The role of Artificial Neural Network in the covid-19 era to support manufacturing Industry resilience

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Abstract: The Covid-19 pandemic has impacted, and in some cases disrupted, the global supply chain (SC)s thus causing a widespread interruption of operations and shortages of raw materials. As a snowball, in a globally interconnected world, such problems have been gradually amplified while moving downstream SCs. Both academia and business have provided suggestions to support companies to overcome the challenges they were facing. However, there is still no consensus regarding what and how technologies could support practitioners to become more resilient. In this research, the authors clustered 3 areas of interest in response to the issue abovementioned: 1) Approach to activities, 2) SC enhancement and 3) Digitalization. Hence, these clusters were detailed into solutions to be adopted that support companies in achieving a resilient network. In particular, the authors focused on how Artificial Neural Networks (ANNs) may support manufacturing firms to solve the challenges they faced throughout the pandemic. Hence, this research aims at proposing an updated framework about the state-of-the-art of ANN applications in manufacturing, proposing twelve fields of application to support operations. These algorithms must be integrated with seven technologies: Industrial Analytics, Additive Manufacturing (AM), Process Management, Advanced Automation, Cloud Manufacturing (CM), Industrial Internet of Things (IIoT), Advanced Human Machine Interface (HMI), and Digital Twin (DT) and related applications. Finally, the research aims at suggesting a prioritization of the solutions to be introduced within companies, identifying smart manufacturing technologies as priorities in building a more resilient network, all stand out Additive Manufacturing, Digital Twin and Industrial Internet of Things.

Keywords: Artificial Neural Network, Covid-19, Resilience, manufacturing

I. INTRODUCTION

Covid-19 pandemic has disrupted most of global value chains thus leading to cascade interruption of operations, shortage of raw materials and lengthening of lead times and costs in most of industrial sectors [1]. Historical data prove that pandemics or other natural disasters represent a major threat for supply chains continuity. Fukushima’s events are another recent example supporting this. As the Fig. 1 shows, which depicts the GDP Production of the European Union and their main countries, the world has been hardly hit mainly during the first wave of the pandemic, when it was completely unprepared for the management of both the health and the social crises occurred.

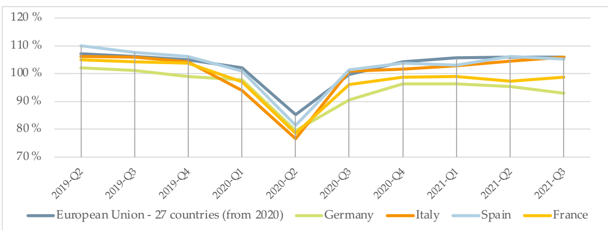

Fig. 1 Evolution of EU countries’ GDP

Focusing, for instance, on aerospace industry, civil aviation dropped in March 2020 by 86,1% with respect to 2019 and by 92,8% in mid-April, the time window during which many European countries activated restriction countermeasures. During the second wave, the values reached a peak of -70% between September and November. To sum up, the European demand for aerospace manufacturing industry decreased by 43% in 2020. According to [2] it is possible to build a resilient supply chain thanks to three levers:

1. The first one is by adopting better risk management strategies and risk awareness.
2. Value chain transparency is the second way to get it with the help of digital technologies.
3. Promoting agility is a third way to get a resilient value chain.

In this scenario, Industry 4.0 and digital technologies proved to be a useful, yet indispensable, lever to overcome or at least mitigate the impacts brought by the pandemic and the necessary measures undertaken to contain it. In particular, the authors have devoted their research on Artificial Neural Network (ANN) applications. ANN are a subset of machine learning techniques. Essentially, they are Artificial Intelligence (AI) systems based on simulating connected “neural units", loosely modelling the way that neurons interact in the brain [3], [4]. As stated by [5], *"ANN are popular machine learning techniques that simulate the mechanism of learning in biological organisms. The human nervous system contains cells, which are referred to as neurons. The neurons are connected to one another with the use of axons and dendrites, and the connecting regions between axons and dendrites are referred to as synapses. [...]. The strengths of synaptic connections often change in response to external stimuli. This change is how learning takes place in living organisms."* There is also a recurrent distinction into this paper among ANN, namely:

1. Feedforward networks, where signals propagate in only one direction from an input stage, through intermediate neurons, to an output stage
2. Feedback networks, where signals may propagate from the output of any neuron to the input of any neuron.

Considering the novelty of the emergency and the still evolving trends of the covid-19 outbreak, the authors have focused their work specifically on the economic implications within the manufacturing industry.

II. Research objective and questions

The call for countermeasures to face the overall disruption of value chains led focal companies on the one side rethink of new SC topologies for the medium-long term and, on the other side, look for more flexible configurations able to better respond to unexpected events. In this sense, the keyword that better summarize this aim is resilience, or rather, *"the ability of an organization (system) to keep or recover quickly to a stable state, allowing it to continue operations during and after a major mishap or in the presence of continuous significant stresses"* [6]. Hence, this research aims at exploring how the ANN applications could enhance manufacturing resilience. The aim is trying to take inspiration from the criticalities emerged during this phase to resolve them by adopting ANN. For this reason, the leading research questions that drove the research are RQ1: "What is the state-of-the-art of the application of Artificial Neural Network in manufacturing?" and RQ2: "Do Artificial Neural Networks support manufacturing resilience through Industry 4.0 technologies?". In this direction, literature has provided valuable analysis of the use of ANN for the purposes expressed in the RQs [7]–[11]. However, such contributions turned out to be specific to a limited set of Industry 4.0 technologies or a limited number or sectors thus lacking an overall perspective of of ANN might be applied in manufacturing to foster resilence.

III. Methodology of the work

Starting from the concept of AI, providing a brief framework of what AI is and how it is spread among manufacturing companies, the goal is to analyze the implications of Covid-19 on manufacturing and operations and then going deeper until how ANN can support and overcome the criticalities emerged during this pandemic. Firstly, as already provided in introduction, a brief overview of what happened in 2020 worldwide in manufacturing is provided. Then, the paper proceeds with an introduction of what is an ANN, and then, starting from the criticalities emerged, it will analyze possible applications trying to update the framework and by always considering the weaknesses emerged from the pandemic. To achieve the research objectives and therefore answer to the research questions, both scientific literature in Scopus, Google scholar (mainly to get definitions) and the reports published by the main consulting firms have been used (Fig. 2).

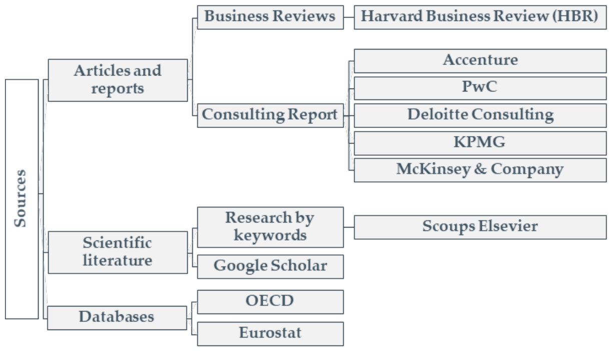

Fig. 2 Sources investigated

The academic literature has been investigated through a systematic literature review (SLR) performed on Scopus while, due to the lack of a peer-reviewing approach, Google Scholar has been mainly used to collect ancillary documents, according to the snowball procedure, and definitions. The authors chose the following keywords to conduct the review: "Artificial Neural Network", "Additive Manufacturing", "Analytics", "Human-Machine Interfaces", "Digital Twin", "Internet of Things", "Cloud manufacturing" and "advanced automation" to investigate the application of ANN in Industry 4.0 (I4.0) context. To investigate the application of ANN in traditional manufacturing the authors chose the following keywords: "Artificial Neural Network", "Engineering Design", "Scheduling", "Monitoring and Diagnosis", "Planning", "Process modelling and Control". "Group Technology" and "Quality assurance". The selection criteria followed the scheme reported in Fig. 3.

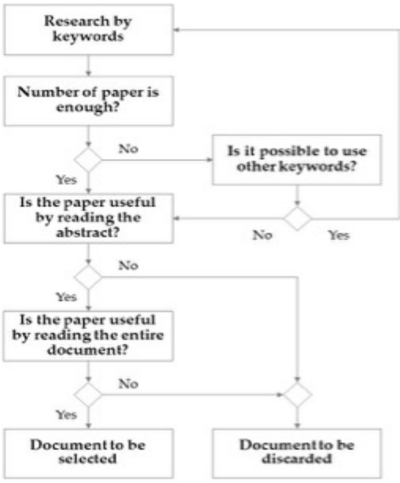

Fig. 3 Approach to the Systematic Literature Review

Overall, 564 documents have been found in literature while, after preliminary screening of double results and a selection of relevant contributions, 55 papers have been considered eligible for the analysis.

IV. Literature review

Neural networks have gained a lot of visibility in recent years, due not only to their ability to replicate human reasoning but to be able to process an enormous amount of data. The topic of big data has recently emerged. So, although they have been studied for decades, since the second half of 1900, *Artificial Neural Networks* find their full application today with the available technologies. The chapter is thus divided into three sections: Paragraph A contains a brief, since it is considered as well consolidated, analysis of the applications of ANN within traditional manufacturing, to capture the current boundaries of application and find any evolutions, starting from the field of applications identified by [12], namely: Engineering Design, Group Technology, Monitoring and Diagnosis, Process Modelling and Control, Process Planning, Quality Assurance, Manufacturing Scheduling. Paragraph B aims to find the contribution that ANN gives to I4.0 technologies, the ones emerged in the last decade to fill the productivity gap within the I4.0 paradigm, trying to clarify if these are well supported by ANNs and they can support the creation of a resilient manufacturing ecosystem. In the last section the results of the analysis will be analyzed and discussed. The I4.0 technologies selected for the investigation are those listed by [13], namely: Digital Twin, Industrial Internet of Things, Cloud Manufacturing, Industrial Analytics, Advanced Human-Machine Interface, Additive Manufacturing and Advanced Automation. Finally, the discussion regarding the knowledge collected is provided in paragraph C.

A. ANN within Traditional Manufacturing

Already at the end of the 2000s, applications of ANN in the industrial field were known. The following section will shed light on industrial applications of Neural Networks. [12] still turns out to be one of the most relevant state-of-the-art research available hence, this research used it as starting point to track the evolution path and update it. Fig. 4 summarizes the proposed framework:

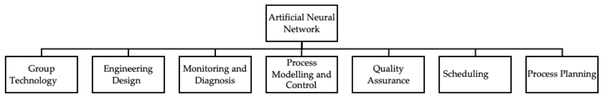

Fig. 4 Artificial Neural Network and Traditional Manufacturing applications

These are the 7 identified clusters according to which it is possible to decline neural network application in a manufacturing context. Starting from the 1995, research, but mainly technology, evolved making available a wide range of opportunities to be coupled with neural network in manufacturing. Neural networks, in fact, since their theorization in the mid-1950s, have found their full application today thanks to the available technologies. In this path, the goal is to describe how they were designed, how they evolved and update the framework by introducing new fields of application. Looking at Engineering design cluster, [14] theorizes how it is possible to reduce the computational cost in engineering design, often approximated through mathematical models called metamodels, with the aid of causal neural network that allows to obtain reasonable improvements in terms of accuracy and cost reduction. Here, the main purpose of the causal-ANN is to overcome the high computational cost challenge of ANNs caused by the unknown structure of the network. Group Technology (GT) is a methodology aimed at getting similarities among parts and machines to optimize operations. Thanks to GT, it is possible to carry out part classification and part family formation following two different approaches: based on geometrical features or based on technological ones. The goal behind GT principle is to group together those similar products to exploit the economies of scale and then increase the productivity thanks to a significant reduction of the changeover. [15] proposed a two sequence-based neural network approaches with the goal of minimizing both transportation costs within the cell and across them by using similarity coefficients between pairs of machines. [16] worked to group parts into different families through the image captured by the vision sensor and a Fuzzy Neural Network. [17] applied a new Self-Organising Neural Network approach to forming cells creating families of parts (the input nodes) were and then assign them to machines. The output layer is constituted by families. The weighted similarity coefficients were calculated in the first stage and the parts were grouped together. [18] integrated for the first time in a consistent way the operating time into a hybrid neural network called fuzzy ART K-means clustering technique that wanted to solve the part machine grouping problem into a manufacturing cell. Concerning monitoring and diagnosis, [19] adopted faults codes to train an Artificial Neural Network and then get monitoring on bearings. To train and test the ANN, coded faults are used as output data. According to [20], *“ ANN-based recognizers have been developed for monitoring and diagnosis bivariate process mean shift in multivariate statistical process control”.* Outside of the boundaries of manufacturing, [21] applied ANN, and many AI algorithms, to classify Electrocardiogram signals. A Graphical User Interface (GUI) supported the user in results consulting by the aid of a laptop or a network of connected smartphones in order to transfer the diagnosis with the estimated results up to a remote-control room. In terms of process planning, since 1993 ANN have been adopted for control into a discrete manufacturing system [22]. [23] adopted ANN algorithm to estimate machines energy consumption. The network was composed by four input neurons, spindle speed, feed rate, depth of cut and width of cut, one hidden layer composed by nine neurons and cutting energy as output. [14] proposed a genetic algorithm-based ANN model for the turning process. This model aimed to obtain a timesaving solution that satisfied all the accuracy requirements. [24] tried to solve a job shop scheduling problem through an ANN where the output is the priority of each task. In [25] neural networks are applied “*for automated sound signaling device quality assurance for embedded industrial control applications”*. The ANN was trained through data labelled by experts in fault detection and performs into a real time microcontroller whose purpose was to substitute manual inspection by classifying the sound into “Good”, “Faulty” and “Unknown”.

B. ANN within Industry 4.0

[26] provided wider research on ANN applications, and it is certainly useful to take inspiration from mainly for future inspiration.

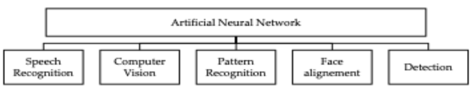

Fig. 5 Artificial Neural Network applications

ANN are suitable for the following applications:

- Speech recognition: Machine Learning (ML) algorithms have been widely applied in areas such as acoustic modelling and Automatic Speech Recognition (ASR);
- Computer vision: for computers to understand and process visual data such as video and images accurately and efficiently;
- Pattern recognition: which focuses on identifying the sequence in each input:
- Face alignment: in face alignment and recognition applications;
- Detection: especially in medical diagnosis.

According to [26], Manufacturing is the sixth field of application which benefits from neural networks, and these are used in the following way: 47% for Pattern Recognition, 37% Prediction algorithm and 16% Classification algorithm. [13] identified the following technologies as part of the concept of Smart Manufacturing: DT, CM, Industrial Analytics, HMI, AM, Advanced Automation and IoT. Concerning DT, the use of ANN in manufacturing context is mainly coupled with the opportunity to make prediction. Manufacturing and processing equipment use ANN by collecting real-time data to get the data integration among physical and information layer [27]. An attempt to integrate DT and ANN has been done by [28] where the DT itself is represented as an ANN model through its life cycle, while parts of them are represented as expert fuzzy rules during the process of creation. In [29] the use of Artificial Neural Networks is tested in a realistic Discrete Event System (DES) model of load-haul-dump vehicle operations of a production area to predict the distribution of random variables during the simulation, based on the values of covariates derived from the state of the model. This approach ensures more accurate modelling and maintains stochastic behavior in the model by arranging arbitrary distributions. In [30] ANN are used to be compared with the real-time data collected. This model uses real-time data to get the neural network. Thanks to real-time monitoring of both operational data of the DT and the sensors from the shopfloor, it is possible to monitor the wear of the equipment and its fault prediction. [31] applied IoT technologies in the wood SC. In this model raw and filtered signals are used as inputs to train an ANN. In [32] the goal of their work was simulating the cavitation with IoT technologies, which is a typical phenomenon managed in an inefficient way with the available methods. In fact, the data collection and acquisition are performed by using IoT, while ingestion into the cloud and data analysis are executed with ANN as the ML algorithm. Already, [33] planned to adopt ANN to enable collaborative Supply Chain Planning (SCP). An agent-based SC network has been broken down into three ANN: (i) supply network, (ii) production network and (iii) delivery network, to pursue complete order fulfilment through the SC with the aim of matching customer requirements and agents’ goals. Here, there are listed the three opportunities enabled by CM and ANN: Real Time Scheduling [34], Mass Customization [35] and Simulation workload [36]. Concerning Industrial Analytics, [37] provided a machine learning-based decision support system to create a data warehouse where ANN oversees estimating failure time of a trained part. In [38] ANN were used to predict flow time procedure to dynamically calculate lead times. Additionally, it implemented a safety lead time to incorporate the underlying cost ratio between finished inventory holding and backorder costs in the order release model. In [39], starting from a dataset containing almost 5942 pellet images, it successfully applied image classification to a Deep Neural Networks (DNN) in a factory where pellets were daily produced and the most relevant features could be detected through pixels. Regarding AM, [40] applied neural networks to an infrared camera, and a laser scanner, for the process of Directed Energy deposition (DED), to estimate the melt pool depth defined as "the distance from the deposited surface to the deepest point of the melt pool." [41] compared the performance of different neural networks in estimating construction times. In [42], ANN was used to get the optimum value parameters (e.g. layer thickness, orientation, and extruder temperature) of fused deposition modelling (FDM). In the study, neural network performed better in comparison with Taguchi method. [43] compared the potentiality of adoption decision tree and ANN in part classification in CAD systems that are a key technology in AM. Also [44] adopted ANN for part classification from user inputs and CAD data. In this research, three sub-systems were developed: ANN-based expert system, cyber-interface IoT simulator and dynamic machine identification system. An AM expert system by the aid of ANN used CAD part files as input to get both design information and user specifications as outputs. Finally, concerning Advanced Automation, many of the papers proposed suggest the adoption of neural networks to solve urban and suburban traffic problems. In [45], a deep learning algorithm analyses image features and train the neural network. Starting from actual images of obstacles, the classification algorithm can predict following obstacles. Also, in [46] the ANN algorithm is used to avoid obstacles and control the path of a driverless vehicle equipped with 3 cameras. Videos are converted into an array of images which is used as to train the ANN algorithm "on how to stay in a lane as well as avoid obstacles, in addition, to classify different traffic signs and take action accordingly". [47] exploits ultrasonic sensors to establish next moves of the vehicle.

C. Literature Review Discussion

From the literature analysis, it is possible to assess the updated framework which meets that distinguish between technologies and applications of ANN in manufacturing. In particular, as shown in Fig. 6, the authors have identified 2 main layers. The first refers to technologies enabled or supported by ANN while the second layer aims at better contextualizing in which domains, namely the application, ANN plays a role in enhancing the related technologies. The layers conjectured are structured as follows:

1. Technologies: Industrial analytics, Additive Manufacturing, Advanced Automation, Cloud Manufacturing, Industrial Internet of things, Human-Machine Interface, and Digital Twin
2. Applications: Predictive Maintenance and Quality Management (both as applications of Industrial Analytics), Engineering and Design, Process Modelling and Control, Process Planning, Autonomous Vehicle and Collaborative Robotics (the last two as applications of Advanced Automation), Real-Time Scheduling, Mass Customization and Simulation Workload (the last three as applications of Cloud Manufacturing), Training (as application of HMI) and Group Technology.

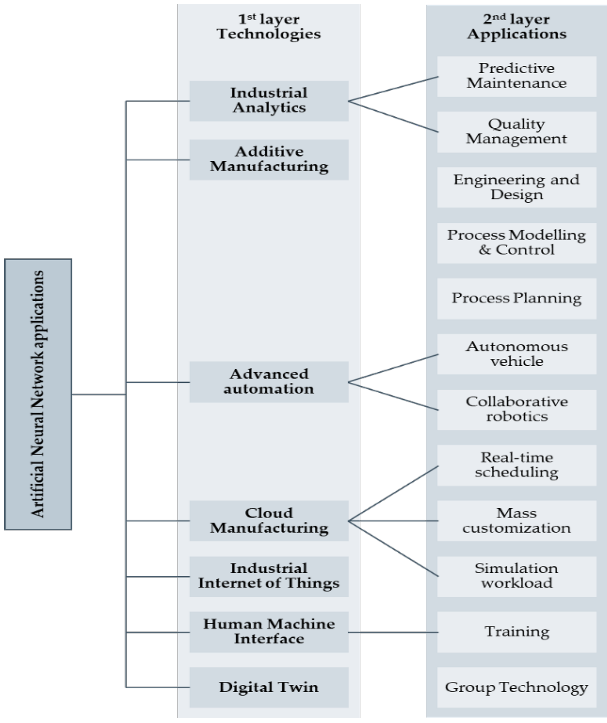

Fig. 6 Updated framework

For the creation of this new framework, some novelties have emerged from the analysis of the literature. Fig. 6 includes technologies in the first layer that, in some cases, are self-explaining (e.g. Digital Twin), others need to be declined (e.g. Cloud Manufacturing) through a second layer of the applications. The analysis of the literature allowed to state that the technologies, with different maturity level, belonging to the Smart Manufacturing framework can be included in this first layer.

V. CONCLUSIONS

The research carried out, which began with an analysis of the implications of the pandemic focused on manufacturing, allowed the identification a new framework to classify ANN uses and supporting I4.0 technologies that guide the construction of a more resilient manufacturing. To conduct the research, the following RQ were formulated, RQ1: "What is the state-of-the-art of the application of Artificial Neural Network in manufacturing?" and RQ2: "Do Artificial Neural Networks support manufacturing resilience through Industry 4.0 technologies?". These were addressed through contributions from both scientific literature and consulting reports. The analysis identified two main guidelines to generate the right conditions to be flexible and ready to face criticalities. The research then dealt with the applications of ANN in manufacturing, taking inspiration from a state-of-the-art written in 1995 to investigate the traditional applications and analysing the research progress. After that, having grasped the key role of I4.0 solutions in the construction of a resilient manufacturing investigating the actual link between both neural networks in smart technologies and applications, verifying that ANN well support them with different shades of maturity. 7 technologies, namely Industrial Analytics, AM, Advanced Automation, Cloud Manufacturing, IoT, HMI and DT, and 12 applications have thus been identified. This research updates the 1995 state-of-the-art applications of ANN in manufacturing, defining a clear framework divided into technologies and applications that allows to support manufacturing companies in creating a resilient network and then gain flexibility that aid companies in facing fast recovery in case of disruption like the one happened with Covid-19 pandemic. This new framework states that ANN well supports smart manufacturing technologies (1st layer: DT, IoT, CM, Industrial Analytics, HMI, AM and Advanced Automation) in Fig. 6. In the second layer of Fig. 6, to create a resilient network, it was included a mix of both smart and traditional applications: Predictive maintenance, Quality Management, Engineering and Design, Process modelling & Control, Process Planning, Autonomous vehicle, Collaborative robotics, Real-time scheduling, Mass Customization, Simulation Workload, Training and Group Technology. Within this layer, while smart manufacturing applications provide a huge support to achieve the resiliency, the traditional ones are assumed as needed condition to perform in the field. The main limitation regarding the contribution proposed refers to the complete reliance on literate analysis. In this sense, an experimental approach based on survey and case studies may represent a valuable continuation of the study. One possible opportunity deriving from this research concerns the quantitative and no longer qualitative assessment of the targets identified as priorities, measuring in a timely manner the contribution of each technology in achieving those given objectives. From the analysis of the literature and the conclusions it is emerged the necessity of software applications supported from the neural networks in a position to supporting the visibility of the supply. In fact, the adoption of smart technologies, such as the IoT, intelligent sensors and the other technologies mentioned in this work, can enable, and strengthen this capability of addressing supply chain risk and increase resilience.

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