Artificial Neural Network Applied to Thermomechanical Fields Monitoring during Casting

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Abstract: In order to estimate the accuracy of the cast parts, continuously are developed and improved software, which estimate the phenomena that occur during the casting process, especially during the shrinkage phase of the melt. For eliminating the problems which may occur during shrinkage phase and may lead to rejection of the part, accurate casting design is necessary. The process can be predicted and designed by using neural networks. In order to control the casting process neural network was trained. The data were calculated using a connection between the input and output data. This paper presents the details of neural network training for prediction of output parameters of the casting process of a hollow cylinder part.

Key-Words: Neural network, Parameters prediction, Casting, Finite element analysis, Numerical simulation

1 Introduction
Casting is an important manufacturing process with applications in automotive and aircraft industries, including many industrial and domestic components. The major stages involved in casting process are moulding, melting, pouring/solidification and inspection/elimination of defective casting parts [1]. In recent years, numerical simulations has become one of the most powerful estimation tool for the manufacturing process. This technique is being used in casting industry in order to solve any problems related to the process optimization and control, because the final product properties and characteristics are an important criterion for the market [2]. Nowadays, finite difference and finite element methods are being used, but is known and accepted that finite element method is the most suitable for casting simulations, because the cast parts design implies very complicated shapes. Identification and control are two fundamentals tasks for solving a problem. Even if mathematical models developed for linear systems exist, the identification and control of non-linear systems are still very difficult tasks. Artificial neural networks are parallel computational models comprised of density interconnected adaptive processing units [1].

2 Numerical simulation of casting process
In the last years, many researchers have focused their attention on the determination of heat transfer coefficient which is influenced by air gap formation at the part/mould interface. The air gap formation is the result of the relative movement of the exterior wall of the part during shrinkage phase [3-7]. Casting solidification simulation technology is used to estimate shrinkage or solidification time of different materials. Solidification simulations of casting provides time-temperature data, displacement, hot spot location and solidification time [8-10]. The numerical simulations results used in this paper for training the neural network were obtained by using V-Shrink [RIKEN Institute Japan], a non-commercial finite element software. The calculation procedure for using V-Shrink software was presented in a previous paper [11]. The accuracy prediction of the shape and dimensions of the mould depends on accuracy description of the physical phenomena of the technological process. It was used I-DEAS™ as a pre-processor in order to generate the part and mould geometry and mesh and to impose the mechanical boundary conditions. Two different meshes were generated for core and mould and both meshes were assembled. The contact conditions were applied. Boundary conditions were applied as it follows: i) mechanical and thermal boundary conditions to the part and ii) only mechanical boundary conditions to the mould. In order to run the numerical simulations, some files were used. These files contain information like: mechanical and thermal properties of the mould and part materials, information about the heat transfer coefficient and output time and parameters. The manufacturing process of a hollow cylinder cast part made of aluminum alloy (AC4CH) was simulated by V-Shrink software. The mould has the internal core and the
external wall made of steel. During part cooling, it was considered that the core is cooled by water, which has the same temperature with the surrounding air (27°C). The uniform initial temperature of the mould is considered to be 40°C.

The methodology used to estimate the air gap thickness at the part/mould interface is the following: i) setting the shape and the dimensions of the cast part and mould and identifying the type of cast and part materials (alloy and steel); ii) mesh generation (part and mould) and applying mechanical and thermal boundary conditions; iii) identifying and input the control parameters and the material properties for the part and the mould; iv) running V-Shrink software and getting the output results [12].

The part and mould meshes were generated using I-DEAS™ software and after that, mechanical and thermal boundary conditions were applied. The mechanical boundary conditions were applied using I-DEAS™ and the thermal boundary conditions were applied using a program conceived in Fortran. For generating the meshes it was used hexahedron element with 8 nodes. In this case, the mould mesh has 10472 nodes and 7680 elements with 8 nodes and the part mesh has 6732 nodes and 5120 elements with 8 nodes. In fig. 1 are shown the part and mould meshes. The geometrical model used for numerical simulation is axisymmetric and, therefore, the simulation was made using one quarter of the part and mould having 2618 nodes and 1920 elements with 8 nodes for the mould and 1683 nodes and 1280 elements with 8 nodes for the part. This will reduce also the simulation time. Both meshes contain very small elements, obtaining a very well defined mesh.

The cast part is a hollow cylinder made of aluminum alloy, with inner diameter of 40 mm and an outer diameter of 128 mm and the part height is 85 mm. The mould is bottom insulated with ceramics in order to obtain a radial heat flux.

Fig. 1. The meshes used for numerical simulation: a – mould; b – part.

The output parameters used for training the neural network were: core, part and mould temperature, Von Misses equivalent stress in the cast, equivalent strain and radial shrinkage of the cast. In fig. 2 are shown the locations where those parameters were calculated by numerical simulation.

The temperature evolution during cooling phase was calculated in T1...T3 locations and the radial shrinkage, equivalent stress and equivalent strain were calculated in D1...D3 locations. D1 corresponds to node number 259, D2 corresponds to node number 835 and D3 corresponds to node number 1411 of the part mesh. T1...T3 correspond to 3 elements located as follows: T1 in the mould mesh, T2 in the part mesh and T3 in the core mesh.

In fig. 3, 4, 5 and 6 are shown the evolution of parameters (temperature, radial shrinkage, equivalent stress and equivalent strain) which were calculated using finite element software. These values were used to learn and train the neural network in order to predict the evolution of part solidification if input data are changing. Equivalent strain calculated in locations D2 and D3 are almost the same.

Fig. 3. Calculated data of the temperature evolution during solidification
3 Shrinkage prediction of the cast parts using neural network method

Nowadays, engineers have to make a series of decisions to obtain a defect-free quality casting and to repeat many times the simulations, which means a lot of wasted time [13]. The goal of introducing neural network method in the shrinkage study of the precision parts is to reduce the necessary time for finding the optimum solution for designing the casting process, to create a fast and accurate tool for providing information about the existing relations between the input and output variables of the deformation process, which are in fact the modelling of the dependent and independent parameters of casting and cooling process. Moreover, the neural network training allows virtual designing of different variables avoiding experiments and even numerical computations.

In this study, NNMODEL 3.1 neural network has been used in order to learn and train in the modeling of the relation between casting process parameters and estimation parameters of the casting process, after shrinkage phase as it shown in fig. 7. The architecture and functioning of NNMODEL 3.1 network, which is used as start point in developing stage of a new network – NNSHRINK – designed for casting process, are shown also in fig. 7.

The network is trained with a set number of input variables which becomes the data matrix. Using a connection between the input and output data, the output data are calculated. The results are compared with the target data, calculating the errors and determining a correction coefficient, which is applied to each input variable. The shares are updated from input to output, so that an input information with large share on input level may become an output information with very small share on output level. This decreasing is done considering the neurons decision that the information is not correct. If the number of trainings is large, one single level of hidden neurons is enough for obtaining very accurate results.

The number of the process parameters is large and difficult to be totally known. This is the reason why it is set a minimum admissible number of input data using Eq. (1):
where: \( N \) is the input-output number, learning data number; 
\( K \) is the nodes number of neurons hidden levels which corresponds to number of input data; 
\( n \) is the input nodes number; 
\( I \) is the output data number; 
\( \varepsilon \) is the calculated error.

In this case \( n = 18 \) cases, \( K = 3 \) levels of hidden neurons, \( N = 6 \) and \( I = 1 \). Estimation error is 0.5%. In case of cast part with 10÷300 mm diameter, the prediction assures a very high class of accuracy, by casting.

### 4 Model of NNSHRINK neural network

The input variables are the temperature evolution in the core, cast and mould of the hollow cylinder casting test, von Mises equivalent stress in the cast, equivalent strain and radial shrinkage of the cast. The output variable is radial shrinkage of the cast part, and, by modeling the relation between input and output, the radial shrinkage of the cast can be predicted for the cases when the casting temperature varies, and therefore, the heat fluxes in the cast during pouring and during cooling. The interval of their evaluation is determined based on the extremes values and there are presented in table 1.

### 5 Creating the data matrix of neural network

Data matrix of the NNSHRINK is a matrix containing the casting cases at different increments of time during the casting process. The case space is generated through finite element simulation aided by V-SHRINK. There are 7 variables – V1 Time increment of the casting process, V2- temperature evolution in the core, V3 – temperature evolution in the cast material, V4 - temperature evolution in the mold., V5 – Equivalent von Mises stress at the middle height of the mold, V6 – Equivalent strain in the mold wall. V7 is the shrinkage that in fact is the most important parameter that characterises the dimensional accuracy of the cast parts.

<table>
<thead>
<tr>
<th>No.</th>
<th>The input-output variable</th>
<th>ID</th>
<th>Variation interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Time increment of the casting process</td>
<td>Input V1</td>
<td>s</td>
</tr>
<tr>
<td>2</td>
<td>Temperature in the core</td>
<td>Input V2</td>
<td>°C</td>
</tr>
<tr>
<td>3</td>
<td>Temperature in the cast</td>
<td>Input V3</td>
<td>°C</td>
</tr>
<tr>
<td>4</td>
<td>Temperature in the mold</td>
<td>Input V4</td>
<td>°C</td>
</tr>
<tr>
<td>5</td>
<td>Equivalent von Mises stress</td>
<td>Input V5</td>
<td>MPa</td>
</tr>
<tr>
<td>6</td>
<td>Equivalent strain</td>
<td>Input V6</td>
<td>%</td>
</tr>
<tr>
<td>7</td>
<td>Shrinkage value</td>
<td>Input V7</td>
<td>mm</td>
</tr>
</tbody>
</table>

### 6 Interrogation of the NNSHRINK

The neural network defines the input and the output parameters as well as the training parameters of the network. The number of the hidden layers of neurons is 3 and the increments of training is 10000. The algorithm of the neural network is backpropagation. The training of the neural network releases a numerical tool able to be interrogated in order to make the prediction of the variables. For example, if the temperature in the core is changed due to various reasons, the neural network is interrogated and with 0.5% error estimates the values of the shrinkage. This rapid answer diminish the time for launching a new process of casting. Preliminary to desiging the cooling system of the mold, the interrogation of a dynamic model saves significant the designing and costs time.
7 Conclusions
Numerical analysis of the casting processes is still a tool that request computation time. A trained neural network with the numerical and experimental experience helps the designers of the casting processes to estimate the precision of the cast parts shortening the production chain. A neural network NNSHRINK was trained with the numerical results of the casting modeling by finite element simulation.

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