"Knowledge discovery and formalisation for Additive manufacturing through Artificial Intelligence and Information Retrieval methods"

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Artificial intelligence, Machine learning, Knowledge, Data analysis, Additive manufacturing, Design rules, Data, Data representation, Data integration, Data-driven decision, Knowledge representation, Knowledge extraction, Knowledge formalisation

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Introduction:

Recent, technological advances in the ongoing digital revolution in the Information Technology (IT) world, has resulted in massive amounts of data being collected and analysed. Most of the data analysis is being done using Artificial Intelligence (AI) tools. AI is based on the concept of automatic learning by machines to simulate human reflection and take actions based on that reflection to achieve a specific task. AI is an enormous domain frequently used in a lot of domains including speech recognition, computer vision, pattern recognition, and, and the focus of this proposal, additive manufacturing (AM).

AI includes many methodologies and software tools. One of the most used is Machine learning (ML). ML is a technique based on mathematical and statistical models. It gives the possibility for machines to perform specific tasks without detailed instructions about how to monitor and execute those tasks. ML systems are really powerful and widely used in some jobs involving both repetitive and complex tasks, often requiring little or no human support for making a decision. From the financial domain where it is being used to identify fraudulent transactions, criminal justice where it can be used to detect criminal activities and also in the automobile industry where it can be used to control a car, there are numerous sectors where AI is being adopted as it enables achieving impressive tasks and improving productivity.

Besides all the assets, certain challenges need to be tackled before the real potential of AI can be quantified and realized. Actually, these challenges limit the development and usefulness of a 'thinking' AI system. Besides all the advantages of such a system, there are some problems with understanding how AI makes decisions – sometimes called explainable AI. Also because of all the statistical correlations used to build AI models, we can't prove that the decision fits well with the initial needs. These aspects raised trustable and provable questions and are obstacles against the full adoption of AI technologies.

In the manufacturing domain, and especially when using Additive Manufacturing (AM), AI is being adopted to optimize manufacturing processes, to improve part quality, and to minimize production costs (Lu et al, 2018). AM, which is commonly called 3D printing, consists of creating a three-dimensional part by joining melted materials in a layer-upon-layer process based on a 3D CAD model [ISO/ASTM52900]. AM parts have significantly more complex geometries and structural properties than traditionally manufactured parts [Gibson, Rosen, and Stucker, 2015]. The AM processes that build those geometries depend on involve interactions among radically different materials, machines, methods, and sensors. Today, the physics models governing these interactions are not completely understood, so, the only way to understand and predict the impacts of those interactions is to use data-driven, specifically AI models, that can quantify the current, and predict the future quality of the parts [Yang et al, 2019], [Hyunwoong Ko, Paul Witherell, Ndeye Y. Ndiaye, and Yan Lu, 2019], [Hyunwoong Ko, Paul Witherell, Yan Lu, Samyeon Kim, and David Rosen, 2020].

Besides all the advantages AM provides, a lot of challenges are raised because of a lack of knowledge of those interactions. These challenges cause inconsistency in quality and defects found in the final product. The product quality often relies on parameters that evolve during the product creation lifecycle. Among these parameters, we can find the type of material used, the material quantity, the laser power, and many other variables that are all equally important. These input data may influence the final part properties, such as the part shape, the part density, and other characteristics. Understanding the relationships between the input parameters and the final quality of the parts is critical to the future success of AM [Yang et al, 2020].

Problem:

The engineering of inter-operating systems is based on different types and levels of abstraction and models. The proposed technological and scientific context focuses on several systems that need to interoperate. The AM processes have multiple characteristics that need to be controlled and optimized and that are in relation between them. These systems have to be modelled and the results must express not only the "structural" aspect of the components of the system but also their behaviour. One of the core problems of this work is to study model interoperability problems by cooperative model-driven systems engineering (David, 2005).

The scientific challenge is thus to provide languages and modelling tools adapted to each part of the modelling project, despite the data heterogeneity and the variety of the processes. This challenge has two dimensions: on the one hand, the capacity of modelling to equip the processes, through the definition and the formalization of their invariants; On the other hand, the study of the conditions of use of models in practice, always evolutive and uncertain.

The Formal Concepts Analysis (FCA) (Ganter, 2004) is a useful and powerful tool to formally describe the links between any objects. This couple forms a formal context. This method is based on the lattice theory (Wille, 2009), which can be used to solve problems of extracting tacit knowledge from formalized systems. An extension of the FCA mechanisms has been introduced in (Rouane, 2013) and called Relational Concept Analysis (RCA), where the focus is on data sets compatible with the Relative Entity Model (ER) or, alternatively, with the RDF (Resource Description Framework). This is a method for extracting conceptual knowledge from multi-relational data. This kind of approach inscribes itself in the Multi Relational Data Mining (MRDM) domain.
The RCA method is not limited to the extraction of knowledge of separate contexts: it aims to express knowledge by inter-operating the semantics of different contexts, that is to say that in addition to extracting the knowledge of a context, the data contained in the other contexts are used in order to enrich the extraction of knowledge.

Scientific proposal:
Our proposed methodology is based on **applying FCA and ML algorithms to predict the impact of AM process parameters on the eventual quality of the manufactured AM part.** Such a prediction would give the actionable information about the factors that come into play while producing an AM part. That actionable information will be based on a variety of in-process sensor data that must be fused before running the ML algorithm/tool or the RCA method. By using ML algorithms, we would train data coming from AM process sensors to create that actionable information. The input sensor data could be in different formats such as images, metrics, 3D models. Other input information would include material properties, current process parameters, and scan patterns among others.

This study will explore various types of algorithms including descriptive, diagnostic, predictive, and prescriptive. Based on the input type, RCA methods and advanced ML techniques such as Artificial Neural Network (especially Deep Neural Network and Convolutional Neural Networks) would be applied to analyse input information and extract association rules. **These association rules would be set as knowledge and represented in various formats. This output would be stored in a knowledge base so we can keep track of any changes to existing knowledge. This knowledge base could be then queried through a tool created to get prediction and make decisions while creating parts using AM processes.**

The AM input data is characterized by multi-modal (CAD model, material property, process control, and monitoring data), multi-rate, and multi-scale. It is vital that the input data is understandable by the algorithms that will extract the AM rules. A methodology would be developed in order to first represent the data, then fuse it when necessary, and finally integrate it depending on the input type. Methodologies would also be developed to represent the extracted rules into knowledge.

Mathematics and physics-based models would be used as a foundation for managing AM data for the use of AI algorithms. To do so, the following outputs would be made:

- Mathematical representation of the different type of data
- Methodology to represent fuse and integrate AM data for the use of AI algorithms and RCA methods
- Tools and techniques using AI/RCA to extract rules from AM data
- Methodology to transform the extracted rules into knowledge
- Methodology to represent, formalize and integrate knowledge data
- Tools with physics-based AM models, advancing the prediction capability
- AI solutions enabling decision making for AM parts based on the predictions

Aims:

The goal of this research would be to identify, formalize, develop and validate AI-based methodologies for discovering and formalizing knowledge based on AM data to make predictions during the creation of the part. The predictions will help improve fabrication decisions, produce high quality parts, and also minimize production costs. The proposed methodology towards the quality improvement for AM products would guide AM industries in the direction of AM decision making and adoption.

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