ModernMethods ofShapingtheSurfaceLayerofIronCasting

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Abstract

The work presents selected methods which augment designingthe properties of surface layer, based on neural networks. Aneuralmodelhasbeenpresentedforthequalityofmanufacturingprocessesbasedondirectandinversemodelling. Moreover, functionality of the MagmaSoft systemintheprocessofdesigningduringcasting,hasbeencharacterised inthework.

Keywords:surfacelayer,neuralnetwork,MagmaSoftsystem

INTRODUCTION

Theproductionofspheroidalgraphiteironcastingsintheworldisconstantlyincreasing,andalthoughinWesternEuropeancountriestheproductionvolumeisstableandconstitutes50÷60% ofoverall productionofironcastings, still e.g.inPoland,remainingatmuchlowerlevel,itwas9,6%in1993, 12% in 1999, and slightly over 14% in 2001 [1, 2].Worldindustrymanufacturesc.80%ofironcastings.Asarule,theyundergomechanicaltreatment,andthereforetheissueofprocessability(machinability)ofdifferentkindsofcastironiscrucialforthe manufacturingprocesses[1].Manysurfacesoftheproductsarenot processedatall,whileothersareprocessedverythoroughly.Atpresent,c.15÷20%ofthecastingweightturnsintochips(andbecomeswastematerial)intheprocessofremovingtheallowance.Reducingtheamount of machining allowance results in measurable materialsavings,reducesenergyuseandmakesitlesstime-consuming[1,2].Castironismainlyusedinautomotiveindustry[3-5].Forinstance,theshareofspheroidalgraphiteironcastingsinworld productionisc.21%[6].

SURFACELAYER

While analysing the formation process of the surface layer ofiron casting, it should be observed that as early as duringvolumecontractionofthecasting,acharacteristiclayerisformedunderthegeometricsurface,possessingdistinctphysicalpropertiesfromthecastingcore.Thisupperlayer formed on the surface of the raw casting can be defined asfollows: "the surface layer of a raw casting is a layer of thematerial limited by the actual surface of a raw object andincorporatingthepartofthematerialunderneaththegeometricsurfaceareatowardsthecentrewhichrevealsalteredphysicalproperties,andsometimeschemicalproperties,compared to thepropertiesofthismaterial[7-9].

The surface layer of a raw casting is thus composed of twozones:

- reaction zone, very thin - c. 0,01÷0,1mm of the surfacelayer, also called the casting skin, which is formed as aresult of a reaction with moulding materials (e.g. oxygen)andhasdifferentchemicalcompositionfromthecore(glass-like),
- transition zone - found underneath the surface layer. Itsformation depends on the conditions of solidification andcoolingofthereactionzone.Thiszonehasidenticalchemicalcompositionasthecasting,butadifferentstructure.

The range and form of the transition zone are influenced byfactorssuchas:metallurgicalprocess,typeofmouldingmaterial andthethermo-physicalconditionsofthesolidification and cooling process (depending on the kind andcomposition of liquid metal and thickness of the casting wall),thermo-physical properties of the moulding compound (e.g.b_2-heat accumulation coefficient), the temperature of mouldfillingetc.[10].

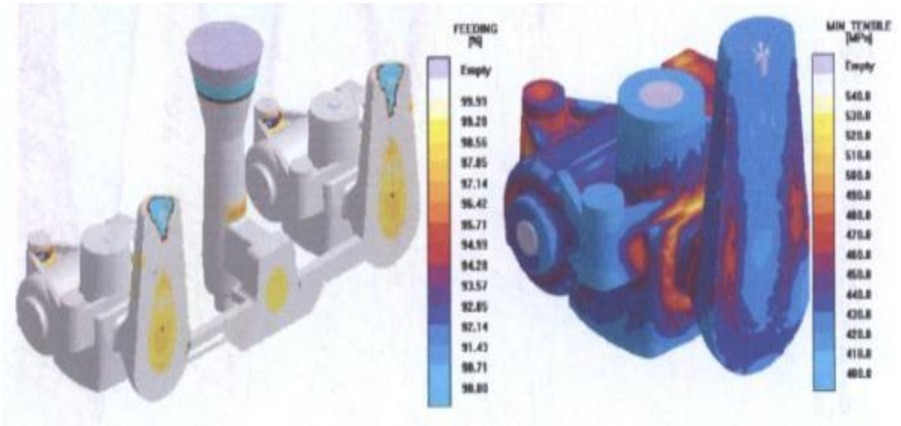
METHODSAUGMENTINGTHEPROCESSOFSURFACE LAYER FORMATION

Extremeworkingconditions(hightemperature)makeitimpossible to control and regulate the course of the process byinstallingappropriatedevices.Thelackofpossibilitytocontrolthefoundryprocesseslimitstheopportunitiesofincreasingproductivityandofobtainingproductswhoseproperties would satisfy present-day needs. With the use ofneuralnetworksitispossibletopredictthephenomena occurring in the furnace, thanks to the analysis of the work ofcontrol-commandsystemsoperatingonthebasisofmathematical models, based on the obtained literature data.Also, applying computer simulations to control the foundryprocesseshassubstantiallyoptimisedthem.

MAGMASOFTSYSTEMAPPLIEDINSIMULATIONOF MOULDING THEIRONCASTINGS

MAGMAironmodule,whichisapart(module)oftheMAGMASOFT system, contains a kinetic model allowing topredict the progress of cast iron solidification in the micro-scale and presenting the resultant structure and the propertiesof cast iron. This module takes account of, among others, themodification procedure,modification mode specific for theparticular foundry, the composition of the alloy, the

White colour in the left picture (Fig. 2) signifies acasting without defects, while other colours denote porosityand contraction cavities. What needs to be underlined, is thefact that a simulation carried out in MAGMASOFT systemlends the possibility to receive an exact representation of thecasting shape, including their required properties of surfacelayer (as well as the core), and minimises the occurrence ofcastingdefects(e.g.contractioncavities).



influenceof the main alloy components on the solidification mode, theinfluence of silicon (Si) content on segregation (fig. 1), phasetransitionsinsolidstate.TheMAGMAironmodulealsoallows to obtain accurate data concerning casting conditionsand information about the cast itself. This module enables toobtain data about the number of grains in the casting duringsolidification, the share of pearlite and ferrite in the structure,Brinell hardness (HBW), and the contraction of cast iron withspheroidalgraphiteinthemacro-scale.ApplyingMAGMASoftsystemallowstoreduceprimecosts ofthefoundryandtobringforwardthephaseofimplementingthe productionbypredictingthequalityofthecastings(identification of occurring and distribution of casting defects:shrinkholes,porosity,misruns,warpingandothers),predictingthestructureandpropertiesofthecastings,predictingtheresultsofapplyingdifferenttechnologies,optimisation of gating systems,verification of the number,shape and distribution of risers and the increased metal yieldrelated to it, the preview of the thermal balance of reusablepermanentmoulds,anddocumentingthemanufacturingprocess[11-16].

Fig.1andFig.2presentexamplesoftheresultsofsimulations conducted with the use of MAGMASOFT system,whose object were wedge-shaped castings made of cast ironcontaining from 3,5% to 1,5% of silicon, and the comparisontothefracturesofactualcastingswhichprovesgoodrepresentationofreality.Fig.2presentstheforecastofporosity and $R_m$for the casting from spheroidal graphite ironSGJ 500-7.

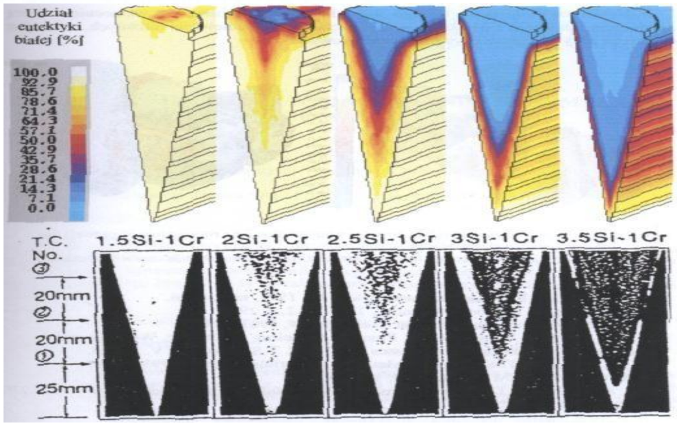


Figure1. Thecomparisonoftheresultsofawedgetestsimulationwiththeexperimentfordifferent contentofsilicon

Figure2. Theforecastofcontractiondefects(ontheleft)andthetensilestrength(ontheright)forspheroidalgraphiteironcasting

APPLICATIONOFNEURALNETWORKS

Neuralnetworksareappliedtosolvetaskssuchas:theanalysis of data sets of large size, which can be analysed onlyautomatically,workintheenvironmentrequiringtheadaptation of the system to rapidly changing conditions, totasks which are complex and difficult to describe with the useofothermathematical[17].

Other frequently encountered applications of neural networksconcern robotics, control engineering, and also control theoryand optimisation issues, motion perception and its planning.Thenetworkalsoperformsthefunctionofatracingandfol low-upsystem,adaptingtochangingenvironmentalconditions.Thefunctionofaclassifier,usedindecision-makingastothefurthercourseoftheprocess,playsasignificantrole, especiallyincontrollingrobots[18,19].Neural network systems also help in solving varied problemsrelatedtocasting.Examplesofsuchsolutionsistheapplication of fuzzy logic to determine the relation betweentemperature and the pace of filling the casting moulds, andsometimesthemechanicalparametersofADI(Austempered Ductile Iron) [20]. Moreover, it is possible to predict Vickershardness and determine the amount of retained austenite, thelatter of which influences e.g. the properties of ADI, in thefunction of chemical composition and the parameters of heattreatment.Developingasystemofneuralnetworkforacasting process consists in establishing the list of parameters(signals)which can have a significant connection with thequality of the product. It is also important to create a model ofquality (Fig. 3.1), meant as finding the relationship betweenthe parameters of the process and the properties of all thematerials used on one hand (the input data), and the qualityparametersoftheproductsontheotherhand.Itisalsosignificant to establish the values which are a part of inputsignals and which are treated as output ones. Fig. 3 presentsthephasesofcastingprocessandtheparameters(thepropertiesofthecastingsand,thepropertiesofinputmaterials, the conditions of the surroundings, time etc.) whichhave influence on the course of this process and at the sametimeonthe qualityparameters ofthecasting(output).

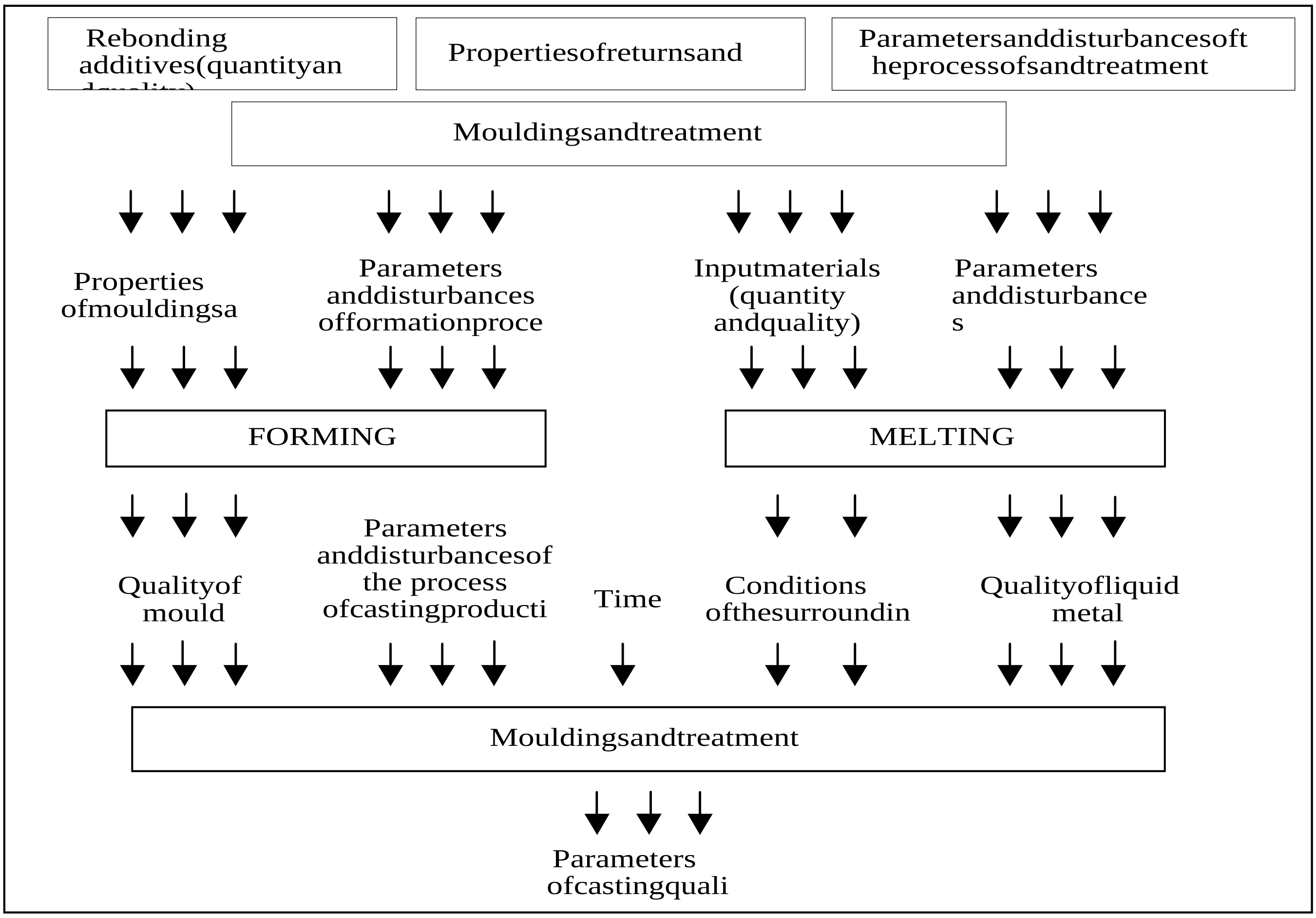


Figure3: Themodelsofqualityformanufacturingprocessesinatypicalfoundry

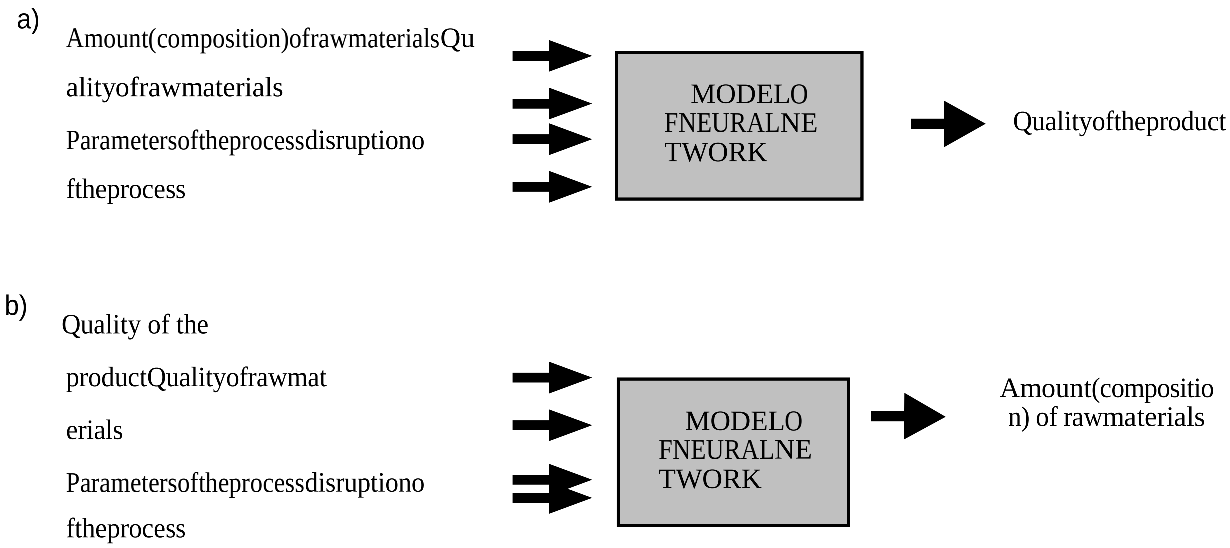


Figure4: Neural modelsofthequalityofmanufacturingprocesses, where:a)directmodelling,b)inversemodelling

Anotherexampleofneuralnetworks'applicationsiscontrolling the content of sulphur and silicon. For instance:low capacity of these elements considerably influences thesuccessoftheblast-furnaceprocess.Thebasicmodelofneural network forecasts the values of the components of hotmetal,silica,andthetemperaturevalues.Thismodeliscombine dwith the model calculating the cost of the inputmaterial and thegroup of rules for changing temperatureofhotblast,itsstream,pressure,theamountofcokeand limestone. Due to operative control and regulation systems,considerableeconomicsavingsaregained,consistinginl owering the production costs, and achieving larger stability ofaggregate work by better insight into the internal processesoccurring in the furnace, and at the same time uniformize theparameters of crude iron and slag. These systems are not aswell applicable in the situations when disturbances occur orthe operating parameters changeconsiderably. The accuracyof forecasting the parameters' values draw particular attention.In such case, statistical methods are usually applied, the mostadvanced of which are neural networks. On the basis of thepresented models and the available data, it can be stated that:neural network has the capability to automatically determinethe relationships between input and output data, and the moresignificantparametersoftheprocesscanbepredictedinadvan ce (2÷3 hours), which in the perspective of productiontime(1cast)canhaveconsiderableimportanceforthepr ocess,alsoneuralnetworkenablestocarryoutthemeasurement of the composition and amount of hot metal andslag without the necessity to apply spectrographic technique,performed only offline. It appears that the share of the neuralnetwork models in control and command systems facilitatingtheworkofblastfurnacesisjustified.Thesemodelscano perate independently. They can also, in a way, duplicate thesolutions based on the description of physical phenomena, andeither corroborate ordenythem.

CONCLUSION

The selected methods of designing (shaping) properties of thesurface layer of iron castings, presented in the article, haveconsiderableinfluenceonimprovingthequalityofmanufactu redcastings.Theapplicationofthesemethodsallows to obtain castings featuring the properties which fulfilthe contemporary requirements concerning materials, withoutincreasing the production costs substantially.And althoughimplementing such a method in the foundry causes certaininvestmentexpenditures,yettheefficiency,economicsofte chnologicalprocessand,aboveall,obtainingcastingspossessing comparable and sometimes even better propertiesthan other materials used in various branches of industry, allallow to receive the returt on investment soon and achieveconsiderable profit. Manufacturing iron casts augmentedinthe designing phase by methods described above, generatesbenefits for the customers as well, who get the opportunity toacquire low-priced castings characterised by good mechanicaland exploitative. The advantages of employing these methodshave been corroborated in numerous scientific studies. Thedescriptionsofsomewaysofapplicationpresentedinthework allow to state that it is worth promoting the developmentof cast iron foundry industry. Two of the methods presented inthe article (called augmentative methods here because of theirindirect influence on the properties of surface layer) confirmthe new directions of progress in industry: the computerisationofthemanufacturingprocessbyemployingartific ialintelligence and computer simulation systems. These methodssignificantly facilitate the casting process. The application ofthedescribedmethodsallowedtocontroltheparametersofthe process which so far could not be influenced in any otherway due to difficult conditions. It allowed to gain a muchbetter control over the casting process, increase efficiency andobtaincastingsfeaturingbetterproperties.

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