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Modular implementation of artificial neural network in predicting in-flight particle characteristics of an atmospheric plasma spray process

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ABSTRACT

This paper presents a modular implementation of an artificial neural network to model the atmospheric plasma spray process in predicting the in-flight particle characteristics from the input processing parameters. The in-flight particle characteristics influence the structure and properties of the thermal spray coating and, thus, are considered important parameters to comprehend, simulate and predict the manufacturing process. The modular implementation allows simplification of the optimized model structure with enhanced ability to generalise the network. As well, the underlying relationship between each of the output in-flight characteristics with respect to the input processing parameters is explored. Smaller networks are constructed that achieves better, or in some cases, similar results. The training process is found to be more robust and stable along with fewer fluctuations in the values of the network parameters. The networks also respond to the variations of the number of hidden layer neurons with some definite trend. The predictable trend enhances reliability of the application of the artificial neural network in modelling the atmospheric plasma spray process and overcomes the variability and non-linearity associated with the process.

1. Introduction

Atmospheric plasma spray (APS) is a highly versatile thermal spray process used for the application of metal or non-metal coatings on a variety of candidate materials; e.g. metals, ceramics, composites and polymers (Fauchais and Vardelle, 1994; Pfender, 1988). APS helps in protecting a functional surface or improving the performance of the various materials onto which a coating is applied.

A greater degree of particle melting and relatively high particle velocity of the plasma spray process results in higher deposition density and bond strengths compared to most electric and arc spray coatings (Davis, 2004). Plasma spray commercial coatings and proprietary nanostructured coating bond strengths typically are 35 MPa and 80 MPa, respectively (Kim and Walker, 2007). A high droplet to substrate adhesion is achieved from the high particle velocity and deformation that occur on impact. The inert gas plasma jet may generate lower oxide content coatings than other thermal spray processes. APS has, thus, become popular in industrial applications.

In APS, a plasma gas mixture, which is generally a mixture of argon (i.e., the primary plasma-forming gas) and hydrogen (i.e., the secondary plasma-forming gas), is subjected to a high intensity direct current arc between 300 A and 700 A at about 40–80 V (Guessasma et al., 2002). The ensuing high enthalpy zone of partially dissociated and ionized gases operates as the process zone for feedstock. The feedstock material, generally a powder that is transported with a carrier gas, is injected into the plasma jet where it is heated above its melting point. The powder is, thus, simultaneously heated and accelerated towards the substrate.

The plasma jets are largely heterogeneous systems incorporating substantial radial and longitudinal variations of temperature and velocity. Over a radial distance of 30 mm (at atmospheric pressure in air), the temperature may drop sharply from 15,000 K to almost room temperature and the velocity may drop from 1500 m s^{-1} to several decades lower (Pfender, 1994). The

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feedstock particles, under ideal conditions, pass through the core of the plasma jet, which is the hottest portion, to provide maximum exposure for complete melting and acceleration of the particle.

The inertia of the incoming feedstock powder distribution defines its path in the plasma jet. The particles, on striking the substrate, flatten and solidify in a few micro-seconds to form thin lamellae, often called splats. There are a large number of parameters that influence splat formation (Alamara et al., 2011). The coating is generated in a layered structure of splats that stack into layers.

The APS coating microstructure exhibits morphological characteristics such as a porosity distribution, embedded oxides, residual stress, macro-cracks and micro-cracks. These features are influenced strongly by the in-flight particle characteristics that are controlled by the spray parameters. Accurate control and suitable combination of spray parameters are crucial since these influence the performance and durability of coatings (Fauchais and Vardelle, 1994).

The thermal and mechanical properties of APS coatings depend strongly on the in-flight particle characteristics (e.g., in-flight particle velocity, surface temperature and diameter), which are controlled by the input spray parameters. The input parameters are close-loop controlled and set to nominally constant values. However, these parameters vary during the APS process and calibration and adjustments of the variable levels are necessary. The particle variations influence the in-flight particle characteristics, which are known to influence the final coating properties (Moreau et al., 1994; Friis and Persson, 2001; Guilemany et al., 2002). The particle variations are, accordingly, considered to be indicators of process control (Vardelle and Fauchais, 1999).

Accurate prediction of the in-flight particle characteristics will assist engineers in reducing the time and complexities related to the spray tuning and parameter setting. Although it is the particle surface temperature that is actually measured at all times, for simplicity in this work and others (Guilemany et al., 2002; Bisson et al., 2003; Guessasma et al., 2003, 2004a), it is referred to as 'particle temperature'; i.e., it is implied that the surface temperature is being measured.

The artificial neural network (ANN) approach to predict the in-flight particle characteristics simultaneously from the variations of the input processing parameters of an APS process has been employed previously. The initial idea of neural network implementation of APS was presented by Einerson et al. (1993). The literature (Guessasma et al., 2004a; Kanta et al., 2008), indicates that the multilayer neural network structure, with an error back propagation algorithm, was used to model the APS process in concurrently predicting the in-flight particle characteristics. Both studies used two hidden layers to design and model the system dynamics. The past study (Choudhury et al., 2012) validated that the use of two hidden layers generated good performance of the ANN in modeling the APS process to predict the in-flight particle characteristics.

The thermal spray process is a complex non-linear process with many permutations (Bisson et al., 2003). The two hidden layer ANN structure has the potential to become complex in overcoming the non-linearity and variability associated with the APS process. The term 'complex', in this context, refers to the computational complexity of the neural network relating to the increased size (neuron number) of the two hidden layer network. Although a single hidden layer network could have the same number of hidden layer neurons, the computational complexity would be far lesser. Furthermore, simultaneous prediction of the in-flight particle characteristics, by ANN models, fails to separate the effects of input processing parameters on the individual in-flight particle characteristics.

This study proposes a modular combination of the multi-net ANN system to model the APS process and predict the in-flight particle characteristics from the input processing parameters. With modular implementation, this work focuses on improving the generalization ability of the ANN in predicting the individual in-flight particle characteristics, as well as simplifying the network structure.

Modular approaches are generally used to improve the performance of a task. The task can be accomplished with a monolithic network. However, breaking down the tasks into a number of specialist modules provides better performance and allows simple ANNs to be built. This enables the system to exploit specialist capabilities and improve the learning ability in the process dynamics of the APS process.

Apart from improving the performance of the designed networks, the modular approach also reduces the model complexity. The overall system is easier to understand, modify and extend (Gallinari, 1995). The segmented approach allows the user to better understand the relationships between each of the in-flight particle characteristics and the input processing parameters. Training times can also be reduced (Pratt et al., 1991) and previous knowledge can be incorporated in terms of suggesting an appropriate decomposition of a task (Gallinari, 1995).

The generalization ability of the overall modular network model is improved. Furthermore, the system reliability is enhanced. Any fault or error in prediction of one of the sub-problems does not affect the solution to the entire problem. The predicted output fluctuations are, thus, greatly reduced resulting in a more robust and reliable network. The results obtained from modular ANN implementation of the APS process were later compared with traditional ANN models based on a two hidden layer architecture.

2. Neural network modelling

2.1. Input processing parameter selection

The choice of the input processing parameters was based on their effects on the following selected output in-flight particle characteristics: (i) the average particle velocity, (ii) temperature, and (iii) particle diameter. The considered in-flight particle characteristics are strongly influenced by the power and feedstock injection parameters (Guessasma et al., 2004a). The values of the particle drag coefficient, heat transfer and particle acceleration depend on the plasma jet properties (gas density, thermal conductivity, etc.), which directly relates to the arc-gas properties and torch design (Pfender, 1988; Fisher, 1972; Henne et al., 2001). The particle trajectory and residence time is strongly influenced by the powder and powder feed variables (Vardelle and Fauchais, 1999).

The selected input processing parameters, within the categories of such analysis, are the following power and injection parameters; namely: (i) arc current intensity, (ii) argon gas flow rate, (iii) hydrogen flow rate, (iv) argon carrier gas flow rate, (v) injector stand-off distance, and (vi) injector diameter. Parameters related to power injection, the type of torch, the spray distance and the torch movement, may influence the in-flight particle characteristics. However, these conditions were not considered in this focused study and they were maintained constant to reference values.

2.2. Multi-net system and the modular combination

A multi-net system (Sharkey, 1999) is a group of ANNs where each network, depending on the type of combination, is assigned to solve a part of the problem or the total problem. The use of a multi-net system improves the generalization ability of the ANN;