealed modelling challenges that are presented in the next section. These challenges have led to additional observations that are also discussed.

3. Modelling challenges

Predictive modelling is a cornerstone of digital manufacturing. Data-derived models have gained a preferred status over statistics and physics-based models used in manufacturing since the first industrial revolution. Modelling from data faces the following issues:

- Model complexity
- Model interpretability
- Model reuse

3.1. Model complexity

Machine learning algorithms have taken the central stage in modelling. The developed models largely involve different classes of machine learning algorithms, from decision tree and classical neural networks to generative adversarial networks and deep learning algorithms. It is generally agreed that the industry prefers simple models over complex ones. The two well-known theorems presented next set a stage for the analysis of performance of models and their complexity.

3.1.1. No free lunch theorem (Wolpert and Macready 1995; Wolpert 1996)

Given a finite set V and a finite set S of real numbers, assume that function f: $V \rightarrow S$ is randomly selected according to uniform distribution of the set S^V of all possible functions from V to S. For the problem of optimising f over the set V, no algorithm performs better than the blind search. The theorem implies that when all functions f are equally likely to be chosen, the probability of observing an arbitrary sequence of m values in optimisation does not depend on the algorithm selected. An instance of function f could be a data-derived model. However, the theorem does not mention any limitations related to finding the best learning algorithm for a particular problem instance.

3.1.2. Universal approximation theorem (Hornik, Stinchcombe, and White 1989)

Any continuous function defined in an arbitrary compact subspace of R^n can be approximated arbitrarily well with a three-layer perceptron. This theorem seems to imply that:

- A multi-layer perceptron with one hidden layer suffices in modelling.
- There is no need to consider perceptrons with more than one hidden layer.

However, the theorem does not mention anything about the number of hidden neurons leading to a desired approximation accuracy. In particular:

- Depending on the function to be approximated, many neurons may be needed.
- A network with more than one hidden layer, each having lower number of neurons, may produce the same approximation accuracy as the one hidden layer network.

Garouani et al. (2022) discussed the problem of selection and configuration of AI models. The problem was addressed by a software platform discussed in the paper. The platform provides insights into the algorithms and models.

Observation 6: Predictive modelling alternatives in manufacturing are limited.

Comment: The results published in the literature usually emphasise accuracy of predictive models. Consideration of alternatives accounting for models of different complexity, data availability, and different data streams need attention. For example, a model that is less accurate but more robust and functions with more than one data stream may be preferred in some applications over a highly accurate model supported by data of uncertain availability.

3.2. Model interpretability

The notion of model interpretability used in artificial intelligence implies that a model is understandable to a user. In more general sense, the term eXplainable Artificial Intelligence (XAI) is used to denote models that can be explained.

Ahmed, Jeon, and Piccialli (2022) surveyed the eXplainable AI methods and discussed their applications in the context of Industry 4.0. Challenges, opportunities, and research directions pertinent to XAI were outlined. Kinkel, Baumgartner, and Cherubini (2022) stated that the focus of AI research has been on AI technologies rather than factors enabling its adoption in industry. Based on a survey of 655 industrial professionals, the authors identified barriers to industry-wide implementation of AI solutions ranging from a company size to the level of research and digital skills. Minh et al. (2021) reviewed and categorised the existing XAI approaches into: (i) pre-modelling explainability, (ii) interpretable model, and (iii) post-modelling explainability. In addition, the terminology surrounding explainability was offered. The emerging concepts in interpretability of deep learning models were outlined. The pre-modelling explainability refers to data processing tasks preceding machine learning. It aims at getting insights into the data, e.g. statistical data analysis, data transformation, data visualisation, and storytelling (Minh et al. 2021). An interpretable model is one that can be easily interpreted by a user, usually because it is explicit. Examples of such models include, liner and logistic regression models, rule-based, decision tree, and k-nearest neighbours models. The post-modelling explainability applies to cases where a model does not meet the interpretability requirements. Here, a model-agnostic or model-specific approach can be applied (Minh et al. 2021). Both approaches may involve techniques, such as textual justification, simplification, feature relevance, and visualisation. Deep learning models offer a separate set of interpretability challenges.

Based on the level of explainability, Doran, Schulz, and Besold (2017) categorised the XAI models into three categories: (i) opaque models, (ii) interpretable models, and (ii) comprehensible models. For an opaque model, a user does not get any insights on how the model output is produced for a given input, e.g. a model is derived by a proprietary algorithm or a neural network. If a user can analyse the relationship between the model input and output, the model is interpretable, e.g. a regression model. A comprehensible model, in addition to generating an output, produces symbols (e.g. rules, visual symbols) allowing a user to relate properties of the input to the output. Depending on the type of these symbols, models can be comprehensible to a different degree. Barredo Arrieta et al. (2020) summarised and categorised the literature on explainability in machine learning. The transparency level of different machine learning models, such as linear regression, decision trees, k-nearest neighbours, rule-based, generalised additive models, and Bayesian models was illustrated graphically. In addition, the machine learning models were classified based on their level of explainability.

Some of the most recent applications of the concept of eXplainable Artificial Intelligence (XAI) in manufacturing are illustrated next.

3.2.1. Classification of fibre layup defects in manufacturing of composite materials

Meister et al. (2021) applied 20 published XAI methods to classify fibre layup defects with a neural network. The neural activations and robustness of a classifier were analysed for unknown and manipulated input data. The study has determined that the smoothed integrated gradients and DeepSHAP methods were most suitable for visualisation.

3.2.2. Classification of welds

Goldman et al. (2021) applied two XAI approaches to classify the quality of welds of ultrasonic battery tabs. A heat map visualised the class activation in several colours. A contrastive gradient-based saliency maps were used to express robustness of the classifier.

3.2.3. Process prediction

The challenges and opportunities in applying XAI to process predictions in a smart Lego-factory were discussed in Rehse, Mehdiyev, and Fettke (2019). A post-hoc explanation approach was applied to a deep learning model predicting process outcomes. The XAI approach was to enhance trust of domain experts in the prediction model.

3.2.4. Predictive maintenance

Upasane et al. (2021) introduced a type-2 fuzzy logic system optimised by the big-bang big-crunch algorithm enhancing interpretability of a multi-layer perceptron model. Performance of the XAI approach was compared with that of the multi-layer perceptron model.

3.2.5. Manufacturing cost estimation

The concept of eXplainable AI as a process of predicting manufacturing cost was presented in Yoo and Kang (2021). The process involved three phases, data collection, exploration of deep learning architecture, and visual explanation of the results.

3.2.6. XMANAI case studies (XMANAI 2020)

Two industrial cases of explainable AI were presented in Lampathaki et al. (2021). The first case study involved management and analysis of real-time data from corporate systems, maintenance, and tooling systems in an automotive engine plant, while the second one involved forecasting models. The authors applied the XMANAI approach (www.ai4manufacturing.eu) designed to make the manufacturing value chain with 'glass box' models explainable.

Observation 7: The progress in eXplainable Artificial Intelligence in manufacturing conditions the scale, scope, and speed of industry-wide deployment of predictive modelling.

Comment: The industry is at ease with using software solutions ranging from payroll systems to enterprise resource planning. Many of these software systems perform relatively simple operations at a massive scale. The logic behind these operations is well understood. Predictive models have different characteristics than the traditional software solutions. Though large data sets are usually needed to develop predictive models, their execution may involve small volume of data, e.g. the values of the input parameters. Yet, the innerworkings of the model cannot be easily explained, and therefore the eXAI solutions are needed.

3.3. Model reuse

When a new technology or a tool emerges, the users tend to compare the new to the old. The fact that physics has served as a basis of modelling in manufacturing since its very beginnings, any new model is usually compared to a physics-based model. The benefits of the data-derived models surpassing those of the physics-based models (e.g. large scope, high accuracy) come at the cost of being application specific, which makes it difficult to deploy them the way of the physics-derived models are. A physics-based model can be used in any application that includes the phenomenon captured by this model. The data-derived models are application specific and therefore it would be highly unusual to fully match a previously developed model with an unrelated application. The data science community is working towards alleviating this problem, e.g. research in transfer learning.

Transfer learning aims at the use of a model developed in one application scenario in another one. This is analogous to humans applying knowledge to solve different problems using the same base knowledge. Progress in transfer learning is needed to accelerate deployment of data science in many domains, including manufacturing. Having an initial data-driven model that could be applied without following the usual model development process would be a great benefit. Performance of such a model could be improved over time as the application-specific data is collected.

Transfer learning was introduced in Lazaric (2012). Based on the application domain setting, three types of transfer learning were defined: (i) transfer from a source task to another target task within the same domain, (ii) transfer from different source tasks to another target task within the same domain, and (iii) transfer from a source task to a target task in a different domain. Three categories of knowledge transfer were listed: (i) instance transfer, (ii) representation transfer, and (iii) parameter transfer. Computational intelligence algorithms offer a promising contribution to transfer learning. Lu et al. (2015) surveyed applications of computational intelligence in transfer learning. The computational intelligence techniques were grouped in three transfer-learning categories: (i) neural network, (ii) Bayes and fuzzy logic, and (iii) genetic algorithm category.

Transfer learning of convolutional neural networks begins to dominate the current literature. An interesting concept of broad transfer learning was discussed in Liu et al. (2021).

Illustrative applications of transfer learning in manufacturing are discussed next.

3.3.1. Aluminium processing

The results of a study demonstrating potential deployment of transfer learning in manufacturing aluminium cans were presented Giannetti and Essien (2021). Two different transfer-learning strategies, weight reuse and fine-tuning, were considered for classification of the speed of nine bodymaker machines in a manufacturing plant.

3.3.2. Defect classification in semiconductor industry

Transfer learning of a convolutional neural network in the presence of data with unreliable labels or labelled data of unrelated tasks was discussed by Imoto et al. (2019). The proposed method provided significant savings in defect classification at a semiconductor fabrication facility.

3.3.3. Bearing life-time prediction

A multi-stage transfer-learning method for transfer of vibration-based fault diagnostics capabilities to a new working environment of a convolutional neural network was proposed by Zhou et al. (2020). A training strategy involving pre-training and fine-tuning was designed to transfer the weights of a pre-trained model to new diagnostics tasks. The proposed method was validated on three bearing fault data from three different applications.

3.3.4. Tool wear prediction

A laboratory-generated data set was applied by Sun et al. (2021) to predict tool wear in a milling process. The initially collected 200 images were enhanced to 3200 images and used for training, validation, and testing. The model robustness and accuracy were validated in a computational study.

3.3.5. Time-to-failure prediction

Liu et al. (2021) proposed a deep transfer approach to predict the time-to-failure in an ion mill etching process. At the first stage, a time-series data was used to develop a model. At the second stage, the deep model of the first stage was fine-tuned with a low volume of data from the previously unseen fault modes. The training and accuracy advantages of the model were validated in computational experiments.

Observation 8: The progress in transfer learning impacts the scale, scope, and speed of industry-wide deployment of predictive modelling in manufacturing.

Comment: The software deployed across industries is largely generic, with limited or no customisation needed for a specific application. Any predictive model to be deployed at this time is application specific (customised). While the traditional software can be used across different applications and companies, predictive models cannot. It is anticipated that transfer learning will allow reuse of predictive models across different applications.

4. Conclusion

A concise review of the recent developments in digital manufacturing was presented. Based on the analysis of a large number of recent papers from four digital libraries, eight representative application areas of predictive modelling in manufacturing were identified and ranked. The ranking demonstrated that some application areas have received noticeable attention by the manufacturing research community, while other domains await research. The predictive modelling areas were mapped against the basic processes of manufacturing systems. The key barriers to further developments were identified. The progress made to date was illustrated with the recently published papers. A deep analysis of the selected survey papers has provided results that could not be accomplished with the bibliometric tools. The analysis results have been captured in the form of three challenges and eight observations. The challenges involve model complexity, model interpretability, and model reuse. These challenges await further research. The attempts to tackle them were illustrated with the published papers. The eight observations formed could guide the future research in predictive modelling. They may also serve as elements of a roadmap for digitisation of the manufacturing industry. The concepts highlighted in this paper are synergistic with an example framework for classification of digital engineering processes and applications.

Data availability statement

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributor

Dr. Andrew Kusiak is a Professor in the Department of Industrial and Systems Engineering at The University of Iowa, Iowa City and Director of Intelligent Systems Laboratory. He has chaired two different departments, Industrial Engineering, and Mechanical and Industrial Engineering. His current research focuses on applications of computational intelligence in manufacturing, renewable energy, automation, sustainability, and healthcare. He is the author or coauthor of numerous books and hundreds of technical papers published in journals sponsored by professional societies, such as AAAI, ASME, IISE, IEEE, INFORMS, and other societies. He is a frequent speaker at international meetings, conducts professional seminars, and consults for industrial corporations. Dr. Kusiak has served in several elected professional society positions as well as editorial boards of over 50 journals, including the Editor position of five different IEEE Transactions. Professor Kusiak is a Fellow of the Institute of Industrial and Systems Engineers and the Editor-in-Chief of the Journal of Intelligent Manufacturing (Springer Nature).

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