AI-driven models for Cold Spray deposition: transforming additive manufacturing for sustainability

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Abstract

The integration of Artificial Intelligence (AI) techniques holds promise for advancing the optimization of industrial processes, such as the use of Cold Spray (CS) in the field of Additive Manufacturing (AM). This paper explores the intersection of AI and Cold Spray technology, highlighting its potential to enhance various aspects of AM, including material deposition, surface properties, and process efficiency. Through the utilization of Machine Learning (ML) and Deep Learning (DL) techniques, AI facilitates the analysis of vast datasets encompassing parameters such as powder properties, substrate characteristics, and process conditions, thereby enabling the identification of optimal deposition strategies. Furthermore, AI-driven predictive models offer insights into the complex interactions between process variables, leading to improved understanding and control of the CS process.

Keywords

Artificial Intelligence, Coldp Spray, Manufacturing

1. Introduction

Industry 4.0, often referred to as the Fourth Industrial Revolution, represents the integration of digital technologies into industrial processes to create smart factories and enable more efficient production systems. This transformation involves the use of advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), robotics, big data analytics, and cloud computing to enhance automation, connectivity, and data exchange in manufacturing. Industry 4.0 aims to improve productivity, flexibility, and customization while reducing costs and resource consumption [1]. A crucial aspect of Industry 4.0 is Additive Manufacturing (AM) a transformative manufacturing process that builds objects layer by layer from digital designs. Unlike traditional subtractive methods, which remove material from a solid block, additive manufacturing adds material precisely where needed, allowing for intricate geometries and customization. This technology has revolutionized various industries, from aerospace and automotive to healthcare and consumer goods, by enabling rapid prototyping, on-demand production, and the creation of complex structures impossible with conventional methods. AM offers benefits such as reduced material waste, faster time-to-market, and the ability to produce lightweight and optimized components [2]. As it continues to advance, AM holds the potential to reshape the future of manufacturing by offering greater design freedom, cost efficiency, and sustainability. Sustainability is now imperative in modern manufacturing, responding to urgent global concerns about environmental degradation and decreasing resources. AM can enhance material utilization, reduce environmental footprints throughout product lifecycles, and enable superior engineering functionalities compared to conventional methods. This holds potential for significant time and cost reductions in producing custom [3]. Advancing sustainability in AM demands a comprehensive approach that extends beyond technical aspects.
Among additive technologies, Cold Spray (CS) is gaining increasing attention owing to its distinctive attribute as a cold or non-thermal process, facilitating the treatment of a wide array of materials, including those sensitive to temperature fluctuations, such as nano-crystalline metals or amorphous materials.

Integrating AI models with AM represents a crucial advancement in the evolution of Industry 4.0, offering substantial benefits in quality control and beyond. By using AI models such as Machine Learning (ML) and Deep Learning (DL) models, manufacturers can optimize production processes, predict potential defects, and ensure consistent product quality [4]. These models can analyze vast amounts of data collected from sensors and cam-

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eras embedded within AM systems, enabling real-time monitoring and proactive adjustments. Specifically, the process of CS remains partially manual and uncontrolled. AI models offer advantageous roads to overcome this challenge by facilitating experimentation and expediting the integration of Low-Pressure CS into industrial workflows. Additionally, AI-powered predictive maintenance can minimize downtime and maximize operational efficiency, further driving sustainability by reducing waste and energy consumption. As such, the synergy between AI and AM can revolutionize manufacturing practices and propel us toward a more sustainable future.

2. Research Fields

The primary objective of our research is to design an innovative methodology for computer-aided manufacturing (CAM) systems by leveraging ML and DL approaches to develop ad-hoc models. These models attempt to use cutting-edge technology to discover the best combination of factors for CS coating techniques. The advanced parameter sensors used are several such as temperature, pressure, gas velocity, and optical and auditory sensors. Our research aims at the creation of automated decision-making systems for monitoring and control, allowing for the deployment of accurate spray strategies. By conducting experiments using a CS machine in real-world situations, our goal is to evaluate the effectiveness of our suggested ML approaches and obtain valuable input to improve the accuracy of our forecasting results. The findings obtained from this research have the capacity to improve sustainability and make a valuable contribution to the scientific literature by increasing the effectiveness and precision of cold spray coating processes.

These activities involve a multidisciplinary team from the University of Salerno and the University of Naples Federico II. The CAIS Lab [1], laboratory from Computer Science Department of the University of Salerno, provides important support in developing algorithms that require significant time and resources. Meanwhile, the University of Naples Federico II focuses its efforts on the thorough collection and organization of data.

3. Cold Spray

CS is an emerging technology for micrometer-sized powder deposition, increasingly utilized in additive manufacturing for creating individual components and repairing damaged parts. Among the advantages of CS is the fact that it mitigates thermal degradation and facilitates efficient deposition between the sprayed material and the substrate, thereby ensuring the integrity of the coating [5].

The CS process is governed by several factors. The size and composition of the powder particles determine the characteristics of the deposited layer and its adhesion to the substrate. Fine-tuning these parameters can optimize material properties and deposition efficiency. The selection of gas type, flow rate, and pressure controls the acceleration and direction of the powder particles during spraying. Adjusting these parameters influences coating density, adhesion strength, and deposition quality. The design and geometry of the cold spray nozzle play a vital role in directing the gas-particle mixture onto the substrate [6]. Optimizing nozzle parameters such as diameter, shape, and exit velocity ensures precise control over deposition conditions and coating morphology. The distance between the CS nozzle and the substrate, known as the standoff distance, affects particle velocity and impact energy. Adjusting this parameter optimizes coating thickness, uniformity, and surface finish [7]. By carefully adjusting these input parameters, manufacturers can tailor the cold spray process to produce high-quality coatings with desired material properties and performance characteristics, all while optimizing for time-consuming and cost efficiency. Fine-tuning parameters such as particle size, gas flow rate, nozzle design, substrate temperature, standoff distance, and powder feed rate not only ensures the quality of the deposited layer but also minimizes production time and resource usage. This emphasis on efficiency is critical for meeting production schedules, reducing manufacturing costs, and improving overall competitiveness in the market.
However, achieving the ideal combination of parameters and selecting their right combinations can be a complex and time-intensive task. This is where the use of AI models comes into play. By leveraging AI algorithms and machine learning techniques, manufacturers can analyze the amounts of data to identify the most effective parameter settings more quickly and accurately than traditional methods. This not only streamlines the optimization process but also enhances the overall efficiency of the cold spray deposition, leading to significant time and cost savings while maintaining or even improving the quality of the final product.

3.1. ML models for CS process optimization

CS, utilizing kinetic energy and operating at temperatures well below the melting point of metallic particles, presents a promising avenue for enhancing the surface properties of polymers. While extensively explored and utilized on metal substrates, the application of this technology to polymers remains relatively uncharted territory, and the underlying physics are not yet fully eluci-

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dated. This is particularly significant because the characteristics of the final coating, such as powder deformation or penetration depth, crucial for coating adhesion, are influenced by a multitude of factors. These factors include the properties of both the metallic powder and the polymeric substrates, alongside the specific spraying parameters employed in the process. Consequently, accurately predicting the behavior of metallic particles upon impact on various substrates remains a challenge. Developing a physical model capable of accurately representing the deposition processes of metallic particles onto nonmetallic substrates proved impractical. Validating such models would require the collection of extensive testing scenarios and outcomes using advanced tools, including sensors and high-speed cameras.

In this context, Machine Learning (ML) offers the potential to reduce the number of necessary experimental trials. However, when we used ML solutions, achieving precise predictions requires feeding the model with accurate and a large amount of data. Therefore, a viable approach could involve training the model with a combination of precise yet limited experimental data and computational data obtained from Finite Element models (FEM), which, while less precise, do not suffer from the limitations of experimental data. Consequently, in our work [8], we used a training dataset composed by 30% of experimental data and 70% of FEM data (mixed data) and a second dataset with only FEM data to train some ML models. The test dataset for both suggested models is fully made up of experimental data. Polyether-ether-ketone (PEEK) and Acrylonitrile butadiene styrene (ABS) substrates were chosen for the deposition process, including both unreinforced and long carbon fiber-reinforced variants. Spherical powders of copper, aluminum, and steel were supplied by LPW South Europe for this purpose. Depositions were carried out using low-pressure cold spray equipment (DYCOMET). The samples were positioned on a platform, with the spraying gun mounted on a robot (HIGH-Z S-400/T-CNC-Technik), which operated remotely and sprayed perpendicular to the substrates. These materials were chosen for their diverse properties and suitability for CS applications.

The input parameters for the strategies employed can be categorized into three main groups:

- *impact velocity*, which encompasses other process parameters such as temperature and pressure;
- *powder parameters (Yp)*, representing the yield strength of the powder material;
- *substrate parameters (Ys)*, indicating the yield strength of the substrate material.

The latter also take into account the presence of fibers. When positioned appropriately beneath a matrix layer similar in size to the powders, these fibers reinforce the substrate, modifying its yield strength.

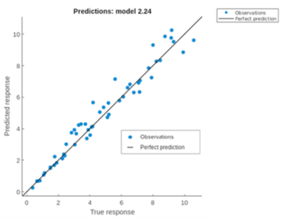
The output parameters under consideration are the *penetration depth* of the particle and the degree of *flattening*. In CS, penetration depth refers to the distance into the substrate material that the sprayed particles can penetrate and adhere to. This depth depends on various factors such as particle velocity, temperature, and material properties. Flattening, on the other hand, refers to the deformation of the sprayed particles upon impact with the substrate surface. It describes how much the particles spread out and flatten upon hitting the substrate. Flattening is influenced by parameters like particle velocity, temperature, particle size, and substrate material properties.

We employed three distinct ML models: Linear Regression (LR), Gaussian Process Regression (GPR), and Neural Networks (NNs). LR is a straightforward technique utilized to establish a linear relationship between variables. This relationship elucidates the functional link between the independent and dependent variables within a given dataset. Consequently, LR models the unknown or dependent variable as a linear equation based on the known or independent variable. Gaussian Process Regression (GPR), on the other hand, is a nonparametric Bayesian approach employed for regression tasks. It excels particularly with smaller datasets and infers a probability distribution model. The Neural Network (NN) used in our study is a three-layer function-fitting model trained comprehensively on the entire dataset. Following training, it can adeptly generalize an input-output relationship. To assess the efficacy of the ML techniques employed, we computed several performance metrics including Root-Mean-Square Error (RMSE), R-Squared, Mean Squared Error (MSE), and Mean Average Error (MAE). Figures 1-2 report the results for penetration depth and flattening predictions. The top models for the penetration on the test set are NN and LR for the flattening prediction for the mixed data.

By examining the results derived from training the model with FEM data, we were able to determine that the most accurate predictions on the test set for penetration and flattening were achieved using the GPR method. Specifically, the GPR model demonstrated enhanced penetration values while exhibiting a decrease in flattening performance. Figure 3 depicted the comparison between the performance of the models.

The conducted experiments indicate that the accuracy of the models improves with an increasing amount of available data. Specifically, the models demonstrate better fit to the data when trained on the mixed dataset. By offering an initial insight into the influence of parameters affecting coating deposition, the integration of ML seems to contribute to the optimization of the CS process.

Penetration depth prediction (NN)	
RMSE	0.5842
R-Squared	0.96
MSE	0.3413
MAE	0.413
Prediction Speed	~400obs\sec



Flattening prediction (LR)	
RMSE	1.8327
R-Squared	0.90
MSE	3.3587
MAE	1.4462
Prediction Speed	~3800obs\sec

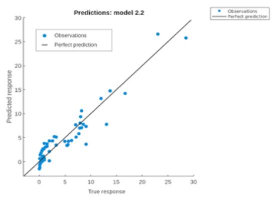
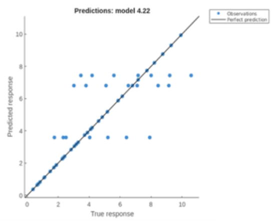


Figure 1: Results for penetration depth and flattening predictions on mixed data

Penetration depth prediction (GPR)	
RMSE	1.45
R-Squared	0.73
MSE	2.1026
MAE	0.7654
Prediction Speed	~2200obs\sec



Flattening prediction (GPR)	
RMSE	4.7387
R-Squared	0.34
MSE	22.451
MAE	2.0051
Prediction Speed	~1900obs\sec

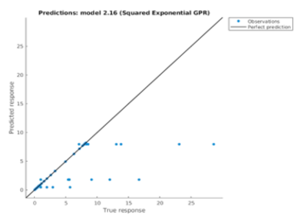


Figure 2: Results for penetration depth and flattening predictions on FEM data

3.2. Genetic Algorithm-Driven DL models: evolutionary approaches to improve CS deposition

In our point of view to elevate the deposition efficiency of CS across a spectrum of materials and to explore the the use of AI models, our attention focused on the integration of DL models. Through the integration of DL models, we aim to unlock new insights and capabilities that propel the field of CS towards greater efficiency, efficacy, and versatility. In this study [9], we had two primary objectives:

- firstly, to investigate various DL models aimed at augmenting automation capabilities within the domain of CS;
- secondly, we explored the employment of a genetic algorithm approach to refine the aforementioned DL models, with the specific aim of enhancing coating properties.

In this scenario, when evaluating potential substrate materials, our study examined a range of options including ABS, PEEK, and Polyamide PA66 (PA66). Furthermore, in selecting powders for the deposition process, we incorporated a variety of metallic options such as copper, aluminum, steel, and titanium. During the initial training phase, we employed two distinct types of datasets to develop our models. The first dataset, known as the mixed dataset, comprised a blend of 30% experimental data and 70% FEM data. Additionally, we utilized a second dataset consisting solely of FEM data, providing a more focused exploration of simulated scenarios. Subsequently, during the evaluation phase, our trained models tested using exclusively experimental data. As input and output parameters, we used the same of our previous work [8]. We employed DL models, specifically focusing on neural network models. These neural networks, inspired by the structure and function of the human brain, are adept at learning complex patterns and relationships in the data. In the development of these networks, we adopted a genetic algorithm approach. Genetic algorithms (GAs) draw inspiration from biological evolution, employing principles of natural selection and genetic recombination to find optimal solutions for complex problems. Traditionally, GAs are utilized to optimize algorithm parameters; however, in our specific scenario, we employed GAs to design the architecture of the networks. The process of GAs requires several steps: $initialization$, where potential solutions are randomly selected; $selection$, which identifies optimal parents based on their fitness; $crossover$, where genetic material is recombined to generate new solutions; mutation, introducing random changes to generate genetic diversity; and $evaluation$, which assesses the fitness of the solutions. Each of these steps plays a crucial role in guiding the evolutionary process towards identifying optimal solutions for complex problems. In this work, we presented two NN as best solutions: Wide Neural (WNN) and Trilayered Neural (TNN) Networks. WNN refers to an artificial neural network architecture that typically has fewer hidden layers but a substantial number of nodes in each layer. The TNN is a form of artificial neural network, also known as a single-layer perceptron, consisting of the input layer, one hidden

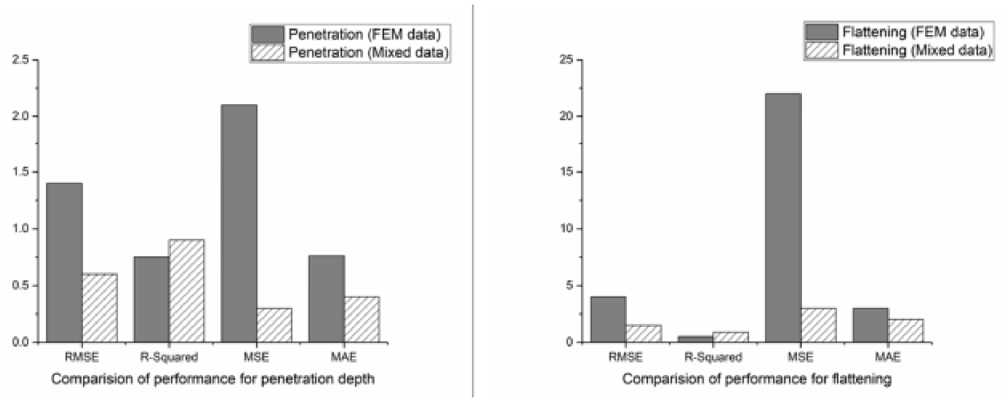


Figure 3: Comparison of the models

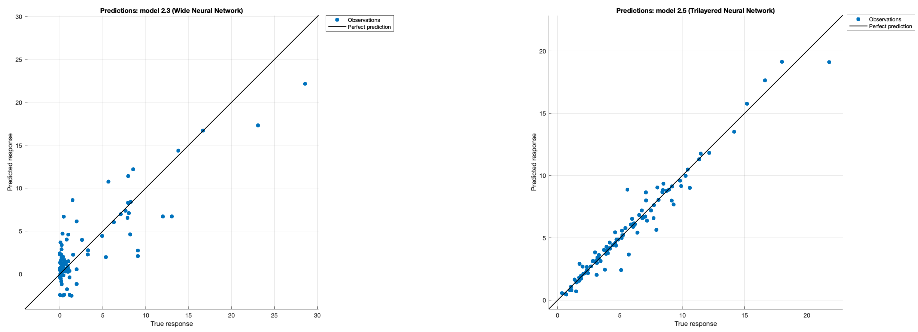


Figure 4: Results flattening (on the left) and penetration depth (on the right) predictions

layer and the output layer. To assess the effectiveness of the DL approaches, we computed several performance metrics, including the RMSE, R-squared, MSE, and MAE. For the flattening, the best results are obtained by the WNN. For the penetration depth, TNN reached the best values, but, except for the R-squared, all the values, on the test set, are high. Overall, the DL models achieved best performance for flattening (see Figure 4).

In our previous study, we evaluated ML algorithms using a mixed dataset. NN model excelled in predicting penetration on the test set, while LR proved optimal for prediction of flattening. To further comprehend our approach, we compared the outcomes of our earlier investigation with those obtained through the integration of GAs and we reported these results in Table 1 and graphically in Figure 1. Interestingly, the WNN demonstrated exceptional performance in predicting flattening, showcasing a marked improvement over previous results. However, it is important to note that for penetration prediction, the TNN constructed with the use of GAs exhibited a less favorable performance compared to our prior findings.

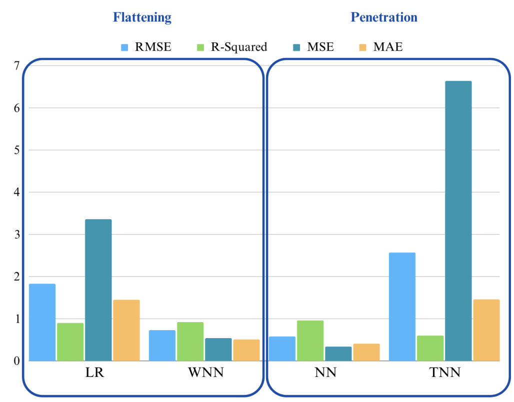


Figure 5: Comparison between ML and DL models

The conducted experiments underscore the potential

Table 1
Comparison between ML and DL models

Output	**Models**	**RMSE**	**R-Squared**	**MSE**	**MAE**
Flattening	LR	1.83	0.90	3.36	1.45
	WNN	0.73	0.92	0.54	0.51
Penetration	NN	0.58	0.96	0.34	0.41
	TNN	2.57	0.60	6.64	1.46

of DL techniques in predicting optimal parameter combinations, enhancing the efficiency and effectiveness of the coating process. With the introduction of the GAs to improve the design of networks, we can streamline the optimization of model architectures, reducing the need for manual hyperparameter tuning, which is often time-consuming and suboptimal.

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