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The scope of artificial neural network metamodels for precision casting process planning

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ABSTRACT

Precision investment casting process planning has been tackled in the past according to experience. Recently, casting simulation software is being increasingly used to predict product quality by implementing 'what-if' scenarios. Input parameters include relatively simple factors such as mould temperature, melting temperature, casting material. They also include factors whose influence is more complex to quantify, such number and location of feeding points, diameter and length of inflow channels, angle of channel with respect to the main sprue axis. Simulation results cannot help the engineer for workpieces other than the one simulated. In this paper a series of feedforward artificial neural network (ANN) models is presented aiming at such generalisation. To achieve this, a large number of software simulation runs were conducted for a number of different small parts, with varying runner geometry and casting conditions. The parameters characterising part geometry have been chosen to be surface area and volume-to-area ratio. The different ANN models predictive capabilities are reflected to the respective training and generalisation errors. A user-friendly interface has been conducted for model execution in a complete application, whose main virtue is expandability.

1. Introduction

Casting is an ancient manufacturing process with remarkable evolution, especially in the past two decades, owing to new materials and control methods. The intricacy of the process is reflected by the complexity of phenomena and mechanisms involved in alloy solidification and the multitude of factors influencing them, commonly referred to as casting parameters. One way to study such influences is simulation, which, in its plain form, materialises on a 'what-if' model, see for instance [1] in the domain of cooling channel analysis in pressure die casting and [2] in the domain of investment casting. In fact, it is necessary to study by simulation as many scenarios as possible for as many critical parameters as possible to formulate a certain process planning logic, general enough to be useful in casting cases other than those simulated. Case-based reasoning has been used to this end for retrieval of a previous case (solution) that is closest to the current case under consideration [3]. The algorithm is driven by product attributes related to geometry (size, shape complexity, section thickness, etc.), quality (surface finish, tolerance, maximum void size) and production (order quantity, production rate, lead time). Shape complexity is quantified based on geometric parameters of the casting model. Weights to attributes are determined using analytic hierarchy process (AHP). Another methodology for manufacturability evaluation uses factors such as shape complexity, die complexity, cycle time, machine size and processing parameters [4]. In a more general approach, multi-response quality design techniques are used to identify favourable settings of process parameters, which, in many situations, are imprecise to some degree and induce imprecise functional relationships. A die casting example is used to illustrate the approach [5]. Expert systems are a good method to capture expert logic on casting defect diagnosis and prevention linked to mould and feeding systems design [6–8].

Efficient and robust optimisation is sought after in mould filling, heat transfer, solidification and microstructure evolution [9], thermal controls and casting shape [10]. Intelligent optimisation usually entails a casting process model in terms of an artificial neural network (ANN) trained through real or simulated results and a simulated annealing [11] or genetic algorithm [12,13].

Simulation is good as a tool for building casting models for a specific mould (part) and experiment with it. However, it does not allow generic insight into the influence of casting parameters for a larger range of parts and casting parameters. In addition, numerical simulation is cumbersome to set up and time

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consuming to run. Therefore, it is tempting to execute a few simulation scenarios and try to generalise them to avoid execution of new scenarios as the need emerges. Statistical techniques are good at generalising from a set of data by effectively interpolating between the data vectors available. However, they are of limited value because first, the number of vectors can never be large enough to allow for safe extrapolation, rather than interpolation, especially because the number of input (free) parameters is usually large, leading to high combinatorial complexity.

Artificial neural networks seem to provide a good alternative to simulation in building manufacturing process models, provided that there is enough data to train the networks [14]. For instance, a neural network is used in [15] to limit gate locations to be tried by simulation and another one is used to generate the process parameters for the pressure die casting process [16]. The degree of success of a neural network model as a predictive model in casting is higher the narrower the domain modelled. In addition, there are inherent difficulties in incorporating in the model geometric factors associated with the feeding system and the actual shape of the mould. These issues are discussed next in the context of investment casting.

2. Solid investment casting simulation

The casting method simulated is a variant of the lost-wax method employing plaster moulds. The mould is produced by surrounding the wax tree with plaster slurry that sets at room temperature. The plaster mould is then burned out, the wax is melted out and the mould cavity is ready to accommodate the molten alloy in a vacuum casting machine. An example of a mould drawing and the corresponding wax tree is shown in Fig. 1.

Jewellery moulds are used in this study. The wax tree has a number of casting parts (see Fig. 2) attached on the runner with one or two ingates each (see Fig. 3). Note the inclination of the runners with respect to the vertical direction to facilitate inflow of the molten alloy. The casting material was 14K gold alloy (58.5% Au–20% Ag–21.5% Cu) with liquidus temperature at 850 °C. The molten metal flows into the vacuum casting machine at 960 °C. A single heat transfer coefficient number was calculated, for three different periods during solidification as: $h = 1000\,\mathrm{W/m^2\,K}$, $0\,\mathrm{s} \leqslant t \leqslant 1\,\mathrm{s}$, $h = 10\,\mathrm{W/m^2\,K}$, $1\,\mathrm{s} < t \leqslant 22\,\mathrm{s}$, $h = 70\,\mathrm{W/m^2\,K}$), $t > 22\,\mathrm{s}$ using a trial-and-error procedure employing as reference to the experimentally measured temperature at four points on the mould walls [2].

Simulation was performed on the Procast system [17]. The results obtained from a simulation run pertain to mould-filling evolution including velocity and pressure fields and to solidification evolution including temperature fields as well as porosity in the casting. It was chosen to evaluate quality of a casting by four factors:

- earliest solidification time (EST) pertaining to the region that solidifies first. In general, low solidification time is desirable to achieve fine microstructure in the casting.
- solidification time range, pertaining to the difference in solidification start of the two regions of the casting that solidify first and last, respectively. Typical distribution of solidification times for a particular casting simulation is shown in Fig. 1(b). In general, low solidification time range leads to high homogeneity (HMG = 1) and avoids defects such as hot cracks and pores.
- mean porosity (MP), which is the volume percentage of the casting that is void. In general, low mean porosity is an indicator of high quality. Typical distribution of porosity for a particular casting simulation is shown in Fig. 4.
- filling time (FT), referring to the time needed for the mould to become full of cast metal. Typically, low filling time is a pre-requisite for homogenous solidification.

3. Artificial neural network metamodels

An artificial neural network is a computational model of the human brain, where information processing is distributed over several interconnected processing elements, called neurons or nodes, structured in layers (input, output and hidden), which operate in parallel [18]. The outputs of the nodes in one layer are transmitted to the nodes in another layer through connections that amplify or attenuate the outputs through weight factors. The net input to each node, except for the input nodes, is the sum of the weighted output of the nodes 'feeding' that node. Each node is activated in accordance with the input to the node, the activation function (modification to the input, e.g., sigmoid, normal distribution) and the threshold (bias) of the node. Thereby the network provides a mapping through which points in the input space are associated with corresponding points in the output space.

Neural networks can capture domain knowledge from examples, do not archive knowledge explicitly, can handle both continuous and discrete data and have a good generalisation capability. Knowledge is built into ANNs through training with typical input patterns and the corresponding output patterns. In

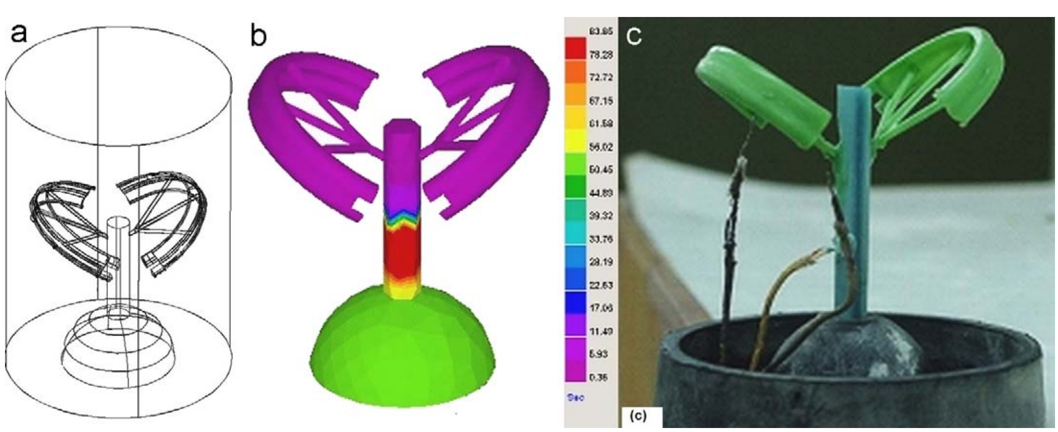

Fig. 1. Examples of investment casting artefact (a) mould model (b) solidification time distribution (c) wax tree.