# Artificial Intelligence in Advanced Manufacturing

**Gianluca Buffa, Livan Fratini, Salvatore Gaglio, Marco Morana**
Università degli Studi di Palermo, Dipartimento di Ingegneria
Viale delle Scienze, Ed. 6,8 – 90128 – Palermo
{gianluca.buffa, livan.fratini, salvatore.gaglio, marco.morana}@unipa.it

## Abstract

In recent years, more than ever before, Artificial Intelligence has driven the transformation of society towards a *smart* direction. Among the several areas affected by this change, industrial production is certainly one of the most impacted. The unit of the CINI AIIS Laboratory at the University of Palermo works on the topic of Industry 4.0 with a research team that brings together competences from the artificial intelligence and production engineering fields. This contribution highlights the characteristics of the research conducted, the results obtained and the future prospects.

## 1 Research Experience

According to recent analyses [Bughin et al., 2021] provided by the McKinsey Global Institute, 50% of companies that embrace AI over the next five to seven years have the potential to double their cash flow with manufacturing leading all industries due to its heavy reliance on data.

Data produced during industrial production processes represent an essential source of information for the realization of a competitive smart industry. One of the most relevant areas in which artificial intelligence methods can be adopted to support manufacturing production is certainly the optimization of process parameters, whose variation drastically impacts on the physical properties of the finished products, and therefore on their quality.

The Palermo unit of the CINI AIIS Laboratory is active on the topic of Industry 4.0 with a research team that brings together the expertise of people operating in the fields of artificial intelligence and production engineering, with particular reference to additive manufacturing.

Industrial applications of artificial intelligence have always attracted the attention of researchers working in different fields. In [Ardizzone et al., 1991] a cascaded neural network made up by 2 stages was proposed in order to recover 3-D shape information from 2-D images. Given a quality control scenario made of video sensors, the first network implements the Boundary Contour System and extracts an approximated brightness gradient map from the image, while the second is a backpropagation architecture using the output of the BCS to perform an estimate of the geometric parameters of the objects in the scene under consideration.

One of the earliest research activities conducted by the group in the area of solid state welding processes was focused in the determination of the so called “process window” in deep drawing processes of steels, i.e., the blankholder force (BHF) path which permits to obtain the maximum height sound component avoiding both wrinkling and tearing [Di Lorenzo et al., 1999]. A design procedure was proposed in order to determine the optimal BHF path in an axisymmetric deep drawing process: in particular, a closed-loop control system based on the fuzzy reasoning was set up and interfaced with a finite element method (FEM) code.

Research conducted on neural networks [Augello et al., 2019] allowed to identify new strategies to design networks with a high generalization capacity. In [Gaglio et al., 1999] a feed forward neural architecture (αNet) that can learn the activation function of its hidden units during the training phase is presented. The automatic learning is obtained through the joint use of the Hermite regression formula and the CGD optimization algorithm with the Powell restart conditions. This technique leads to a smooth output function of αNet in the nearby of the training points, achieving an improvement of the generalization capability and the flexibility of the neural architecture.

In [Fratini et al., 2007] neural networks were adopted in order to predict the average grain size in Friction Stir Welding (FSW) processes of AA6082 T6 aluminum alloys, a properly trained neural network was linked to the FEM model of the process. The network, which took as inputs the local values of strain, strain rate, and temperature, was trained starting from experimental data and numerical results. The obtained results showed the capability of AI in conjunction with the FE tool to predict the final microstructure in the joint section. The performance of the NN were compared to a simple analytical expression depending on a few material constants in FSW of AA6082-T6 and AA7075-T6 aluminum alloys demonstrating the higher potential of the AI tool in the prediction of complex, multi variable dependent phenomena [Fratini et al., 2008]. To further assess the capability to generalize of the AI tool, a NN was trained starting from experimental data and numerical results of butt joints and then tested on further butt, lap and T-joints. The obtained results show the capability of the AI technique in

conjunction with the FE tool to predict the final microstructure in the FSW joints [Fratini et al., 2009]. NNs were also used to predict mechanical properties and microstructural during FSW of dual phase titanium alloys [Buffa et al., 2012]. In particular, two neural networks were designed and properly trained on the basis of experimental data obtained at the varying of the rotational and advancing speed of the tool. The developed artificial intelligence tools were linked to the 3D FEM model of the process in order to directly utilize the main field variables as input. The results, in terms of local microhardness values and local phase of the utilized Ti6Al4V titanium alloys (i.e. Fully lamellar, Duplex and "Parent material" microstructure, i.e. equiaxed α grains outlined by β phase and prior β grains) were compared to the experimentally measured ones obtaining a good agreement.
NN were also used to predict the bonding occurrence starting from the results of specific numerical models developed for different manufacturing processes, i.e., Friction Stir Welding, Porthole Die Extrusion and Roll Bonding [Buffa et al., 2012]. Both sound and not welded joints were produced. The Plata-Piwnik criterion was used in order to define a quantitative parameter taking into account the effectiveness of the bonding. A neural network was developed which was able to predict, starting from the evolution of temperature, strain, strain rate and pressure on the bonding line, the occurrence of the solid bonding as well as a quantitative parameter Q providing information on the "quality" of the weld. Excellent predictive capability of the network is obtained for each process. Finally, a similar approach was used for the prediction of bonding in Linea Friction Welding (LFW) of AA6082-T6 aluminum alloy [Buffa et al., 2016]. The NN, integrated in the FEM environment, was designed in order to calculate both a Boolean output, indicating the occurrence of welding, and a continuous output, indicating the quality of the obtained solid-state weld. The analysis of the obtained results allowed three different levels of bonding quality, i.e., no weld, sound weld and excess of heat, to be correctly identified and predicted.

One of the most interesting perspectives on the use of AI tools in advanced manufacturing processes envisages the Additive Manufacturing (AM) technologies. AM is a new way to operate where the object is fabricated layer by layer from a CAD model without any geometry limitation, thus promoting the production of complex parts. Moreover, AM technology do not require additional resources like coolants, cutting tool, fixtures, resulting in resource efficiency and production flexibility. Another advantage is to produce low waste and to have a low environmental impact. All these factors make AM suitable for the fabrication of metal parts with a disruptive level of innovation with respect to conventional approaches. However, due to the high number of processing parameters, a high number of experimental trials should be required to make robust and reliable process optimization. In this way, the use of AI tools, for example considering the integration between machine learning and evolutionary computation for prediction-optimization of AM processes, would contribute significantly in a faster and wider diffusion of these processes for industrial applications.

## 2 Research Unit

The research unit of the University of Palermo involves people with knowledge in the fields of information processing systems (i.e., artificial intelligence, distributed systems, data analysis) and materials processing technologies and systems, material transformation and manufacturing.
To be more specific, the research topics of the Artificial Intelligence Laboratory, directed by Prof. Salvatore Gaglio, includes knowledge representation models, probabilistic inference, multi-objective constrained optimization, machine learning, deep learning. The Manufacturing Technology Group (MTG) directed by Prof. Livan Fratini, studies the processes of transformation of traditional and innovative materials for the realization of manufacturing products and aims at reaching an effective and consistent innovation of products and processes. The group has several laboratories which allow to carry out precise experimental and numerical campaigns.
The competences of the unit are proved by a high-quality scientific production, as long as the participation in several projects, such as FRASI - *FRamework for Agent-based Semantic-aware Interoperability* (FAR MIUR D.M. 8 agosto 2000), Bigger Data (D.D. MIUR n. 2690 dell'11.12.2013, Piano di Azione e Coesione), SeNSori - *SEnsor Node as a Service for hOme and buildings eneRgy savIng* (Industria 2015: Bando Nuove Tecnologie per il Made in Italy), THALASSA - *TecHnology And materials for safe Low consumption And low life cycle cost veSSels And crafts* (PON R&I 2014-2020), TITAFORM - *Precision Hot Forming, development of innovative hot-forming processes of aeronautical components in Ti-alloy with low buy/fly ratio* (PON 2007-2013).

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