PROPOSING A HYBRID MODEL AND METHODOLOGY FOR THE OPTIMIZATION OF CASTING PARAMETERS

A DOCTOR OF PHILOSOPHY (PhD) THESIS

in

Modeling and Design of Engineering Systems (MODES)

Atilim University

by

BURCU DEVRİM İÇTENBAŞ

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Prof. Dr. K. İbrahim Akman

Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy.

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ABSTRACT

PROPOSING AN HYBRID MODEL AND METHODOLOGY FOR THE OPTIMIZATION OF THE CASTING PARAMETERS

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Casting defects cause losses for a foundry: loss of time for reworked items and loss of material for scrapped unusable products. Investigating the reasons followed by eliminating the causes will reduce the defect percentages and positively contribute to productivity. The main goal of this study is to propose a hybrid model based on experiments by using Artificial Neural Networks (ANN) and Decision Trees (DT) for estimating casting defects. This study also proposes an individual model of ANN and DT for prediction of casting defects and compare the performance of these models. The primary objective is to make use of these models to develop a decision support system for engineers and executives working for describing the relationship between the casting parameters and casting quality .

Keywords: casting defects, artificial neural networks, decision trees, hybrid model, decision support systems

ÖZ

DÖKÜM PARAMETRELERİ OPTİMİZASYONU İÇİN HİBRİD BİR MODEL VE METODOLOJİ ÖNERİSİ

Devrim İçtenbaş, Burcu

Doktora, Mühendislik Sistemlerinin Tasarlanması ve Modellenmesi

Tez Yöneticisi: Yrd.Doç.Dr. Hakan Özaktaş

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Haziran 2013, 86 sayfa

Döküm hataları tekrar işleme için geçen zaman kaybı ve hurdaya ayrılan malzeme kaybından dolayı dökümhanelere zarar vermektedir. Bu hatalara neden olan faktörleri incelenip düzeltici önlemler alınması hata oranlarını azaltırken verimliliğe de olumlu yönde katkı sağlayacaktır. Bu çalışmanın ana amacı, Yapay Sinir Ağları ve Karar ağaçları analizi tekniklerini kullanarak döküm hatalarını tahminleyen bir hibrid sistem önermektir. Çalışmada ayrıca Yapay sinir Ağları ve Karar ağaçları analizi metodlarının tek başına döküm hataları tahmini için kullanılması ve tahmin performanslarının karşılaştırılması çalışmada yer almaktadır. Modellerin oluşturulmasındaki esas amaç mühendisler ve yöneticiler için döküm parametreleri ve döküm kalitesi hakkında karar verme sürecine yardım edecek bir karar destek sisteminin oluşturulmasıdır.

Anahtar Kelimeler: döküm hataları, yapay sinir ağları, karar ağaçları, hibrid model, karar destek sistemleri

To my Mom

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LIST OF ABBREVIATIONS

AHP	-	Analytic Hierarchy Process
ANOVA	-	Analysis of variance
ANN	-	Artificial Neural Network
ASE	-	Average squared error
BB	-	Back propagation
BPNN	-	Back- propagation Neural Network
CART	-	Classification and Regression Tree
CCD	-	Central Composite Design
DOE	-	Design of Experiment
DT	-	Decision Trees
EPC	-	Evaporative Pattern Casting
GA	-	Genetic Algorithms
GA-NN	-	Genetic Neural Network
MLP	-	Multilayer Perception
MVLR	-	Multivariable Linear Regression
LSD	-	Least Squared Deviation
OA	-	Orthogonal Array
RBF	-	Radial Base Functions Network
POE	-	Propagation of Error
PNN	-	Probabilistic Neural Network
PVA	-	Polyvinyl alcohol

RASE	-	Square root of the average squared error
RSM	-	Response Surface Methodology
SC	-	Squeeze Casting
S/N	-	Signal to Noise Ratio
UTS	-	Ultimate Tensile Strength

CHAPTER 1

INTRODUCTION

1.1 Background to the Study

Metal processing is the significant part of the economy and metal processing industry requires large scale investments with complicated machinery and equipment. Casting dates back to the Bronze Age (3rd millennium B.C) and the initial castings were ornaments, copper arrowheads, and various other objects. Casting did not lose any importance since it has advantages over other metal processing activities in the sense of production of huge pieces or eccentric shapes in an economic way (Kalpakjian, 1989). Contemporary casting applications include mechanical and engine parts in automotive, maritime and aerospace products and many industrial and domestic components as well (Karanukar and Datta, 2008).To illustrate its importance, more than 90% of all manufactured, durable goods and 100% of all manufacturing machinery for the U.S. industry contain casting parts (Metal Casting Industry Technology Roadmap, n.d.).

Casting and metal processing is not a recent process for Turkey. Actually, melting of metal to give the desired shape goes back to prehistoric Anatolia. Bronze Age products such as copper beads were later on followed by alloyed products using arsenic, tin and zinc to produce spearheads, household or personal goods. Further later, forging and wrought iron products were developed by the Hittites. Ironwork was passed over the subsequent civilizations of Anatolia, namely the Romans, Byzantines, Seljuks and the Ottomans. Following the Industrial Revolution the Ottoman industrialization began in the 19th century with new foundries established to produce weapons, stoves, sanitary piping products and other heavy duty goods. Further industrialization followed with the establishment of the Turkish Republic in 1923 to catch up with the western world. State sponsored processing plants during the first half of the 20th century became the locomotive force for industrialization and starting by the 50s private enterprises emerged with capital investments in the foundry sector with the establishment of technologically advanced facilities. Towards the end of 20th century Turkey became a major supplier of casting products for the European industries (Turkish Foundries and Suppliers, n.d.).

In Turkey total production in 2010 was 1,292 million tons and the following year in 2011 became 1,433 million tons. Based on the figures of 2010, Turkey is the fourth largest producer in Europe coming after Germany, France and Italy. Turkey's world ranking is 13, amounting to 1,4 % of the global production. With 2000 foundries and about 33,000 workers the casting sector is a significant contribution to Turkish economy (Turkish Foundries, n.d.).

However, there is an increasing pressure from international competitors. Customers demand defect-free castings with on-time delivery schedules. The foundry managers try to get rid of production defects by trial-and-error methodologies based on know-how and experience. However, this approach has many disadvantages such as being nonsystematic, time consuming, error-prone and requirement for long durations of experimentation (Rai et al., 2008). There is a necessity to replace this traditional approach to produce higher quality casting products within reasonable periods of time making better use of statistics, artificial intelligence knowledge acquisition neural networks and data mining tools. Computer science and artificial intelligence techniques have been utilized for solving various problems in manufacturing, such as reduction of costs and quality maximization. Similar tools can be used to solve the problems in casting industry especially to reduce the defect percentages to reasonable levels (Santos, 2002).

1.2 Casting Industry

1.2.1 Description of Casting Process

Casting is a manufacturing process which involves pouring of metal into a mold patterned after the part to be manufactured, followed by removal of the solidified metal from the mold (Kalpakjian, 1989 ; DeGarmo et al., 1999).

Quality is essential for casting just like other manufacturing processes. The objective is to produce parts that are free from defects and meet product specifications with requirements of strength, dimensional accuracy and surface finish. The important factors which have effects on quality characteristics are:

- Flow speed of molten metal into the mold cavity.
- Heat transfer during solidification and cooling speed of the metal in the mold.
- Type of mold material.
- Solidification of the metal from its molten state.

There are many different kinds of casting technologies, however two major types of casting are important and the available literature in statistical based techniques to deal with defective products are concentrated on those two: sand casting and die casting.

Sand casting: The traditional method of casting metals used for thousands of years where sand is used as the mold material. Sand casting consists of placing a pattern in sand together with a gating system to pour inside the molten metal, allowing the metal to cool in the cavity until solidification. The cast product is taken out by breaking the sand mold, therefore we have single-use molds. The flowchart of sand casting is given in Figure 1.1.

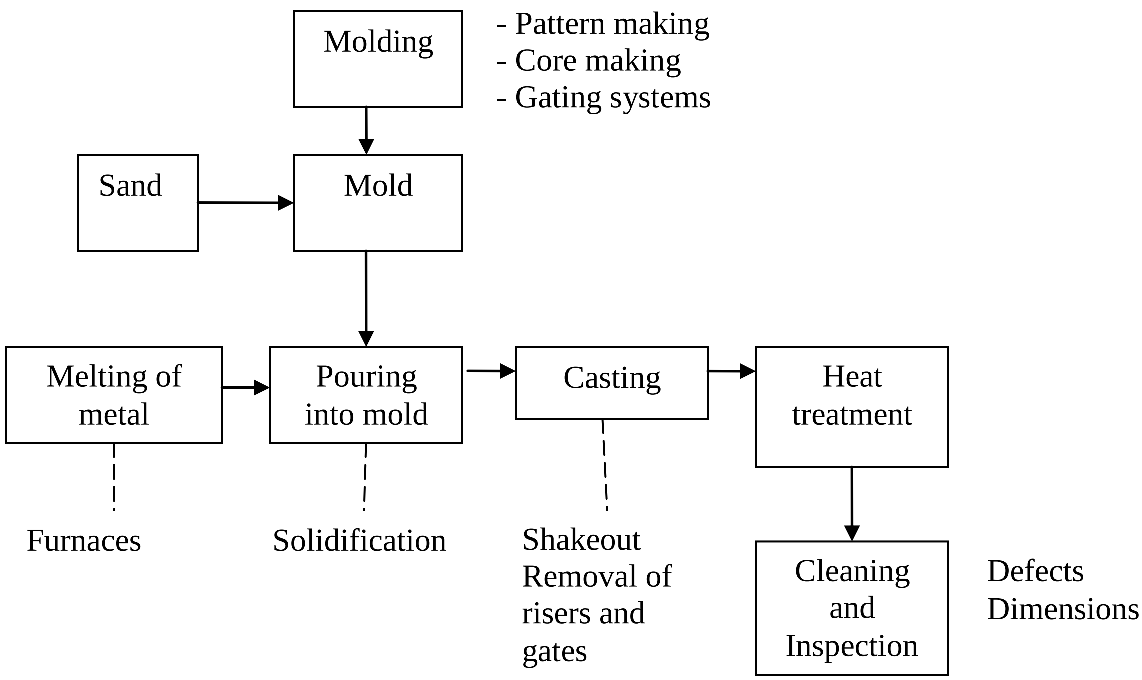

Figure 1.1: Flowchart of sand casting (Source: Kalpakjian, 1989,p. 290)

Die casting: Instead of sand a multiple-use metal mold and pattern with heat resistant properties is used. In die casting the liquid metal is flow inside is maintained with pressure and at relatively high speed. Metal dies are expensive and most usually they consist of two pieces which are opened to extract the cast product after solidification.

1.2.2 Casting Defects

Despite the advantages of casting the process has a major shortcoming: the defects of the outcoming product. There are various possible defects of the product which is taken out of the mold and a partial list of casting defects can be summarized as follows (American Foundry Society, 2007).

Cracks and crushes: Cracks or crushes can occur while the casting is taken out of the mold, poor design of pattern and clamping can also be the reasons

Cuts: Cuts are rough spots due to erosion of mold or core surface. Soft or nonuniform molds or excessive pouring temperature

Drops: Drops are caused by molding sand dropping over casting during solidification or careless handling while breaking the mold.

Erosion scabs: Scabs are defective sections over the cast metal due to improper molding sand eroding away during the cooling process. Typical reasons are high moisture content, excessive pouring temperature, and interrupted pouring.

Expansion scabs: Undesired rough layers of metal over the casting. Reasons could be related to sand composition or pouring molten metal too slowly.

Gas defects: Porosities and gas holes in cast metal in the product taken out of the mold. This can be due to presence of dissolved gas or undesired substance in the molten metal. Other reasons could be inadequate permeability of the molding material or poorly mixed sand causing high concentration of gas at certain areas.

Misruns and cold shuts: Misruns occur when the liquid metal does not properly fill the mold cavity. Cold shuts are undesired discontinuities in casting due to improper fusion of metal. Insufficient temperature of molten metal during pouring or improper metal composition are typical reasons.

Rough surface: Casting products which do not have desired smoothness of the surface. Problems in sand grains could be a reason for rough surface.

Shrinkage defects: There is a variety of shrinkage problems, but it happens when there is a shortage of molten metal to properly feed the cavity when shrinkage occurs due to solidification.

Vein defects: Veining happens on the surface of the casting if there are cracks inside the mold filled by liquid metal.

Undesired metallurgical properties: The properties of the cast product such as the tensile strength or ductility are identified at the molecular level and they are closely related with the processes which it has gone through. The composition of molten metal, the temperature of molten metal, the cooling speed are effective.

As already explained the defect formations are the results of various factors. It should also be noted that a remedy which can remove a certain type of defect can cause another one. The listed defects are mostly relevant to sand casting. Some of those such as misruns and cold shuts can be frequently faced with in die casting as well.

1.3 Statement of the Problem

In casting; obtaining the desired quality is a challenging task since this involves deciding on a large number of process parameters with complex interactions of operations such as metal composition, methods design, molding, melting, pouring, shake-out, fettling and machining (Mane et al., 2010).Determining the optimal process parameter setting significantly influences quality of casting products. In the material processing literature there are many studies based on various methodologies to optimize casting parameters. These methodologies are Artificial Neural Networks (ANN), Taguchi method, Fuzzy logic, Genetic Algorithms (GA) and Response Surface Methodology. These methodologies have been applied in casting industry successfully but when the methods are analyzed separately, it can be observed that each method embodies critical deficiencies. The analyzed studies reveal that utilizing a hybrid methodology supporting the optimization process by predicting the casting defects will bring operational advantages rather than using a single methodology and in this way combine the positive impacts of different methodologies.

The researchers have carried out studies on determining the optimal value of casting parameters, but very limited work has been reported on integrating these results through a decision making procedure. The aim of this study is to come up with a holistic approach which will relate the process parameters along the quality target, instead of experience based ad hoc solutions to reduce the percentage of casting defects.

1.4 Research Objectives

The main goal of this study is to propose an hybrid model based on experiments by using Artificial Neural Networks (ANN) and Decision Trees (DT) for estimating casting defects and to investigate the performance of prediction models and prediction accuracy. This study also proposes an individual model of ANN and DT for prediction of casting defects. The primary objective is to make use of these models to develop a decision support system for engineers and executives working for continuous quality improvement in the casting industry. The idea will be to support the decision maker to choose the appropriate casting parameters by providing corrective actions for all kinds of faults autonomously by extracting rules directly from the database.

1.5 Significance of the Research

Casting defects cause losses for a foundry: loss of time for reworked items and loss of material for scrapped unusable products. Investigating the reasons followed by eliminating the causes will reduce the defect percentages and positively contribute to productivity. A decision support system to support decision making for appropriate choice of parameters will be a handy tool.

Casting industry could possibly benefit from this decision support system in the sense of:

- Optimization of the performance measures of the casting process,
- Improvements of the processing efficiency and reduction of scraps,

- Knowledge and experience building of the combined effects of the process parameters which are otherwise difficult to evaluate by direct measurement techniques.

Therefore this system will be specific in:

- Developing a hybrid model to estimate casting defective percentage utilizing decision trees and artificial neural networks.

- Being one of the pioneer examples of decision support systems for casting industry supported by data mining techniques.

1.6 Thesis Outline

This thesis consists of six chapters. Chapter 1 summarizes a brief history of casting, the problem of defective production and the outline of a suggested model to deal with this problem. In Chapter 2, a literature review of tools to reduce the defective production percentage is given. A broad outline of most commonly used statistical based methods is given with special emphasis on Taguchi methods, decision trees and artificial neural networks. Proposed hybrid model for the prediction of casting parameters and defects, the implementation of the proposed model and the comparison of this model with the other models developed are presented in Chapter 3. Chapter 4 describes the methodology of designing a decision support system to give suggestions in order to meet the acceptable casting defect percentage. Finally, Chapter 5 outlines the conclusions of this study and suggest future directions of research.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

It is natural that some statistical tools are employed to reduce the negative impact on production of casting defects in a foundry. This chapter is divided into two parts. In the first part a classification of the articles dealing with casting defects will be given. We classify the articles based on the grouping given as follows:

(i) Artificial Neural Networks,
(ii) Taguchi methods,
(iii) Genetic Algorithms,
(iv) Other methods.

In the second part we will be outlining in some detail the foundations of the hybrid approach which is developed in this study. For that purpose we will elaborate on the tools (also classified in the first part) which are to be included in the hybrid model: Taguchi methods, Artificial Neural Networks, Decision trees and the Regression Model. The emphasis of the first part is a taxonomy attempt of researches in the area whereas the emphasis of the second part will be on specific details of these methods which will be essential while developing the model in Chapter 3.

2.2 Overview and Classification of the Literature

The papers in this review can be divided into four main categories according to methodologies which were utilized to optimize the casting parameters.

2.2.1 Artificial Neural Networks

Thanks to their capability to learn and adapt to the changing conditions, ANN can be used for dealing with a large variety of tasks where the traditional methods are difficult to employ, analytical solutions are unavailable or very difficult to obtain with the incomplete or inaccurate information at hand (Dobrzański et al., 2005). The casting industry has benefited from this method recently, mainly to establish the relationship between the input-output parameters. Papers categorized in this group are dedicated to ANN on account of contribution to optimization via prediction of thecasting parameters.

Molasses is an ecofriendly and cheap material that can be used as binder for producing strong molds. In order to investigate effectiveness of molasses, Mandal and Roy (2006) predicted the compressive strength of the sand mix through central composite design (CCD) and Back propagation neural network (BPNN) with different configurations using inputs such as molasses, cement and setting time. Central composite design is one of the statistical design of experiment technique that investigate complex effects of number of independent variables on response factor. Even though statistical models are not feasible when studying with new data, in artificial neural networks new data can be used at any stage to refine the model. The back-propagation algorithm is a learning algorithm that has been used widely in feed-forward multiplayer neural network. Lacking of criteria for selecting the number of layers and the number of neurons, back propagation neural network (BPNN) with different configurations were utilized to obtain guidelines for selecting the configuration. The study showed that the compressive strengths predicted from the BPNN models are much closer to the experimental values than those predicted from the statistical models.

Since designing the green sand parameters plays important role in getting a quality casting, a comparative study utilizing ANN and Genetic Algorithms was conducted by Karunakar and Datta (2007) in order to determine the set of desired mold properties. ANN and GA have successfully predicted the set of controlling parameters but GA gave more accurate results as searching the set of control parameters optimum in nature. The authors also indicated that ANN is not feasible for practical implementation, it may suggest only particular mold controlling parameter value along with the other controlling parameters while GA suggest the controlling parameter by lower and upper bounds leads to be more feasible.

Most studies analyze casting defects after occurrence. The study by Karunakar and Datta (2008) is an exception for this by attempting to predict major casting defects like cracks, misruns, scabs, blowholes and air-locks by using back-propagation neural networks from the data collected from a foundry just before pouring stage.

Compression strength, green shear strength, permeability, moisture percent and melting conditions were fed to the Neural Networks as inputs and ‘presence’ and ‘absence’ of each defect were fed as outputs. However the neural network did not predict occurrence of defect as ‘1’ or ‘0’ , in their study the decimal value higher than 0,5 is accepted as defect and lower than 0,5 is accepted as all right. At the end of this study, the authors suggested some actions in order to prevent the predicted defect.

For on-line control of process it is important to determine the set of input parameters for a set of desired outputs. Parappagoudar et al. (2008) utilized back-propagation neural network (BP-NN) and genetic-neural network (GA-NN) to model green sand mold system in forward mapping (to predict the responses from the known input parameters) as well as reverse mapping (to predict the set of input parameters for a set of desired outputs).There is a chance of back-propagation algorithm for being trapped into a local minimum since it works based on the steepest descent approach. Therefore an alternative approach is developed (GA-NN) which is a Genetic Algorithm based search reducing the chance of being stuck at local minima. In their study, the training data were generated by using the response equations obtained by regression analysis. The performance of the methodologies showed that GA-NN outperformed the BP-NN in predicting all the responses in both reverse and forward mapping due to reasons mentioned above. The same authors in a different study utilized the same algorithms to predict mold properties of sodium silicate-bonded, carbon dioxide gas hardened molding sand system. However in this study, BP-NN performed better than GA-NN in predicting all outputs because of the nature surface (Parappagoudar et al., 2009).

The casting stage is critical to the production of good quality castings in die casting which is a manufacturing process which produces high quality parts and incorporates automation to enhance productivity. The principal die casting parameters include the selection of the right injection speed, injection pressure, die temperature and melt temperature. Prasad and Yarlagadda (2000) used a multi-layer feed forward back propagation network as a tool for mapping the complex and highly interactive casting variables: molten metal temperature, die temperature, casting weight, and injection pressure in order to predict the optimum injection time for the pressure die casting process. Three specific neural network training algorithms, i.e. error back propagation algorithm, momentum and adaptive learning rate algorithm, and Levenberg-Marquardt approximation algorithm were used to train the network. The size of a hidden layer is one of the most important considerations when solving actual problems using multi-layer feed forward networks. The problem of the size choice is still under intensive study with no conclusive answers available In their work, the number of neurons in the hidden layer was determined by a trial and error approach. The Levenberg-Marquardt approximation, with its sophisticated training algorithm, was found to be suitable for this application as it can reduce the sum of squared error to a very small value, thus generating better accuracy of predictions.

Dobrzański et al. (2005) used artificial neural network and image analysis for classifying the flaws identified in the aluminum alloys in order to create an automated computer evaluation system for aluminum cast quality. The classification task was done with different types of network such as linear, multilayer perceptron (MLP), radial base functions network (RBF) and probabilistic neural network (PNN). The best results were obtained employing the PNN and MLP networks, as the classification correctness of the test vectors was 90% and 81%, respectively, and 85% and 94.5% for the validation vectors.

Krimpenis et al. (2006) indicated that systematic knowledge accumulation is vital for casting industry as other manufacturing processes to obtain optimal process parameters. They gathered knowledge from experiments conducted on casting simulation software which is designed according to orthogonal arrays and these results were used as data sets for ANN training and verification. Thus lengthy casting simulation runs were eliminated after ANN training. In their study, ANN model was used for defect existence and prediction of solidification time and this knowledge was used to construct the objective function in Genetic Algorithm to optimize process parameter values.

Rai et al. (2008) developed a feed-forward multilayer supervised neural network architecture for predicting three outputs namely as filling time (tf), solidification time (ts), and porosity for a given set of four input variables having a major impact on productivity and part quality such as (i) inlet melt temperature, (ii) mold initial temperature, (iii) inlet first phase velocity and (iv) inlet second phase velocity. The architecture consists of five layers which are the input layer, three hidden layers and the output layer. The obtained mean absolute error of 3.5% with three outputs from a single ANN configuration show better prediction accuracy over its other counterparts having minimal absolute error ranging from 8 to 15% for a maximum number of four input parameters and one output (either filling time or solidification time) by using back propagation algorithm.

Gas porosity is the formation of bubbles and holes within the casting after solidification. Perzyk and Kochański (2003) applied ANN to detect the causes of gas porosity defects in steel castings. The inputs include about the process parameters materials used and even workers involved in the production (as the network inputs) and about the appearance of a given defect (as the network output).Most training algorithms and the network coefficients (synapses' weights) using gradient methods to minimize the network's error, starting from a random set of initial values. However, it is generally observed that methods of that type often lead to local minima, especially for the tasks which are based on experimental data with inherent noise. This means that the network can be easily trained in a way which is far from the optimum. Hence the training method called `simulated annealing 'combined with the conventional back propagation method was applied in this study. The simulated annealing method was used for better selection of the initial values of the synapses while the back-propagation phase of the learning decreased the network error. Both phases were repeated several times, providing a chance to jump out of the local minimum of the network's error. ANN seems to be useful in finding actual causes of defects in other products where the defects are influenced by a large number of randomly changing production parameters. The authors indicate the need of utilization of different methodologies for training networks.

Özerdem and Kolukısa (2009) utilize artificial neural network (ANN), multi layer perceptron (MLP) architecture with back-propagation algorithm to predict the mechanical properties of Cu–Sn–Pb–Zn–Ni cast alloys. In Artificial Neural Network training module, Cu–Sn– Pb–Zn–Ni (wt%) contents were employed as input while yield strength, tensile strength and elongation were employed as outputs. Also the authors indicated that ANN could be also employed in predicting other physical properties of metal alloys if reliable process parameters and test results are given as ANN input and output data, respectively.

2.2.2 Taguchi Methods

Taguchi method is a very popular technique regularly used to design and optimize the process parameters of the casting process. Parameter design is an investigation conducted to identify the settings of design parameters that optimize the performance characteristics and reduce the sensitivity of engineering design to sources of variation (noise). The analysis about the published articles related to optimization of casting process parameters based on the Taguchi method are presented below.

"Evaporative Pattern Casting (EPC)" is a method utilized for the production of complex parts which cannot be produced by common methods. Kumar et al. (2008) constructed an Ishikawa cause-effect diagram to identify the process parameters which affect the quality of the casting process (tensile properties such as tensile strength and percent elongation after fracture) produced by EPC process then they obtained the optimal levels of parameters (grain fineness number, time of vibration, degree of vacuum and pouring temperature) for the best tensile strength and percent elongation after fracture by Taguchi's parameter design. Their study showed that the grain fineness number and pouring temperature were most significant parameters that affect the tensile strength and percent elongation after fracture. The same authors utilized Taguchi Method in order to evaluate the effect of process parameters such as grain fineness number, time of vibration, degree of vacuum and pouring temperature on surface roughness of EPC process castings (Kumar et al., 2006). All of the parameters were found significant except the pouring temperature.

Quality of die casting is affected by many parameters related with machine, shot sleeve, die and metal. Syrcos (2003) determined the effects of the selected process parameters on the casting density and found the optimal settings of parameters of die casting process by Taguchi method. While constructing Orthogonal arrays (OA), the interaction of parameters were also considered. Verran et al. (2008) conducted an experimental design for analyzing the influence of three injection parameters (slow shot, fast shot and up set pressure) on the porosity and density which affect internal quality of die casting.

Squeeze casting (SC) is one of the new casting techniques which has got great potential to eliminate casting defects. Vijian and Arunachalam (2006) analyzed the influence of the process parameters (squeeze pressure, die preheating temperature and die material) on surface roughness in squeeze casting of LM6 aluminum alloy using Taguchi method . They used a three level orthogonal array that has been utilized to determine the S/N ratio. The signal-to-noise ratio is simply a quality indicator by which the effect of changing a particular process parameter on the performance of the process or product is evaluated. Based on analysis of variance and the '*F*'-test values, the squeeze pressure was found as the most significant factor that affect the surface roughness. The authors indicated the need of further investigations that include the interactions of the considered parameters and the possible effects of new parameters like pouring temperature, die coat material and duration of pressure application.

In the study by Guharaja et al. (2006), undesirable outputs related to many internal defects (shifts, warpage, blow holes, drop, etc.) have been selected as the most representative quality characteristics in the green sand casting process. Taguchi's parameter design approach was utilized to analyze significant process parameters namely green strength, moisture content, permeability and mold hardness and the impacts of their levels on the casting defects. Also this study gives an estimation of the optimum process parameters of green sand casting process which leads to a minimum number of casting defects. Kumar et al., (2011) applied Taguchi Method in order to select the most significant factors namely moisture, green strength, pouring temperature, mold hardness vertical and mold hardness horizontal that causes variations in quality characteristics same as the previous research in the sand casting process.

Recent researches for sand casting focus on identifying process factors affecting sand mold properties, especially composition of sand mixture. Saikaew and Wiengwiset (2012) used mixture experimental design, response surface methodology (RSM), and propagation of error (POE) to optimize the composition of the moldings and mixture for reducing the number of casting defects in the iron casting sand mold process. They obtained optimal proportion of the sand mixture components such as 93.3% of one-time recycled molding sand, 5% of bentonite, and 1.7% of water (percentages in terms of mass) and this mixture yielded the mold properties optimal green compression strength of 53,090 N/m2, the optimal permeability of 30 A.F.S. permeability numbers and the overall desirability of 72%.

Gating system design is important for the casting quality, since molten metal flows through the gating system into the mold cavity (Kalpakjian, 1989). The Taguchi method with multiple performance characteristics such as product yield, shrinkage porosity, and filling velocity were used for obtaining a set of optimal gating system parameters in the study of Sun et al (2008). Mold filling and solidification processes of the magnesium casting were simulated with the MAGMASOFT software. The simulation results indicated that gating system parameters significantly affect the quality of the magnesium casting. In an effort to obtain the optimal process parameters of gating system, an orthogonal array, the signal to-noise (S/N) ratio, and analysis of variance (ANOVA) were used to analyze the effect of various gating designs on cavity filling and casting quality, using a weighting method.

It is important to predict and control microporosity which decrease the tensile strength, ductility and pressure tightness of cast aluminum parts, in the design stage of casting. Savaş and Kayıkçı (2007) applied Taguchi's approach to investigate the relationship between the microporosity and process variables in a sand cast A360 aluminum alloy. Results showed that within five casting parameters investigated, the local solidification time and the dissolved hydrogen level of the melt were significant on the microporosity.

The relationship between casting process parameters and mechanical properties (UTS-ultimate tensile strength) of high-silicon cast irons was statistically investigated using Taguchi method in (Kim et al., 2007). Melting temperature, misch metal addition, and pouring temperature were chosen as process parameters and experiment was conducted within an L8 (27) orthogonal array, having 8 as the experiment number of eight and using 7 rows. Their study indicated that a desired UTS of around 110–150 MPa can be obtained when melting temperature is 1,650 °C, when the misch metal treatment is added, and pouring temperature is 1,350 °C.

Pull-down is one of the casting defects that leads to non-conformities and thus affect productivity. Many factors may be the cause of pull-down defects. Senthilkumar et al. (2009) investigated the most significant factors that were contributing to pull-down defect and obtained their optimum values leading to a minimum number of defects using Taguchi method. The optimized factor values in practical runs had reduced the pull-down defects and increased the approved casting percentage from 86.22% to 96.17%.

Falamaki and Veysizadeh (2008) applied Taguchi method for the first time to optimize the manufacture of sintered one-step alumina microfilter/membrane in the centrifugal casting .Acceleration (3 levels), slip volume (3 levels), binder content (3 levels) and pH (2 levels) were selected as controlling parameters (L-9 array) to evaluate surface porosity and average surface pore diameter of membrane. Their study showed that the Taguchi approach could be successfully applied to improving the centrifugal processing route for membrane support manufacture. Slip casting is one of the common techniques used to fabricate ceramics with simple to complex shapes from particle suspensions. Barmala et al. (2009) implemented Taguchi method with L9 orthogonal array design to optimize experimental conditions for the preparation of ceramic membranes from porosity point of view using sintering temperature, solid content and polyvinyl alcohol (PVA) as input parameters in slip casting. Sintering temperature was found the most effective parameter on porosity with negative correlation.

Chhabra and Singh (2012) conducted Taguchi method to find the effect of process parameters such as different volumes of casting, pouring temperature of different materials and shell mold wall thickness on the surface roughness of castings obtained using ZCast process. Their study concluded that the pouring temperature and shell mold wall thickness had the most significant factors on the surface roughness of the casting.

The papers in this subsection shows that Taguchi method has usually been used to investigate the relationship between casting process parameters and quality characteristics and /or defects; by determining the most significant parameters which affect the quality of casting. It is evident that this method is superior to typical trial-and-error approaches in terms of reduced cost and time; since the radical number of experiments required for a trial and error application can be extensively decreased by using Taguchi's orthogonal arrays. This property of Taguchi Method explains why this methodology is mostly preferred in an environment where the factors have wide operating ranges that normally requires a large number of data to be analyzed (Mason, 1989).

The main disadvantage of the Taguchi method is that the results obtained are only relative and do not exactly indicate which parameter has the highest effect on the quality characteristic. The Taguchi method has been criticized in the literature for its difficulty in accounting for interactions between parameters. Another limitation is that the Taguchi methods are offline, and therefore inappropriate for a dynamically changing process such as a simulation study. Furthermore, since the Taguchi methods deal with designing quality rather than correcting for poor quality, they are applied most effectively at early stages of process development (Unitek Miyachi Group,1999).

2.2.3 Genetic Algorithms

An algorithm is developed which incorporates optimization strategies to determine the best operating parameters for the continuous caster by Santos et al (2002). The algorithm incorporates search techniques to find the casting objectives of maximum production rate as a function of casting constraints which can represent product quality and process feasibility through limits on strand shell thickness at the mold exit (Sm), metallurgical length (LM), minimum surface temperature (Tmin surface), casting rate (Vcasting), reheating of the strand surface in the sprays zones(DTmax) and temperature at the unbending point (Tcenter and Tsurface). The authors indicate the main reasons for utilizing GA follow as finding the best solution for processing by generating a collection (population) of potential solutions (individuals) for the problem and through recombination operators, better solutions are hopefully generated out of the current set of potential solutions until an acceptably good solution is found in terms of product quality and process feasibility.

Tsoukalas (2008) applied Genetic Algorithm (GA) to model the complex relationship between the die casting process parameters and the porosity formation of AlSi9Cu3 aluminum alloy castings. The author conducted experiments using L27 orthogonal array of Taguchi method for holding furnace temperature, die temperature, plunger velocities in the first and second stage, and multiplied pressure in the third stage parameters. Then MVLR (multivariable linear regression) was applied to establish relationship between the input and output parameters. The proposed MVLR – GA model is efficient since the predicted values of the process parameters and the calculated minimum porosity by GA are in agreement with the experimental values.

Casting-mold design is vital process for foundries to ensure the desired final cast product. In the design process, the thermal control in the solidification process was investigated by Wong and Pao (2011). The authors utilized GA to optimize heat transfer coefficients given an arbitrary casting geometry in die casting. At the end of the study, they concluded that GA gave favorable solution for their intended objective although the sheer computational time and resources involved.

3.4 Fuzzy Logic

Fuzzy logic is a mathematical approach to solve problems with uncertain and huge amount of information originated by Zadeh (1965). Grey relational analysis is the quantitative analysis to describe the degree of relationship between an objective sequence and a reference sequence in the grey system. Chiang et al. (2008) combines the grey relational analysis with fuzzy logic to determine the optimal machining parameters for the die casting process of thin-walled magnesium alloy parts. The casting density, warpage and flow mark of the LCD panel cover components were considered as the criterion affecting the results of surface quality, and were adopted as the quality characteristics in the die casting process. They used five principal machining parameters as (A) the die temperature, (B) the pressure of injection, (C) the plunger velocity (first stage), (D) the plunger velocity (second stage), and (E) the filling time. They obtained data through DOE using L16 (45) orthogonal arrays for five machining parameters and four levels and each of experiments were repeated three times to make accurate results. Also the analysis of variance (ANOVA) is carried out to examine the influence of machining parameters on the quality characteristics. The die temperature and the pressure of injection were found to be the most significant machining parameters that affect the quality characteristics. The authors indicate that the proposed algorithm is more effective and simple to make the determination of optimal settings for the complicated multiple performance characteristics.

2.3 Results

When the methods are analyzed separately it can be observed that each method embodies critical deficiencies. While the Taguchi Method is very efficient in data preparation for the other methods such as Neural Network and Genetic Algorithms by means of orthogonal array design; it misses to detect some of the interactions between the parameters. Working offline and lacking to be updated through the changes in the system is another common problem for the studies utilizing this methodology. On the other side, although the Neural Network approach is a very powerful tool for modeling the relations between the input and output parameters and the further interactions between the input parameters themselves; it does not work as an optimization tool alone, it requires the support of optimization tools such as genetic algorithms. Another difficulty of the neural network approach appears in discovering the most efficient architecture fitting the relational model. When it comes to evaluating the genetic algorithm as an optimization tool, it is observed that this approach lacks the opportunity to be used as a separate method in this area as it needs a basic mathematical model to cope with during the optimization process. Fuzzy logic is in a similar situation with the genetic algorithm as it is used as an assisting tool for the other methods to deal with verbal or vague data.

2.4 Foundation for Some Tools to be Used in the Hybrid Model

It can be determined based on the analyzed studies that utilizing a hybrid methodology will bring operational advantages than using a methodology alone to take support from the powerful side of every methodology. In that sense "decision tree approach" seems to be an applicable tool for constructing the basic input-output relationships. After this first step, a further model may be developed based on the initial results obtained from the "decision tree" approach and by taking the advantage of the strong input-output relations certified by the "decision tree" model; this further model may be time and memory efficient in finding the optimum results whatever decision tool may be utilized.

At the final step of the procedure, the developed tool may be designed to be an intelligent decision support facility, with a strong user interface to put into contact with the user by means of receiving the inputs and advising the user about the possible results that can be obtained with the given input set.

2.4.1 Taguchi Method

Taguchi's method is statistical method developed by Genichi Taguchi to improve the quality of manufactured goods. He proposes that fractional factorial designs ("orthogonal arrays") which are effective in obtaining useful information at minimum cost instead of running all combinations in the experiment. The method has three purposes:

a) to design and processes that perform on target and are robust to uncontrollable factors.

b) to design products that resistant to component variation

c) to minimize variation around a target value (Gryna et al., 2007).

Taguchi defined signal-to-noise (S/N) ratio which is a statistical measure of performance that estimates the inverse of the coefficient of variation, that is, estimates the ratio μ/σ, with μ being the processes mean (signal) and σ (noise) the process standard deviation. In the Taguchi method, the term signal represents the desirable target and noise represents the undesirable value .The larger value of S/N ratio is desirable because larger S/N ratio will result in smaller product variance around the target value (DeVor et al., 1992). So, the level with maximum S/N ratio is considered as the optimal level of the control factor.

Taguchi defined three signal to noise ratios based on three different quality characteristics namely "Nominal is the best", "Larger is better" and "Smaller is better". For each level of process parameters, signal-to-noise ratio is calculated based on *S/N* analysis.

Nominal is the best;

$$\eta = {}^{\mathrm{S}}/_{\mathrm{N_T}} = 10log\left(\frac{\bar{y}}{s_y^2}\right) \qquad (2.1)$$

Larger is better;

$$\eta = {}^{S}/_{N_L} = -10log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y^2}\right) \qquad (2.2)$$

Smaller is better;

$$\eta = {}^{S}/_{N_S} = -10log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (2.3)$$

where $\bar{y}$ is the mean of the observed data, s_y^2 is the variance of y, n is the number of observations and y is the observed data (Taguchi, et al. 1989)

Taguchi method constitutes of steps as follows (Upadhye and Keswani, 2012):

- Determine the quality characteristic and objective function to be optimized.
- Determine the control factors and their levels.
- Determine the appropriate orthogonal array.
- Assign the control factors to be selected orthogonal array and conduct the experiment.
- Determine the optimum levels for the control factors by analyzing data.
- Conduct the confirmation experiment and improve the quality characteristics.

2.4.2 Decision Trees

Decision tree can be defined a map of reasoning process that helps solve the task of classifying cases into individual categories (Waheed et al., 2006). It describes a data set as a tree-like structure involves a collection of decision nodes, connected by branches, extending downward from the root node until terminating in leaf nodes. Beginning at the root node, which by convention is placed at the top of the decision tree diagram, attributes are tested at the decision nodes, with each possible outcome resulting in a branch. Each branch then leads either to another decision node or to a terminating leaf node (Tsai and Chiou, 2009).

Decision trees are very popular among the data mining techniques applied in many real-world applications as a powerful solution to classification and prediction problems(Mahjoobi and Etemad-Shahidi, 2008) because of their simplicity and efficiency. Decision tree results are easy to understand and interpret since readable rules can be easily derived from the models (IF…THEN…).

Accuracy of the classification and performance of the tree based on several issues like missing values, continuous data, pruning, choosing the splitting and the number of splits .The most important issue is choosing the splitting attributes since some attributes may not have valuable information to split data set in an efficient manner. Besides, the order of the splitting attributes and the number of splits affect the accuracy of classification. Impurity -based measures were developed such as entropy (Quinlan, 1986) and gini-index (Breiman et al., 1984) in order to select significant attributes by minimizing the impurity function.

Several decision tree algorithms were proposed to realize the functions of decision tree. ID3 is mostly used to solve classification problems. The algorithm used the information gain as a rule to select attributes for segmentation. Another algorithm is C4.5, which is an extension and revision of ID3 algorithm in terms of using information gain-ratio instead as a measurement method. CART (Classification and Regression Trees) is another decision tree algorithm proposed by Breiman et al. (1984) that generates a binary decision tree. Like ID3, it uses entropy as a measure to select splitting attribute (Chang and Chen, 2009).

2.4.2.1 CART Algorithm

The CART is a tree-based classification and prediction algorithm that is suggested by Breiman et al.(1984).The CART procedure performs ‘‘binary recursive partitioning’’ manner. The ‘‘binary partitioning’’ implies that the parent nodes are always split into two child nodes and ‘‘recursive’’ means that the process is repeated by treating each child node as a parent node. This procedure continues until a stopping criterion is achieved (Waheed et al., 2006). It works both with continuous and categorical responses and input values. If the dependent variable is categorical, CART produces a classification tree when the dependent variable is continuous, it produces a regression tree(Mahjoobi and Etemad-Shahidi, 2008).

CART algorithm uses different impurity measures to split data according to type of the response variable. For categorical response, three measures can be used namely as gini, twoing and ordered twoing measures. If the response value is continuous, least squared deviation (LSD) impurity measure is used for splitting rules and goodness of fit criteria. It is the weighted within-node variance for each node and denoted by R(t) (Breiman, et al. 1984). It is defined as:

$$R(t) = \frac{1}{N_W(t)} \sum_{i \in t} w_i f_i \left((y_i - \bar{y}(t)\right)^2 \qquad (2.4)$$

where $N_W(t)$ is the weighted number of records in node t, w_i *is* the value of the weighting field for record i, $f_i$is the value of the frequency field; y_i is the value of the target field, and $\bar{y}$ (t) is the (weighted) mean for node t. The split is chosen to maximize the LSD criterion function below (Mahjoobi and Etemad-Shahidi, 2008):

$$\Phi(s,t) = R(t) - R(t_L) - R(t_R) \qquad (2.5)$$

where, $R(t_R)$ is the sum of the squares of the right child node and $R(t_L)$ is the sum of squares of the left child node. The split is chosen to maximize the value of $\Phi(s,t)$.

2.4.3 Artificial Neural Networks

An artificial neural network constructs the model inspired by the brain with highly interconnected units called neurons which are analogous to the biological neurons. The neurons are structured in layers (input, output and hidden) and are being operated in parallel as shown in Figure 2.1 (Vosniakos et al, 2009).

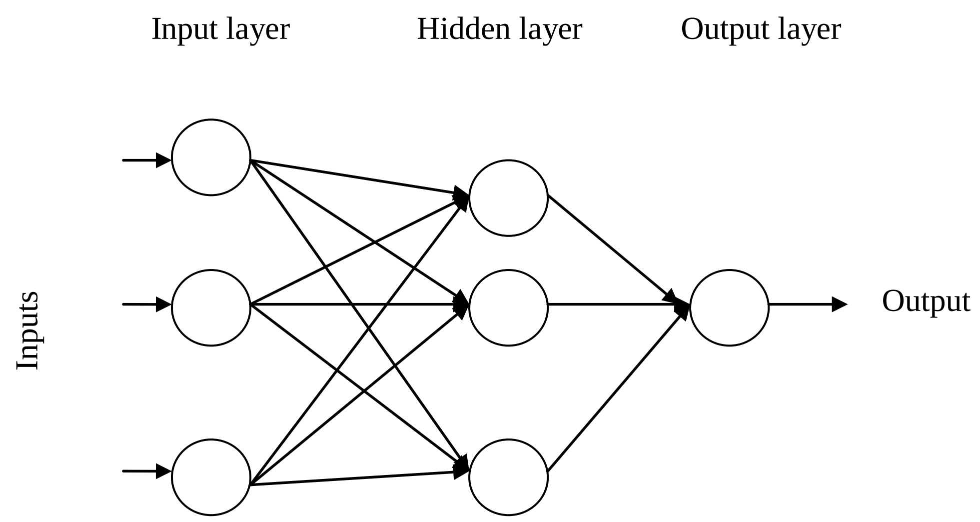

Figure 2.1: Network architecture.

The signals passing from one neuron to another one are computed by weighted links whose weights are proportional to the strength of the relation. Each neuron sums the weighted inputs transferred from the neighboring neurons and then applies a linear or nonlinear function to the resulting sum to compute the its output (Shi et al,2010). This function is a reflection of the purpose of the neuron. Weights are the primary means of long-term storage in neural networks, and learning usually takes place by updating the weights (Negnevitsky, 2002). Learning from the data by updating the related parameter scan be identified as the most important capability of a neural network. This way, the neural network takes the shape of the specific phenomena of the interest that enables her to adapt the changing conditions. In constructing an ANN model, the available data set is divided into two sets, one is used for training of the network, the other is used for testing the prediction (generalization) capability of the trained network. The ANN architecture is designed to minimize the error between the predicted and actual value by adjusting the weights. (Özerdem and Kolukısa, 2009).

2.4.3.1 The Artificial Neuron

A neural network can be defined as a model of reasoning based on the human brain. The brain constitutes of basic information -process units called neuron, and 60 trillion connections, synapses, between them. An neuron consists of a cell body, soma, and a number of fibers called dendrites, and a single long fiber called the axon neurons is a basic building block of every artificial neural network (Negnevitsky, 2002). Similarities between biological and artificial neural networks with respect to design and functionalities are shown in Fig 2,2, where the left side of a figure represents a biological neuron with its soma, dendrites and axon and where the right side of a figure represents an artificial neuron with its inputs, weights, transfer function, bias and outputs (Krenker et al., 2011).

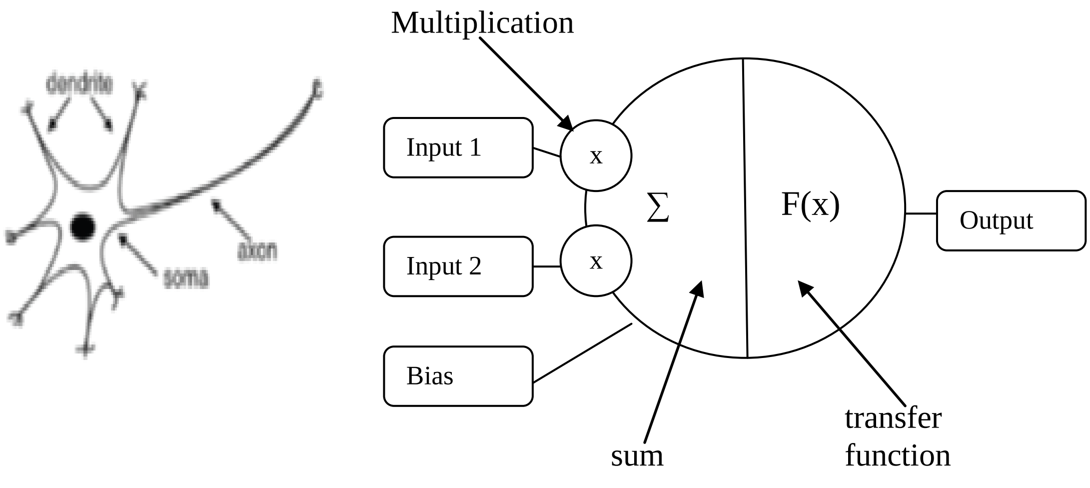

Figure 2.2: Structure of a neuron (Source: Krenker et al., 2011)

Biological neuron information comes into the neuron via dendrite, soma processes the information and passes it on via axon, similarly artificial neuron the information comes into the body of an artificial neuron via inputs that are weighted (each input can be individually multiplied with a weight). The body of an artificial neuron then sums the weighted inputs, adds a "bias" and “processes” the sum with a transfer function. At the end an artificial neuron passes the processed information via output(s) (Krenker et al., 2011). Mathematical description of artificial neuron is as follows:

$$y(k) = F(\sum_{i=0}^{m} w_i\,(k)\,.\,x_i(k) + b) \tag{2.6}$$

where

- $x_i(k)$ is input value in discrete time where i goes from 0 to m,
- $w_i(k)$ is weight value in discrete time k where i goes from 0 to m,
- b is bias,
- F is a transfer function,
- $y_i(k)$ is output value in discrete time k.

Transfer function defines the properties of artificial neuron and can be any mathematical function. Selection of the appropriate function based on the problem needs to solve by ANN and in most cases Step function, Linear function and Non-linear (Sigmoid) function are used.

2.4.3.2 Learning: Back-propagation Algorithm

There are several learning algorithms, that are used to adapt the artificial neural networks to the given data set, and the most widely used is back propagation (BP) training algorithm (Prasad and Yarlagadda 2000;Mandal and Roy,2006; Karunakar and Datta ,2007; Parappagoudar et al.,2008; Özerdem and Kolukısa,2009). In the back-propagation network , initially the weights are set randomly and consequently the outputs are calculated randomly. The difference between actual and the calculated outputs is called the "error". The weights are updated by transmitting the error to the previous layer. The iteration process may be terminated either by a convergence limit or simply by the limiting the total number of iterations. The steps of the BP algorithm as follows (Karunakar and Datta,2008):

Step 1: The network synaptic weights are initialized to small random values.
Step 2: From the set of training input/output pairs, an input pattern is presented and the network response is calculated.
Step 3: The desired network response is compared with the actual output of the network, and all the local errors are computed.
Step 4: The weights preceding each output node are updated according to the following formula based on the error amounts transferred from the previous layer:

$$w_{ij}(t) = \eta\ \delta_j\ o_i + \ \alpha\ \Delta w_{ij}\ (t-1) \qquad (2.7)$$

Where

- η the learning rate
- δ the local error gradient
- α the momentum coefficient
- o_i the output of the ith unit
- t the number of layer
- Δw_{ij} the error between the ith neuron of the input vector and jth neuron of the output vector.

w_{ij} represents the weight connecting the ith neuron of the input vector and jth neuron of the output vector. The local error gradient calculation depends on the whether the unit into which the weights feed is in the output layer or hidden layers. Local gradients in output layers are the product of the derivatives of the network 's error function and the units' activation functions. Local gradients in the layers are the weighted sum of the unit's outgoing weights and the local gradients of the units to which these weights connect.

Step 5: The cycle (Step 2 to step 4) is repeated until the calculated outputs are converged sufficiently close the desired outputs or an iteration limit has been reached.

2.4.4 Regression Model

Regression analysis can be defined as statistical technique for estimating the relationships among variables and it includes many techniques for modeling and analyzing several variables based on to investigate the relationship between a dependent variable and one or more independent variables. Regression analysis helps to understand how the value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. The process is based on fitting equations to data. The purpose of regression is to learn relationship between the dependent (response) variable and several independent (predict) variables. Regression analysis is to estimate the quantitative functional relationships between the dependent and one or more independent variables from the actual data .

Linear regression is an example of multivariate modeling techniques when several varaibles are considered to predict the values of a continuous dependent variable and it can be used to indicate the unique influence of each predictor on the desired variable, controlling for the influence of all other predictors. The relative importance of each predictor can be understood by examining all of the predictor's simultaneous influences on the dependent variable, coefficient of each predictor are generated and show that what proportion of variability of dependent variable is uniquely explained by each indiviual predictor.

The regression equation in cases on simple linear regression can be expressed as representing a line in two dimensional or two variable spaces. A simple linear regression model is shown in Equation 2.8.

$$Y = \beta_0 + \beta_1 x + \epsilon \qquad (2.8)$$

In the equation, the dependent variable 'Y' is expressed in terms of constant 'β_0', slope 'β_1' times the independent variable 'x' and a random error term 'ϵ'. The constant is referred to as the intercept and the slope of the regression coefficient. It is called as a simple linear regression model as it has only one independent variable or regressor. It is assumed that each observation Y, can be described by the above model (equation) where ϵ is a random error with mean zero and variance 'σ^2'. Fitting a regression equation to a data-set is done to describe the data and predict the response from the independent variable. For predictive purposes it is always desired that the predicted values obtained by using the fitted regression line should be close the actual observed values, i.e., the residuals should be small. Hence while assessing the fit of a line; the vertical distances of the points to the line are the only distances that matter. The parameters 'β_0' and 'β_1' in Equation 2.8 are estimated in order to minimize the sum of squares of the vertical deviations. This approach to estimating the regression coefficients is called the *method of least squares*. It is a general method of finding estimated values of parameters such that the sum of squared values between the fitted values and the corresponding observed values is as small as possible (Montgomery and Runger,2011,p 402-410).

Multiple regression models are used in situations where more than one regressor variable is required. In the multivariate case where there is more than one independent variable, the regression line cannot be visualized in two dimensional space. There is a continuous random variable called the dependent variable 'Y' and a number of independent variables, $x_1, x_2, \ldots, x_p$. The aim is to predict the value of the dependent or response variable using a linear function of the independent variables. The values of the independent or regressor variables are known quantities for the purpose of prediction. A multiple linear regression model in Eq. 2.9.

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \epsilon \qquad (2.9)$$

The ϵ or the noise variable is a normally distributed random variable with mean equal to zero and standard deviation σ. The values of the coefficiens $\beta_0, \beta_1, \dots, \beta_p$ are estimated from the available data (Montgomery and Runger,2011,p 450-452).

In non-linear regression, the fitted value of the response variable is a non-linear function of one or more independent variables. A non-linear function is one that cannot be made into a linear function by transforming the dependent variable. Two of the most common type of non-linear relationships are represented in quadratic cubic forms and can be modeled through polynomial regression. Polynomial regression simply adds terms to the original equation to account for non-linear relationships. A second-degree polynomial regression model in one variable can be given by Equation 2.10 (Mendenhall and Sincich, 2011,p 274-288).

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \epsilon \tag{2.10}$$

2.5 Summary of Literature Review

As a consequence of literature survey performed with many data mining methods, it can be observed that artificial neural networks, regression and decision trees stand as powerful tools that can construct an input-output relation in casting process. So, either these methods or combinations of them can serve successfully in order to improve the efficiency of the casting processes and introduce new approaches that can serve as decision making tools in this area.

CHAPTER 3

THE PROPOSED HYBRID MODEL AND THE COMPARISON OF MODELS FOR PREDICTING CASTING DEFECTS

3.1 Introduction

Sand casting still remains as one of the most widely used casting processes today in spite of the many advanced technologies developed for metal casting taking advantage of the low cost of raw materials and practical utilization of recycling molding sand (Saikew and Wiengwiset, 2012). This chapter focuses on the development of a hybrid model which integrates decision tree and neural network techniques for predicting the percentage of casting defects in sand casting. This model will be used as the core of a decision support system which will direct the users to finalize their casting designs as effective as possible.

3.2 Proposed Models for the Casting Analysis and the Introduction of the Hybrid Model

As expressed in the literature survey, the “artificial neural network” (ANN) models have been used in the casting industry. Also "decision tree" approach was sensed to be an efficient tool to deal especially with the rule base of the casting systems. In this study following the utilization of these two methods separately, a new hybrid model was proposed aiming a more efficient result in finding the optimal input parameters for a successful casting process.

Like many other areas of manufacturing "artificial neural networks (ANN)" are widely used for modeling the casting processes in casting industry; for the sake of its practical application that is not requiring any assumptions of statistical models (Prasad and Yarlagadda, 2000; Dobrzański, et al., 2005; Mandal and Roy, 2006; Krimpenis et al., 2006; Karunakar and Datta, 2007; Parappagoudar et.al., 2008; Rai et al., 2008). However, during the optimization process ANN tends to reach the local minimum using the stochastic gradient descent technique and thus it is not guaranteed to converge to the global optimal solution by this technique (Tsai and Chiou, 2009). On the other hand, decision tree (DT) approach which is one of the data mining techniques for classification and rule extraction is able to generate the classifier in the forms of trees and its learning algorithm is able to provide a solution that is always convergent; therefore it classifies the training dataset correctly (Ardiansyah et al., 2012).

Performance of an ANN is based on the ANN architecture and the learning performance of the training parameters on the given training data. This training performance is strongly related with the number of significant input parameters and their ability to build effective relations with the output values. Therefore, the possible detection of the significant parameters before the application of an ANN should bring an advantage to obtain more accurate results—possibly in shorter time—at the end of the design process. DT technique seems to be an effective alternative for finding the significant parameters affecting the output values in many different complex processes. So, to handle such complex processes where so many parameters are included in the design, the basic idea of combining ANN and DT can result in a more effective result which is not always possible with the application of a single technique. The combination of these two techniques have been used in economy, medicine and various areas of engineering (Günay and Yıldırım, 2013; Chang and Chen, 2009; Chang, 2011) in the industry, but unfortunately an application is not existent in casting industry which is an appropriate example of such complex processes, in which an huge amount of data and many parameters are included in the process.

3. 2.1 The Proposed Hybrid Model

In certain works it can be observed that "decision trees" can be used to classify data with respect to significant parameters (Günay and Yıldırım, 2013). So, the modeling of this reduced space by ANN, can result more efficiently in the sense of reflecting the relation of the input variables of the molding processes in the sand casting design.

The steps of constructing such a hybrid model should be as follows (Figure 3.1):

1. Obtaining raw data.
2. Classifying the data with decision tree to obtain the critical input parameters.
3. Obtaining the new training data set with respect to significant parameters.
4. Predicting the defect percentage by the execution of a neural network design on this new data set.
5. The new neural network architecture will be the new-proposed model.

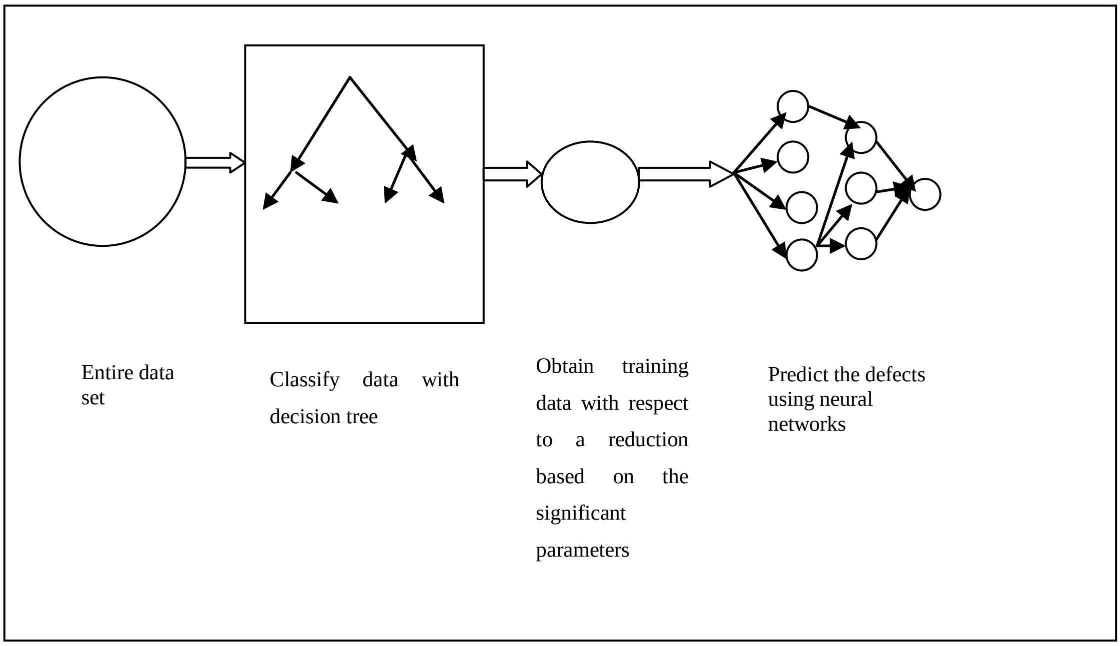

Figure 3.1: The steps of the hybrid model

3.2.2 Introduction to the Model Building Phase

This part focuses on development of three models for predicting casting defects in sand casting. These models are namely decision tree, neural network and hybrid model based on combining decision tree and artificial neural network (ANN), utilized for predicting the casting defects occurring due to molding process and compare the predictions. The training data for decision tree and ANN generated from the regression equations acquired by the Taguchi experiments. The same data set was reduced by decision tree and fed to ANN in the hybrid model. The research methodology is shown in figure 3.2.

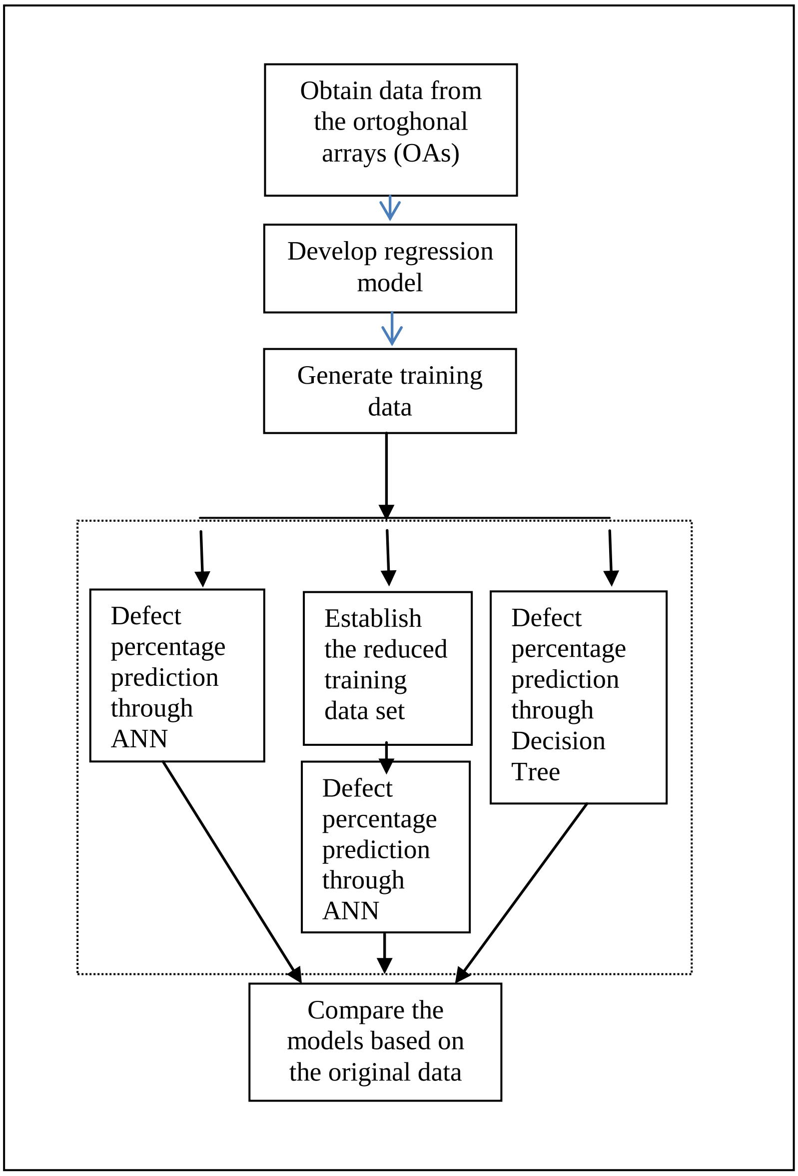

Figure 3.2: The Research Methodology

3.2.3 Data Collection

The experimental data based on (Upadhye and Keswani,2012) were used to develop the mathematical models. The purpose of their study was to optimize the process parameters of sand casting by maximizing the signal to noise ratios and minimizing the noise factors using Taguchi method.

The basic steps of achieving the above target are summarized below (Sycros,2002):

1. Casting defects have been selected as the most representative quality characteristics in the green sand casting process.
2. The most significant parameters that causes variations in the casting defects have been chosen.
3. Orthogonal array and parameter levels were chosen. The data were collected based on these experimental conditions.
4. An analysis of variance (ANOVA) table is generated to determine the statistical significance of the parameters.
5. The optimum settings of the control parameters were predicted.
6. The optimum settings were verified by the predicted reduction in the casting defects.

In this study, casting defects were selected as the most representative quality characteristics as they are related to many internal defects such as sand blow holes, scabs, mold cracks, and sand drops in the green sand casting process, strongly related with the critical process parameters. The casting defects are the “lower the better” type of quality characteristics. Based on this conception, moisture content, green compression strength, permeability, mold hardness, sand particle size, pouring temperature, pouring time and pressure test were considered as the main process parameters. The selected sand casting process parameters, along with their ranges, are given in Table 3.1.

Table 3.1: Control factors of process parameters and their levels

Factor designation	Control factors	Range	Level 1	Level 2	Level 3
A	Moisture(%)	3,5-4	3,5	4	…
B	Sand particle size (AFS)	50-55	50	53	55
C	Green compression strength (g/cm^2)	900-1200	900	1100	1200
D	Mold hardness (nu)	50-80	50	70	80
E	Permeability (nu)	150-220	150	185	220
F	Pouring temperature (deg c)	1300-1420	1300	1390	1420
G	Pouring time (sec)	20-28	20	24	28
H	Pressure test (Mpa)	1,5-2,5	1,5	2	2,5

(Source: Upadhye and Keswani,2012)

In order to find the optimal levels of these parameters, an L18 orthogonal array was formed with 18 experimental runs and eight columns since moisture percentage has two levels while other parameters has three levels. The assigned experimental array is shown Table 3.2.

In order to study significance of the parameters, three way of analysis of variance (ANOVA) was performed for casting defects and S/N ratios. The results showed that green compression strength, moisture, pouring temperature and permeability affect both the mean and variation of the casting defects-thus can be considered as critical-while sand particle size, mold hardness, pouring temperature and pressure tests are insignificant.

Table 3.2 Experimental orthogonal array (Upadhye and Keswani ,2012)

Trial no.	A Moisture content (%)	B Sand particle size (AFS)	C Green compression strength (g/cm^2)	D Mold hardness (nu)	E Permeability (nu)	F Pouring temperature (deg c)	G Pouring time (sec)	H Pressure test (Mpa)	Casting defect (%)
1	3,5	50	900	50	150	1300	20	1,5	5,053
2	3,5	50	1100	70	185	1390	24	2	5,206
3	3,5	50	1200	80	220	1420	28	2,5	6,24
4	3,5	53	900	50	185	1390	28	2,5	4,376
5	3,5	53	1100	70	220	1420	20	1,5	5,866
6	3,5	53	1200	80	150	1300	24	2	7,083
7	3,5	55	900	70	150	1420	24	2,5	3,186
8	3,5	55	1100	80	185	1300	28	1,5	4,806
9	3,5	55	1200	50	220	1390	20	2	7,25
10	4	50	900	80	220	1390	24	1,5	6,136
11	4	50	1100	50	150	1420	28	2	6,766
12	4	50	1200	70	185	1300	20	2,5	9,306
13	4	53	900	70	220	1300	28	2	7,283
14	4	53	1100	80	150	1390	20	2,5	6,066
15	4	53	1200	50	185	1420	24	1,5	6,526
16	4	55	900	80	185	1420	20	2	4,586
17	4	55	1100	80	220	1300	24	2,5	6,69
18	4	55	1200	70	150	1390	28	1,5	7,523

3.2.4 Regression Model

Regression analysis was performed for generating the training data for decision trees and artificial neural networks. The data gathered from (Upadhye and Keswani, 2012) was analyzed by the regression technique through a statistical software Minitab 13. The obtained regression equation through this raw data is given in Table 3.3.

$$defect = \exp(-4{,}11 + 1{,}77 * moisture\ content - 0{,}000021 * mould\ hardness * permeability - 0{,}000024 * sand\ particle\ size * green\ strength + 0{,}0512 * permeability - 0{,}0208 * pouring\ temperature - 0{,}00768 * permeability * moisure\ content + 0{,}000003 * green\ strenght^2 - 0{,}000018 * green\ strenght * permeability - 0{,}00727 * permeability * moisture\ content) \quad (3.1)$$

Table 3.3: Minitab Multiple Regression Output for the data set

```
The regression equation is
LND = - 4,11 + 1,77 A -0,000021 D*E -0,000024 B*C + 0,0512 E - 0,00208 F
           - 0,00768 E*A +0,000003 2*C -0,000018 C*E

Predictor        Coef      SE Coef          T        P
Constant       -4,107        3,041      -1,35    0,210
A              1,7714       0,9074       1,95    0,083
D*E       -0,00002094   0,00001045      -2,00    0,076
B*C       -0,00002446   0,00000984      -2,49    0,035
E             0,05119      0,02085       2,45    0,036
F          -0,0020750    0,0005738      -3,62    0,006
E*A         -0,007685     0,004919      -1,56    0,153
2*C        0,00000264   0,00000069       3,86    0,004
C*E       -0,00001753   0,00000734      -2,39    0,041

S = 0,09218     R-Sq = 92,7%     R-Sq(adj) = 86,2%

Analysis of Variance

Source            DF          SS          MS         F        P
Regression         8     0,97395     0,12174     14,33    0,000
Residual Error     9     0,07648     0,00850
Total             17     1,05042
```

The analysis of variance (ANOVA) technique is used to check the adequacy of the developed models. F-ratios of the models developed are calculated and compared with the corresponding tabulated values for 95% level of confidence. If the calculated values of F-ratio exceeds the corresponding the tabulated value then the model is considered adequate. The model is adequate since p-value is very small (0,000) and one can conclude that at least one of the regressors is related to the response y. A normal probability of the residuals and plots of the residuals versus the fitted values also verify the adequacy of the model (Appendix A).

3.2.5 Generated Training Data

300 training data were generated artificially by selecting the values of the input variables being parallel to the distribution parameters of the original data and determining response by utilizing above regression function. The data set is presented in Appendix B.

3.2.6 Test Data

To test the feasibility and effectiveness of the proposed model, benchmarking is required to be performed. The square root of the average squared error (RASE) is selected as a performance measure. The experimental data based on Upadhye and Keswani (2012)'s study were used to compare the different models based on their prediction performance indicated by RASE.

3.3 Neural Network Modeling

The ANN employed in this study was a multilayer feedforward network trained by a backpropagation algorithm. As a result of the initial trials, the number of hidden layers was set to one and the neuron values were varied between one and ten to identify the best ANN structure. By a similar logic, "Levenberg-Marquardt" is used as the training algorithm and stopping criteria used is 300 epochs. Tan-sigmoid and log-sigmoid functions were chosen as transfer functions. The different network configurations based on these values were used for ANN training and the performance of the developed ANN models were compared using coefficient of determination (rsquared) between the outputs and targets. The program was run using MATLAB 7.11.0 (R2010b) neural network toolbox. The model with the highest r-squared value was chosen as our final ANN model with the 10 neurons in the hidden layer and having tan-sigmoid as the transfer function. The designed network was used to predict the casting defect percentages of the training data, the performance results and the parameter estimations can be observed in Figure 3.3 and Table 3.4.

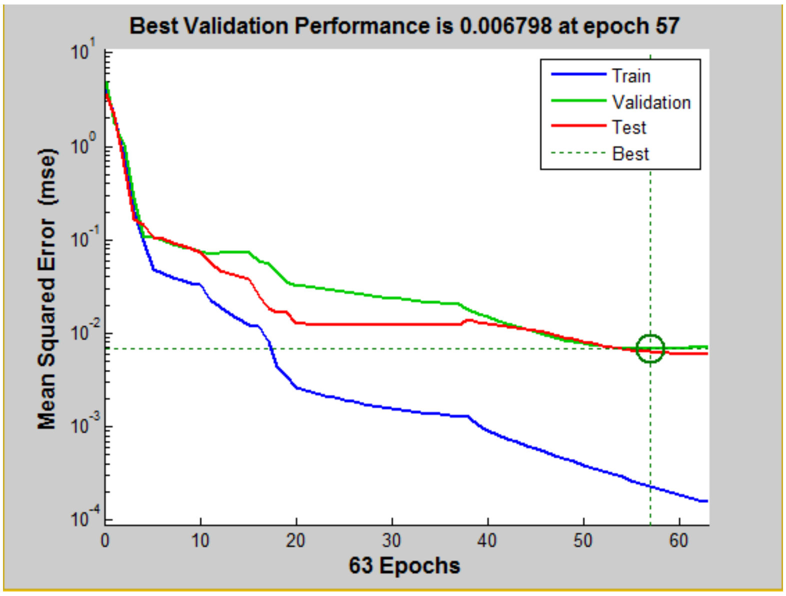

Figure 3.3: Training performance

3.4 Decision Tree Modeling

CART model is one of the data mining techniques that can be used either as a classification or prediction function (Mahjoobi and Etemad-Shahidi, 2008). In this study, the generated data acquired from the regression equation were used in the CART analysis in order to predict the percentage of casting defects. CART models were developed for three different criteria being based on the maximum number of tree levels, a minimum number of cases for the parent nodes and a minimum number of cases for the child nodes separately; consequently the one with the highest accuracy were chosen to be compared other models. The higher accuracy is indicated by the increase in the proportion of variance explained by the model (%) (Bevilacqua et al., 2003). Since the objective variable is continuous, the least squared deviation (LSD) method is applied as an impurity measure (Waheed et al., 2006).

Table3.5 provides the CART experimental results for the five different models with respect to different executive criteria namely the maximum number of tree levels, the minimum number of cases for the parent nodes and a minimum number of cases for the child nodes. As the minimum number of cases for the parent node and minimum number of cases for the child nodes was increased, proportion of the variance explained by the model has been decreased. However when the depth of tree was increased, proportion of the variance explained by the model has been increased too. The results also indicated that "green strength" is a predictor variable splitting root nodes that is common to all trees developed.

While model 4 has higher accuracy (86%), it has a total of 43 nodes with a depth of tree of 5 which brings a disadvantage about its readability. A good trade-off between accuracy of the classification tree and its readability must be considered when selecting the best tree (Bevilacqua et al., 2003). Model 1 is selected as the best model in our study because of its acceptable explained proportion of variance and its high readability with 21 nodes and a tree depth of 5.

Table 3.4: Parameter estimation of the neural network

iw {1,1}-Weight to layer 1 from input 1

[1.825 -0.11208 0.91902 0.036015 -0.54202 -0.5896 0.69265 0.93984;
-0.69303 0.72758 -0.31828 0.34729 -0.88474 1.0654 -0.65382 -0.52475;
-0.90469 0.18914 0.67533 -0.52236 1.5579 0.237 -0.031249 0.55554;
-0.039124 -0.19554 -0.16205 -0.13387 0.26718 -0.32342 0.028813 0.086882;
0.73183 0.38964 1.4463 -1.3721 -0.36308 -0.59229 -0.010185 0.79306;
-0.86134 -0.61574 -0.46048 0.38508 -1.3146 0.60759 0.29079 0.37185;
0.05755 -0.14881 0.84599 -0.084104 -0.4293 -0.1109 -0.058518 -0.069705;
0.72273 0.25427 -0.26494 0.6144 1.3908 0.36883 0.053074 -0.058755;
0.85563 0.58669 1.1996 0.10124 -1.7514 -0.08762 -0.97111 0.42771;
0.93227 0.16681 1.3528 -0.53574 1.2816 -0.43205 -0.21494 0.17043]

lw{2,1}-Weight to layer

[1.286 -0.10245 -0.11093 1.1225 -0.047445 -0.12398 2.1711 0.29376 -0.03236 1.2289]

b {1}-Bias to layer 1

[-3.3041;
-1.259;
1.0614;
-0.33577;
1.2433;
0.16284;
-1.1307;
1.0974;
1.4505;
2.4305]

b{2}-Bias to layer 2

[1.5653]

Derivation of mathematical model from the ANN

E1=A* iw1.1+B*iw1.2+C*iw1.3+D*iw1.4+E*iw1.5+F*iw1.6+G*iw1.7+H*iw1.8-3.3041
E2=A* iw2.1+B*iw2.2+C*iw2.3+D*iw2.4+E*iw2.5+F*iw2.6+G*iw2.7+H*iw2.8-1.259
E1=A* iw3.1+B*iw3.2+C*iw3.3+D*iw3.4+E*iw3.5+F*iw3.6+G*iw3.7+H*iw3.8+1.0614
E1=A* iw4.1+B*iw4.2+C*iw4.3+D*iw4.4+E*iw4.5+F*iw4.6+G*iw4.7+H*iw4.8 -0.33577
E1=A* iw5.1+B*iw5.2+C*iw5.3+D*iw5.4+E*iw5.5+F*iw5.6+G*iw5.7+H*iw5.8+1.2433
E1=A* iw6.1+B*iw6.2+C*iw6.3+D*iw6.4+E*iw6.5+F*iw6.6+G*iw6.7+H*iw6.8+ 0.16284
E1=A* iw7.1+B*iw7.2+C*iw7.3+D*iw7.4+E*iw7.5+F*iw7.6+G*iw7.7+H*iw7.8-1.1307
E1=A* iw8.1+B*iw8.2+C*iw8.3+D*iw8.4+E*iw8.5+F*iw8.6+G*iw8.7+H*iw8.8+1.0974
E1=A* iw9.1+B*iw9.2+C*iw9.3+D*iw9.4+E*iw9.5+F*iw9.6+G*iw9.7+H*iw9.8+1.4505
E1=A* iw10.1+B*iw10.2+C*iw10.3+D*iw10.4+E*iw10.5+F*iw10.6+G*iw10.7+H*iw10.8+2.4305

defect(%)={[2/(1+exp(-2*E1))-1]*1.286}+{[2/(1+exp(-2*E1))-1]*-0.10245}+{[2/(1+exp(-2*E1))-1]*
-0.11093 }+{[2/(1+exp(-2*E1))-1]* 1.1225 }+{[2/(1+exp(-2*E1))-1]* -0.047445 }+{[2/(1+exp(-2*E1))-1]*
-0.12398}+{[2/(1+exp(-2*E1))-1]*2.1711}+{[2/(1+exp(-2*E1))-1]*0.29376}+{[2/(1+exp(-2*E1))-1]*
-0.03236 }+{[2/(1+exp(-2*E1))-1]* 1.2289}+1.5653

Table 3.5: Results of the decision tree application

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Characteristic of Algorithm Impurity measure	LSD	LSD	LSD	LSD	LSD	LSD
Stop Criteria						
Max number of levels	5	5	5	5	5	3
Minimum number of cases for parent node	10	100	20	3	10	3
Minimum number of cases for child node	5	50	10	1	2	1
Minimum change of impurity level	0,0001	0,0001	0,0001	0,0001	0,0001	0,0001
Final tree						
Dimensions						
Total number of nodes	21	5	9	43	31	15
Total number of terminal nodes	11	3	5	22	16	8
Depth	5	2	3	5	5	3
Risk analysis (Performance)						
Total variance (root node)	1,16	1,16	1,16	1,16	1,16	1,16
Proportion of variance due to error (%)	0,26	0,62	0,52	0,14	0,20	0,31
Proportion of variance explained by the model (%)	**0,74**	**0,38**	**0,48**	**0,86**	**0,80**	**0,69**
Predictor variable splitting root node	VAR03	VAR03	VAR03	VAR03	VAR03	VAR03

This model was used to generate decision rules resulting in the extraction of different percentages of casting defects. These rules will give the information about the significant casting parameters and their possible values to obtain the minimum percentage of casting defect. The significant parameters were found as the moisture content, green strength, permeability and pouring temperature. The correlation of 0,75 indicates a high positive correlation between actual and predicted casting defects which indicates the model is not robust but is acceptable to select the final setting of the parameters.

Table 3.6: Correlation between actual and predicted casting defects

		Actual	Predicted
actual	Pearson Correlation	1	,749**
	Sig. (2-tailed)		,000
	N	18	18
predicted	Pearson Correlation	,749**	1
	Sig. (2-tailed)	,000	
	N	18	18

**. Correlation is significant at the 0.01 level (2-tailed).

The rules were extracted from the final model giving the best conditions to minimize the percentage of defect. The completed tree is given in Appendix C. The sample rules are given below; having the highest effect in directing the model to an optimum purity in classification will lead to a higher percentage of defectives and these two rules will be mainly used to develop the hybrid model in the next section.

Table 3.7: Critical rules

Rule 1:

IF green strength>1284,90 THEN defect (%) =9,767

Rule 2:

IF green strength>1125.05 AND green strength ≤1284.91 AND pouring temperature≤1370,43 THEN defect (%) = 7,465.

3.5 DT-ANN Hybrid Model

The hybrid model is composed of a combination of the decision tree approach with the neural network system. The critical rules acquired from the decision tree were utilized for reducing the data, and this reduced data were used as input to the neural network system constructed by the same logic addressed in the previous section.

After decision tree construction, the data which will lead to higher percentage of defectives were removed from the data set using the rules acquired from the decision tree approach. Then the ANN model were constructed using the reduced data set containing 267 data points. In this study, the percentage of 7 was accepted as the lower level of high defectivity, as the values lower than 7 constitutes 90% of all the data set. The reduced data set is given in Appendix D.

The different network configurations based on these values were used for ANN training and the performance of the developed ANN models were compared using coefficient of determination (rsquared) between the outputs and targets as discussed in Section 3.3. For this hybrid model, ANN model with the 10 neurons in the hidden layer and transfer function tan-sigmoid was chosen final model for the reduced data set (Table 3.8).

3.6 Performance Measure

The square root of the average squared error (RASE) is selected as a performance measure to compare models in this study. The RASE is defined as (Tso and Yau, 2007):

$$RASE = SSE/n \qquad (3.2)$$

where SSE is the sum of squared error, n is the number of observations.

3.7 Results

The square root of the average squared error (RASE) was calculated for each model. The results are shown in Table 3.9. 12^{th} data element were extracted from the model due to its radical-differentiable defect percentage and the error amount reflected in the decision tree model and the hybrid model, which is a probable sign of an outlying element, lacks the efficiency of being placed in the general "parameter directed" mapping style of the decision tree approach.

It can be observed that, the hybrid model having a RASE of 0,2056 functions slightly better than the neural network model (RASE=0.21) and much better than the decision tree model (RASE=0.7861). Although the hybrid model seems only slightly better than the pure neural network model, when the performance of the neural network architectures of the two models were compared, the hybrid model can be differentiated from the other one due to the efficiency of the neural network. The hybrid model reaches the conclusion with 13 iterations, whereas the pure neural network model should make 29 iterations to reach the result. Therefore, it can be concluded that the hybrid model proposed in this study reaches a more accurate result than the neural network and the decision tree models, in a much more time efficient way.

Table 3.8: Parameter estimation of the hybrid model

iw {1,1}-Weight to layer 1 from input 1

[0.76857 -0.42999 -0.58485 1.609 1.4513 0.34393 0.79807 -0.93845;
0.52284 -0.4006 1.0378 -0.32933 -0.25007 -0.77532 -0.0096018 -0.038231;
1.1965 -0.85202 -1.8456 -0.063514 0.48461 1.8023 -1.3596 -0.49796;
0.61473 -0.22594 0.53573 -0.062323 0.46284 -0.37366 -0.071731 -0.056438;
1.8652 0.99797 1.0684 -2.2364 -0.10367 -0.47342 0.078571 -0.51927;
-1.749 -0.058319 0.95765 -0.21625 0.23398 -0.057351 0.28495 0.29602;
0.9498 1.0328 -0.35129 -0.80546 -0.051424 2.549 -0.7798 -2.1703;
-0.29505 -0.26348 -0.74645 -0.24086 0.84924 -0.5165 0.058762 0.051418;
-0.62817 -0.83126 -0.38815 -0.58589 -1.4988 -0.78692 0.090867 -0.081755;
-0.45052 -0.21287 0.8735 -0.55352 -1.2056 -0.53261 -1.2103 1.4507]

lw{2,1}-Weight to layer

[-0.090706 2.0355 -0.020178 1.2419 0.021475 0.19257 -0.023862 1.3296 -0.27768 -0.0086317]

b {1}-Bias to layer 1

[-2.4642;
-1.3102;
-1.1561;
1.0671;
-0.31193;
-1.592;
-1.2499;
-1.3013;
-1.0383;
-0.92395]

b{2}-Bias to layer 2

[1.7847]

Derivation of mathematical model from the ANN

E1=A* iw1.1+B*iw1.2+C*iw1.3+D*iw1.4+E*iw1.5+F*iw1.6+G*iw1.7+H*iw1.8-2.4642
E2=A* iw2.1+B*iw2.2+C*iw2.3+D*iw2.4+E*iw2.5+F*iw2.6+G*iw2.7+H*iw2.8-1.3102
E3=A* iw3.1+B*iw3.2+C*iw3.3+D*iw3.4+E*iw3.5+F*iw3.6+G*iw3.7+H*iw3.8-1.1561
E4=A* iw4.1+B*iw4.2+C*iw4.3+D*iw4.4+E*iw4.5+F*iw4.6+G*iw4.7+H*iw4.8+ 1.0671
E5=A* iw5.1+B*iw5.2+C*iw5.3+D*iw5.4+E*iw5.5+F*iw5.6+G*iw5.7+H*iw5.8 -0.31193
E6=A* iw6.1+B*iw6.2+C*iw6.3+D*iw6.4+E*iw6.5+F*iw6.6+G*iw6.7+H*iw6.8-1.592
E7=A* iw7.1+B*iw7.2+C*iw7.3+D*iw7.4+E*iw7.5+F*iw7.6+G*iw7.7+H*iw7.8-1.2499
E8=A* iw8.1+B*iw8.2+C*iw8.3+D*iw8.4+E*iw8.5+F*iw8.6+G*iw8.7+H*iw8.8-1.3013
E9=A* iw9.1+B*iw9.2+C*iw9.3+D*iw9.4+E*iw9.5+F*iw9.6+G*iw9.7+H*iw9.8-1.0383
E10=A* iw10.1+B*iw10.2+C*iw10.3+D*iw10.4+E*iw10.5+F*iw10.6+G*iw10.7+H*iw10.8-0.92395

defect={[2/(1+exp(-2*E1))-1]*-0.090706}+{[2/(1+exp(-2*E2))-1]*2.0355}+{[2/(1+exp(-2*E3))-1]*-0.020178}+{[2/(1+exp(-2*E4))-1]*1.2419}+{[2/(1+exp(-2*E5))-1]*0.021475}+{[2/(1+exp(-2*E6))-1]*0.19257}+{[2/(1+exp(-2*E7))-1]*-0.023862}+{[2/(1+exp(-2*E8))-1]*1.3296}+{[2/(1+exp(-2*E9))-1]* -0.27768 }+{[2/(1+exp(-2*E10))-1]* 0.0086317}+1.7847

Table 3.9: Comparison of models

Test no	Defects(%)	Percentage of defects using Neural network			Percentage of defects using Decision Tree			Percentage of defects using DT-ANN		
		ANN	**Error**	**Squared error**	**DT**	**Error**	**Squared error**	**DT-ANN**	**Error**	**Squared error**
1	5,053	4,5639	0,4891	0,2392	5,8650	-0,8120	0,6593	4,7446	0,3084	0,0951
2	5,206	5,5576	-0,3516	0,1236	6,8530	-1,6470	2,7126	5,6177	-0,4117	0,1695
3	6,24	6,0449	0,1951	0,0381	6,2720	-0,0320	0,0010	6,3019	-0,0619	0,0038
4	4,376	4,9151	-0,5391	0,2906	5,6550	-1,2790	1,6358	4,7727	-0,3967	0,1574
5	5,866	5,3564	0,5096	0,2597	5,6550	0,2110	0,0445	5,4406	0,4254	0,1810
6	7,083	6,5691	0,5139	0,2641	7,4650	-0,3820	0,1459	6,6377	0,4453	0,1983
7	3,186	3,6224	-0,4364	0,1905	4,4650	-1,2790	1,6358	3,6620	-0,4760	0,2266
8	4,806	5,6365	-0,8305	0,6897	5,8650	-1,0590	1,1215	5,6255	-0,8195	0,6716
9	7,25	6,4785	0,7715	0,5952	6,2720	0,9780	0,9565	6,4933	0,7567	0,5725
10	6,136	6,1630	-0,0270	0,0007	5,6550	0,4810	0,2314	5,8328	0,3032	0,0919
11	6,766	6,5633	0,2027	0,0411	5,6940	1,0720	1,1492	6,7216	0,0444	0,0020
12(extract)	**9,306**	**9,6551**	**-0,3491**	**0,1219**	**7,4650**	**1,8410**	**3,3893**	**7,7950**	**1,5110**	**2,2830**
13	7,283	7,0781	0,2049	0,0420	6,9660	0,3170	0,1005	6,9675	0,3155	0,0995
14	6,066	5,7646	0,3014	0,0908	5,6940	0,3720	0,1384	5,7934	0,2726	0,0743
15	6,526	7,2974	-0,7714	0,5951	6,2720	0,2540	0,0645	7,2017	-0,6757	0,4566
16	4,586	4,6438	-0,0578	0,0033	5,6550	-1,0690	1,1428	4,6601	-0,0741	0,0055
17	6,69	6,8101	-0,1201	0,0144	6,9660	-0,2760	0,0762	6,6721	0,0179	0,0003
18	7,523	7,2211	0,3019	0,0911	6,2790	1,2440	1,5475	6,8237	0,6993	0,4890
Sum of squared error				3,5681			13,3635			3,495
Average of squared error				0,21			0,7861			0,2056
Square root of the average squared error				**0,4582**			**0,8866**			**0,4543**

CHAPTER 4

THE METHOD FOR DESIGNING A DECISION SUPPORT SYSTEM

4.1 Background

A decision support system is a knowledge based framework that is organized in order to assist human users to finalize their decision-making activities towards an optimal route. Decision support systems can function efficiently in planning and operational activities of complex organizations where decision making is not easy with conventional apprehensions. A “decision support system” can be identified as an interactive, or pro-active knowledge based system, usually extracting its rule base through supplies like raw data, experience based knowledge or previous active models to direct the users towards the practical ways to cope with their organizational problems.

Although not many, some current decision support systems were developed in the area of casting. The first study in that area comes from Tiwari and Banarjee (2001), who had applied the Analytic Hierarchy Process (AHP) to select the most suitable casting process for a given product. The hierarchical structure of the proposed method allows the decision maker to compare the different casting processes with respect to the material suitability and flexibility, geometrical complexity, dimensional tolerance and surface finish of the casting, and the cost as the criteria for selection.

Another study of this area deals with the design of a decision support system for the scheduling of production in steel casting foundries (Teixeira Jr. et.al, 2006). In this study, three viable decision models for production scheduling were proposed: a binary integer programming model, a model based on classical approximation methods, specifically the method known as beam search, and a model based on a meta-heuristic to replace the former production control system known as Period Batch Control .

The third study of this area deals with two batching problems for steelmaking and continuous-casting production in an integrated iron and steel enterprise. The tasks of the problems are to make the decisions as how to consolidate ordered slabs into *charges,* and then how to group *charges* into *casts.* The effective decisions on these batching problems can help to balance the requirements of materials in downstream production lines, improve the customer satisfaction levels, and reduce production costs (Tang, Wang, 2008). The decision supports system was arranged on integer programming models for considering the practical constraints and requirements supported by two heuristic algorithms for the corresponding batching problems.

Unfortunately still, there is not an existing decision support model in the literature to help the users dealing with the choice of the input parameters in a sand casting system, which will give an efficient casting product. Another aim of this study is to establish the background of such a system, using the models developed.

4.2 The Potential Method for a Decision Support System

As discussed in the previous chapter, a hybrid model was proposed in this study to predict the percentage of defectives in a sand casting system based on the input parameter values. Being parallel to this result, as an advantage of the model the critical input parameters affecting the casting performance, and the rule base constructing the relations between the critical inputs and the casting performance were also extracted. Two examples of these critical rules were given in Table 4.1.

Table 4.1: Critical rules

Rule 1:
IF green strength>1284,90 THEN defect (%)=9,767
Rule 2:
IF green strength>1125.05 AND green strength ≤1284.91 AND pouring temperature≤1370,43 THEN defect (%) = 7,465.

Also as a result of the hybrid model, a mathematical model to establish the relations between the 8 input values and the output value (defect percentage) were also developed as can be seen in Table 4.2.

Table 4.2: The mathematical expression of the hybrid model

defect={[2/(1+exp(-2*E1))-1]*-0.090706}+{[2/(1+exp(-2*E2))-1]*2.0355}+{[2/(1+exp(-2*E3))-1]*-0.020178}+{[2/(1+exp(-2*E4))-1]*1.2419}+{[2/(1+exp(-2*E5))-1]*0.021475}+{[2/(1+exp(-2*E6))-1]* 0.19257 }+{[2/(1+exp(-2*E7))-1]* -0.023862 }+{[2/(1+exp(-2*E8))-1]* 1.3296 }+{[2/(1+exp(-2*E9))-1]* -0.27768 }+{[2/(1+exp(-2*E10))-1]* 0.0086317}+1.7847

By relying on both the extracted rules and the mathematical model, it is possible to direct the user towards a more efficient performance in his/her casting design. The steps of the core decision support system should follow these steps:

a) The input is requested from the user, possibly for all input parameters including green strength, pouring temperature, etc.

b) Initially, if the input values fires one of the critical rules the user will be warned about the situation with the phrase

"If you use these levels for your input parameters, you will face with an inefficient result",

or even

"You should decrease your green strength, in order to have a better value for defect percentage".

In this step, the user will have a chance of updating his input values to overcome a possible deficiency in the casting performance.

c) If any of the critical rules is not fired, then the decision support system will switch its strategy to a direction to deal with the mathematical model. Also, after a possible firing of the critical rules the algorithm will again be directed to the mathematical model for a final check.

d) Based on the input values received from the user, the defect percentage will be predicted, and if this percentage is greater than 7 the critical value of 7, the user will be warned again about a possible inefficiency of the casting product like:

"If you use these levels for your input parameters, you will face with an inefficient result"

e) After the first warning the critical parameters of the model will be determined according to the data set given by the user, by a comparison of the "total amount of contribution" to the predicted defective percentage by the interaction of the input value with the calculated weights of the input parameters. For instance in the below case even though the two parameters effect the result in reverse directions because of the signs of their weights, the second parameter, seems to have a higher effect in the result than the first parameter due to the greater size of its weight:

defect={[2/(1+exp(-2*E1))-1]*-0.090706}+{[2/(1+exp(-2*E2))-1]*2.0355}…

f) So directing the concentration of the user towards the input parameters having an higher effect in the result, an updated data set will be asked from the user. As an addition the user will be asked to start the updating procedure from the most critical parameter indicated by the most powerful weight:

“You should increase the value of the second parameter to achieve a product with a lower percentage of defective”.

g) The warnings will continue following the sequence constructed with respect to the impact of the input parameters, until the user will have the chance of achieving a better result with a smaller percentage of defective values.

The framework for the proposed decision support system is given in Figure 4.1.

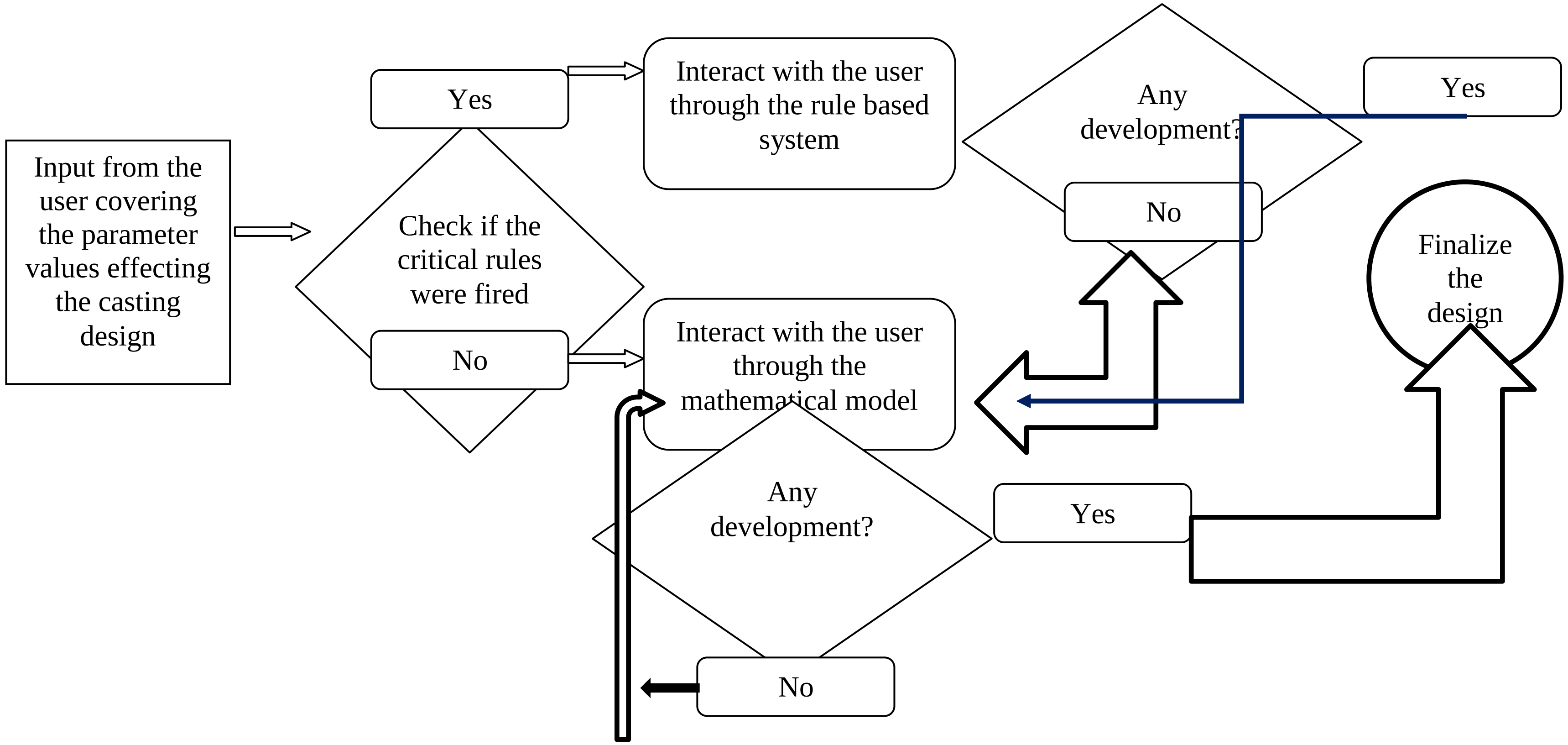

Figure 4.1: Framework for the decision support system

CHAPTER 5

CONCLUSIONS AND DISCUSSIONS

Among the industrial activities sand casting process still remains as one of the most complex and indefinite activities. In such a critical process like sand casting, which determines the success of the casting process which is the backbone of the industrial activities; being complex and indefinite can have many negative consequences. Many, metallurgical and material engineers are complaining about the problems they face while trying to achieve the desired success in casting, with the defined input values. Normally, in such process like sand casting where many defined or undefined natural effects can take place, it is very hard to construct a "definite" model that will lead the users towards a guaranteed success. Therefore, starting the process of model development by taking a data set whose success or failure were certified seems to be the only possible way to develop a realistic model.

Within this study, three different models aiming to establish the relations between the input values and the casting quality were developed on a hypothetically produced data set. The first two models were conventional ones making use of the artificial neural networks and decision trees, the third model is a unique one taking the data reduction advantage of the decision tree to prepare a more compact data set for the artificial neural network, thus called the "hybrid model". When these three mathematical models were tested with the original data set used for the production of the hypothetical set through the regression analysis, it was observed that the proposed hybrid model stands as the most "accurate" and most "efficient" of the three models.

This study carries original contributions to the literature in three main ways:

a) The proposed hybrid model is the first application of a combination of two classical data mining approaches namely as, decision tree and artificial neural network in the area of casting. Furthermore, the combination of the data reduction capability of decision tree approach based on its efficient classification procedures, with the input-output mapping capability of the artificial neural network resulted in a very original result. By this combination, the "point-to-point" learning approach of the artificial neural network, was successfully replaced with a procedure directed to learn only the critical points which are supplying the "clues" for the shape of the final pattern of data. So, with this new model, a very similar version of the given input-output pattern can be learned, with a smaller amount of input-output mapping, resulting in a remarkable decrease in execution time and memory consumption.

b) The method for designing a decision support system which seems to be differentiated from the previous approaches in the area with its capability of directing the user towards a more efficient casting procedure, by utilizing the power of the hybrid model for relating the input values to the casting quality performance. By this procedure, the user is directed step by step to a more efficient result, using both the rule-based system acquired from the decision tree approach and the mathematical model acquired by the artificial neural network application. The pro-active character of the system will be another advantage to choose the shortest way to direct the user to an efficient design.

c) The proposed model stand as an efficient media to present the critical input parameters affecting the quality of the casting process which supplies supportive knowledge to enlighten the indefinite procedures lying beneath the vague sand casting procedure.

In complex processes such as medicine and economy where there is an huge number of outputs, determining the most significant input parameters with respect to their effects on the output parameters is a very critical problem. The developed model will be especially useful where there is an huge amount of the data acquired through many different parameters, so the casting industry can be considered as a fruitful area of application of this model. The model can efficiently construct the relation between the casting parameters and casting quality for complex processes of casting, and it will not be beneficial to apply the model for the applications for which few data can be obtained. Another issue must be considered is the aspect of data quality by means of collection and consistency; in that sense a low quality data can lead to misleading results. The system which can assure the data quality should be founded before the development of the models.

There are some limitations to the study: first the models are developed based on hypothetical data that are generated from regression equations using Taguchi experiments related to molding process. The models should be verified with real-life casting data for molding processes as well as other operations of casting in order to certify the consistency of the model. Second, in this study, it is assumed that the hypothetical data meet the data quality feature. The results can be changeable for different data sets, and problematic results can occur when low quality data is fed to the system. So the robustness of the model should be verified for different data sets gathered from the different potential areas of casting and neigbouring areas for the sake of measuring the sensitivity of the system with respect to the input data.

Third the model is verified/tested only with the mentioned data set acquired through the literature. The results should be evaluated by an expert from the casting industry for certifying the consistency of the application with the real life activities.

Shortly, the model can further be developed, analyzed and updated if it can be possible to achieve real-life values from the operational units in the casting industry. The execution of the model with the appearance and support of the new techniques and models can further increase the efficiency of the results achieved. Despite the advantage of the Decision Tree in this hybrid model in reducing the sample space, this technique is open to instability. This means that mostly same variables enter the decision tree but the order in which they enter the tree may be different when performing several tests. Therefore, a small change in the sample data may shift the split in the tree from one variable to another if the two variables are highly correlated. As a future study, integrating a Bayesian Network, descriptive probabilistic graphical model, with Decision Tree in order to select its decision nodes using conditional probabilities will be considered to handle the mentioned problem.

The developed model can be identified as a compact and efficient system to create a platform for the construction of the relation between the casting parameters and casting quality. This platform is practical and usable for the engineers working in the casting area, to receive help in their search for a more efficient, robust and defined system for the casting industry. As a future study, the implementation of the proposed decision support system and the strengthening of the "intelligent" side of it can be a stimulating way to follow.

This study can bring a modest contribution to the casting literature by being an applicable tool, that can simplify the works of the engineers and other operational personnel in this industrial branch.

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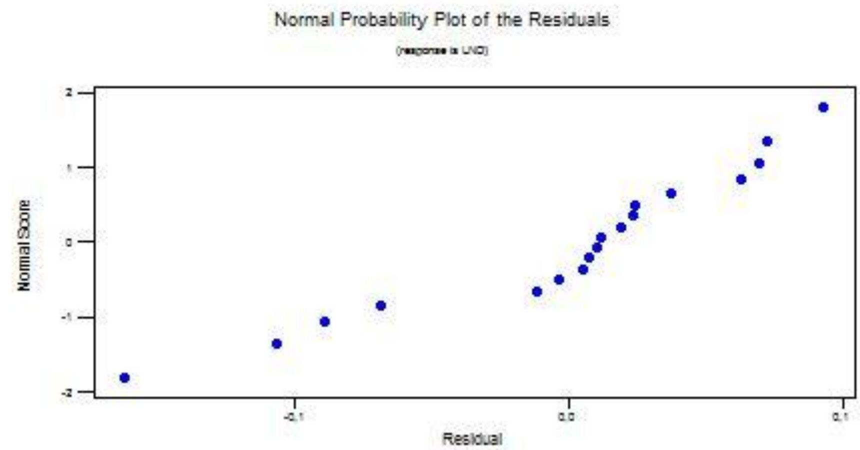
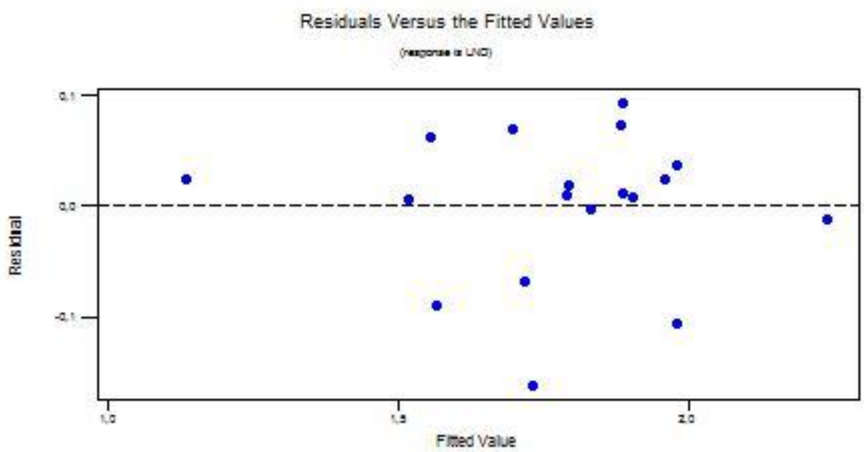
APPENDICES

APPENDIX A (Normal Probability Plot of Residuals)





APPENDIX B DATA SET

A: Moisture content (%) **D: Mold hardness (nu)** **G: Pouring time (sec)**
B: Sand particle size (AFS) **E: Permeability (nu)** **H: Pressure test (Mpa)**
C: Green compression strength (g/cm^2) **F: Pouring temperature (deg c)**

	A	B	C	D	E	F	G	H	Defect (%)
1	3,84504	53,3897	1014,05	57,0487	219,23	1320,52	23,4263	1,90251	6,957413
2	3,91024	55,7114	1058,42	79,7555	195,654	1343,54	21,809	2,39604	5,618455
3	3,74821	54,1944	1209,67	61,6602	158,631	1375,68	27,7944	2,47723	6,820357
4	3,7089	55,0156	1053,3	60,841	174,006	1406,68	22,9397	2,28699	4,800409
5	3,81246	52,7062	925,75	65,1701	211,057	1364,47	25,0945	2,35473	5,997376
6	3,62737	52,0983	1019,71	53,5456	135,224	1362,38	23,3668	2,06555	4,576737
7	4,1012	52,6842	1004,94	72,7971	161,898	1355,18	22,8834	2,359	6,067891
8	3,73734	53,0634	1006,47	43,2738	182,468	1330,09	17,9356	1,68536	6,274022
9	3,70469	52,7685	1017,41	72,1029	145,181	1307,53	22,3594	1,98741	5,21637
10	3,47565	51,8759	1154,42	64,0033	186,121	1447,93	20,5012	2,31421	5,149897
11	3,83582	53,8396	1193,98	70,6063	204,22	1413,82	29,9019	1,17089	6,067127
12	3,51242	52,7892	919,48	68,899	153,949	1367,57	26,8068	1,69302	3,832386
13	3,33713	51,7589	1282,43	65,2586	203,912	1351,73	20,6415	2,1856	7,875425
14	3,34046	53,1818	1060,84	76,9485	176,482	1343,98	23,0628	1,62953	4,710623
15	3,62518	52,2072	860,02	61,6728	197,242	1355,89	20,4718	1,59127	5,634737
16	4,1439	54,2517	1015,06	72,9929	244,916	1307,12	24,0597	1,45685	6,683679
17	3,59619	53,2219	1122,25	61,0726	177,177	1400,98	21,5957	2,11392	5,371692
18	3,89078	52,3138	902,3	69,6259	174,855	1367,72	25,5815	1,86474	5,174556
19	3,89866	52,1856	1194,04	72,4672	208,951	1380,41	20,335	1,56057	6,817982
20	3,92915	50,2508	1002,22	69,3984	168,765	1326,09	20,8542	2,13391	6,386566
21	3,69808	53,5131	1118,71	72,6739	162,67	1445,28	22,1795	2,71474	4,715569
22	3,68665	51,1221	1035,8	63,8751	186,086	1376,22	28,1591	2,4503	5,645581
23	3,61959	52,4077	939,1	53,6799	206,655	1366,22	28,0453	1,87199	5,990386
24	4,2131	54,173	1025,13	70,2592	196,926	1325,92	21,5291	2,72707	6,664755
25	3,77252	49,9287	1335,72	53,6483	187,805	1332,8	18,0269	1,89367	11,58187
26	3,80961	54,2794	918,79	75,5891	202,107	1364,24	22,3822	2,12174	5,328117
27	3,84513	53,3708	1082,54	62,6384	169,104	1364,48	24,1496	2,51926	5,942465
28	4,02887	51,5981	1019,45	72,5864	196,248	1365,03	21,466	2,27262	6,16361
29	3,9684	54,6291	1113,08	70,7918	163,678	1320,89	20,9552	1,83291	6,792822
30	3,84186	53,83	1075,92	79,6761	135,842	1320,15	24,5077	1,31672	5,771358
31	3,69884	52,426	1087,37	74,0295	176,454	1278,73	20,6209	1,9689	6,677146
32	3,79644	54,0878	1076,28	59,3248	141,218	1351,78	21,2458	2,22551	5,563861
33	3,52646	53,1982	994,14	69,7141	209,936	1354,66	27,0469	1,60248	5,677438
34	3,63822	52,1787	794,63	41,5402	175,579	1301,02	16,2517	2,23713	5,877729
35	3,84368	52,4947	976,57	62,7702	192,959	1334,81	21,2648	2,24137	6,151153
36	4,10412	53,2292	1063,12	58,293	226,505	1332,52	22,5451	2,19035	7,033794
37	3,80221	52,1456	1081,98	77,7395	159,037	1345,39	29,0392	1,72338	5,846159
38	3,70135	53,5169	1107,29	75,7266	164,583	1403,8	20,2155	1,92709	5,012281

39	3,70185	51,8551	1124,48	67,0985	150,688	1345,15	21,6933	1,99542	6,146623
40	3,67892	57,8197	1139,87	65,9912	179,46	1289,82	31,0011	2,18747	6,236202
41	3,73633	49,8634	1100,12	54,4803	181,659	1369,11	23,0187	1,85414	6,662056
42	3,65457	49,6594	1098,44	65,1148	220,156	1431,11	24,2523	1,93915	6,022176
43	3,79477	52,7513	1049,17	62,3842	192,801	1361,2	23,7839	2,00164	6,0005
44	3,94758	52,2294	1157,36	73,8602	139,633	1387,53	24,1421	1,86078	6,869736
45	3,54718	52,9232	1013,03	60,3269	217,116	1322,99	29,0551	1,69703	6,651285
46	3,49304	52,9182	1088,5	68,2855	183,137	1333,75	26,2141	2,15768	5,665175
47	3,36881	53,2482	969,94	60,3925	169,263	1422,34	16,8393	2,55201	3,743254
48	4,06082	51,837	989,62	59,6349	175,772	1367,76	25,1559	2,07825	6,187471
49	3,85936	53,5336	1162,36	67,6876	192,869	1393,05	24,3478	1,95	6,252872
50	3,82549	55,2962	1128,57	66,1204	196,088	1371,26	22,7541	2,20027	5,943293
51	3,81281	53,0489	1191,3	65,404	182,79	1326,5	26,056	2,08753	7,604746
52	3,75273	55,6531	1014,65	65,5245	191,397	1391,41	23,9693	2,49786	4,957643
53	3,62272	50,5926	1117,81	69,6973	131,227	1352,98	26,3299	2,08593	5,581047
54	3,70286	52,1592	1176,86	61,3303	187,683	1387,36	25,4416	1,69333	6,56737
55	3,61836	52,8825	1083,63	72,5378	188,789	1371,44	21,4082	1,74495	5,455405
56	3,44635	53,1449	1087,76	52,1536	174,354	1358,73	23,0651	1,95567	5,368301
57	3,77575	52,7446	1025,48	84,0433	140,227	1378,78	26,591	2,19925	4,551001
58	3,88878	50,1065	922,56	62,2174	197,094	1392,86	25,7294	2,20726	5,826462
59	3,641	50,1895	1073,31	60,5658	198,485	1377,2	21,1401	1,34731	6,227549
60	3,78615	53,2513	1032,36	65,9422	164,244	1356,26	24,7201	1,57427	5,387324
61	3,81825	53,0738	1080,55	52,9316	226,661	1333,26	23,366	1,9396	7,220818
62	3,87254	52,5468	1165,36	67,847	207,895	1356,74	19,7639	2,0125	6,943005
63	3,70234	53,4964	957,72	66,5482	195,017	1221,11	29,5828	1,49711	7,200424
64	3,79658	50,0241	1088,72	73,1065	199,464	1374,73	19,2221	1,76438	6,305723
65	3,40164	51,9537	1093,93	69,6525	187,915	1333,04	20,7915	1,79713	5,760469
66	3,86472	54,8349	868,89	71,7799	214,832	1414,59	24,1365	2,81053	5,222154
67	3,82853	52,1095	1003,63	51,5265	127,142	1384,54	22,6366	1,62654	4,832853
68	3,73337	51,675	1028,72	67,0288	220,992	1424,82	23,9408	2,08144	5,584621
69	3,72657	52,5904	1071,94	67,847	178,985	1328,43	19,0077	2,66606	6,117116
70	3,56267	51,586	1133,93	49,885	214,806	1420,68	21,878	2,28536	6,297723
71	3,93646	51,4178	1032,7	42,0861	142,278	1363,59	15,9897	1,43541	6,241689
72	3,84462	51,1961	1133,17	80,5898	195,083	1289,97	25,242	1,47362	7,50501
73	3,71447	53,4958	1253,21	46,1399	153,559	1385,14	27,2798	2,33073	7,849067
74	3,73001	54,1357	1023,63	57,2804	225,283	1392,23	20,0169	2,24733	5,953492
75	3,80182	52,204	1187,15	67,0099	174,717	1332,47	25,7394	2,41384	7,578474
76	3,77642	50,3737	1137,88	50,4848	185,952	1315,16	20,216	2,07354	8,054355
77	3,88687	54,4817	1060,52	58,1508	180,161	1320,86	31,799	1,74363	6,459478
78	3,66312	53,1473	898,48	66,7469	153,951	1442,74	24,9103	1,66914	3,51925
79	3,93232	53,3496	1044,13	65,2454	168,899	1368,47	23,3834	1,65065	5,779879
80	3,98216	52,5041	1065,1	73,3483	200,088	1322,69	23,9342	1,86994	6,722822
81	3,66014	52,8373	1239,99	50,2691	158,854	1369,6	29,3179	1,89907	7,648591
82	3,76019	54,3159	995,07	57,8714	192,951	1391,12	25,9141	1,81453	5,265149
83	3,76133	52,6364	988,09	69,4887	163,224	1379,44	22,9334	2,03058	4,813322
84	3,88353	56,5924	964,74	64,707	172,474	1355,31	20,6905	2,45933	5,01582

85	3,74506	54,1935	857,83	72,6166	198,834	1339,82	23,7418	1,99769	5,561177
86	3,88972	50,7579	943,88	56,3527	168,228	1357,44	18,814	2,0905	5,740152
87	3,97928	53,4957	896,73	56,755	204,707	1452,7	26,9998	2,58447	5,12792
88	3,86876	52,6544	1167,76	77,6542	205,003	1277,38	25,0812	2,02925	7,852093
89	3,48577	53,551	1172,8	82,1624	203,017	1363,1	24,9472	1,81846	5,842243
90	3,41091	49,5488	1034,01	59,3325	139,44	1327,61	20,1471	1,7773	4,626468
91	3,52405	53,1709	1074,29	56,0905	149,218	1371,13	22,3387	1,72548	4,720755
92	3,94311	52,6249	1156,85	59,3879	187,505	1322,37	25,2441	1,86478	7,83558
93	3,48995	53,8944	894,22	71,1186	179,94	1349,87	29,3987	2,06045	4,494098
94	3,80455	53,7653	913,55	48,515	166,437	1381,52	28,894	1,94401	4,887726
95	3,64413	54,6232	1141,91	61,4177	176,74	1344,76	19,3466	1,49014	6,092523
96	4,08244	52,7794	956,84	72,3199	188,575	1351,37	22,5213	1,77408	5,99291
97	3,59433	51,8516	1058,15	78,4814	196,464	1336,28	24,1081	1,78294	5,83667
98	3,68932	50,8891	1074,83	77,6133	170,512	1313,59	24,688	1,92621	6,164262
99	3,76668	52,9136	1050,72	57,2647	145,722	1332,41	26,0004	1,94149	5,684376
100	3,68294	53,0699	1119,34	68,2261	144,746	1364,07	23,5005	1,79752	5,512219
101	4,06796	53,6305	1047,88	73,2624	176,475	1379,57	23,9872	2,16313	5,841036
102	3,87193	52,7743	902,98	83,5304	164,487	1333,47	23,7166	1,97137	4,982782
103	3,52077	49,9842	971,52	81,1459	136,864	1382,09	20,4475	2,24127	3,688784
104	3,97034	51,0495	931,54	46,8918	176,019	1351,03	23,8589	1,83687	6,314779
105	3,73055	49,5623	1110,47	70,4475	186,728	1388,43	26,6949	1,72144	6,199281
106	3,78831	49,8733	1130,67	53,4995	195,761	1295,31	23,0771	2,43258	8,447925
107	3,66945	50,7207	1050,09	72,2481	170,147	1378,76	27,1997	2,5043	5,273533
108	3,89717	50,8292	905,54	55,6493	218,28	1303,5	25,8521	2,59135	7,749344
109	3,78902	54,5164	926,27	80,648	147,283	1345,01	23,9181	1,6033	4,281826
110	3,66856	54,6497	1161,96	65,4834	169,827	1380,61	26,5258	2,40171	5,762198
111	3,75029	52,6307	1090,2	57,7521	199,641	1352,22	21,4283	2,38699	6,511948
112	3,67159	50,6484	1110,29	58,9478	193,693	1420,65	22,551	1,76836	5,863911
113	3,6152	50,92	1079,55	57,9924	199,947	1398,36	27,7698	1,69474	5,935823
114	4,00361	52,4981	958,08	76,9381	183,518	1372,41	29,2812	1,90245	5,475314
115	4,05889	52,1494	1049,04	68,5748	199,039	1326,89	27,8026	1,9148	6,896184
116	3,66344	50,1976	916,71	70,036	183,982	1331,88	24,14	1,49245	5,604896
117	4,02313	46,778	1158,52	74,0614	191,199	1438,92	24,5769	2,03562	7,015008
118	3,66073	53,974	1147,76	78,3103	210,249	1377,7	28,5245	1,72116	5,778635
119	3,7991	54,972	980,98	75,1817	182,958	1429,47	26,0306	1,77627	4,339434
120	3,80645	52,7891	992,99	64,3922	181,154	1411,9	22,2813	1,55336	4,970011
121	3,69488	53,3913	1082,78	62,7045	188,658	1339,53	24,7211	2,08691	6,119439
122	3,72084	51,9739	1116,29	64,1986	187,842	1356,88	19,7089	2,23183	6,392983
123	4,09215	53,3077	1090,84	76,2319	154,551	1331,31	25,3785	1,73211	7,010811
124	3,30109	52,5892	955,79	57,1057	182,977	1342,69	31,1814	2,18988	4,839574
125	3,61395	50,7194	987,93	71,9563	145,107	1340,94	24,096	2,25562	4,61637
126	3,73262	47,8356	1078,38	70,9451	162,024	1339,02	28,4822	1,89849	6,537211
127	3,85688	51,2072	1000,46	67,4131	206,169	1352,39	23,6606	1,93085	6,323483
128	3,48982	53,7649	1121,91	66,1679	180,895	1397,44	22,0582	2,00533	5,067839
129	3,87786	52,1769	908,84	65,4483	207,329	1331,94	21,0962	1,6525	6,464733
130	3,8414	53,0372	953,63	51,2692	198,61	1337,98	21,3151	2,13722	6,39356

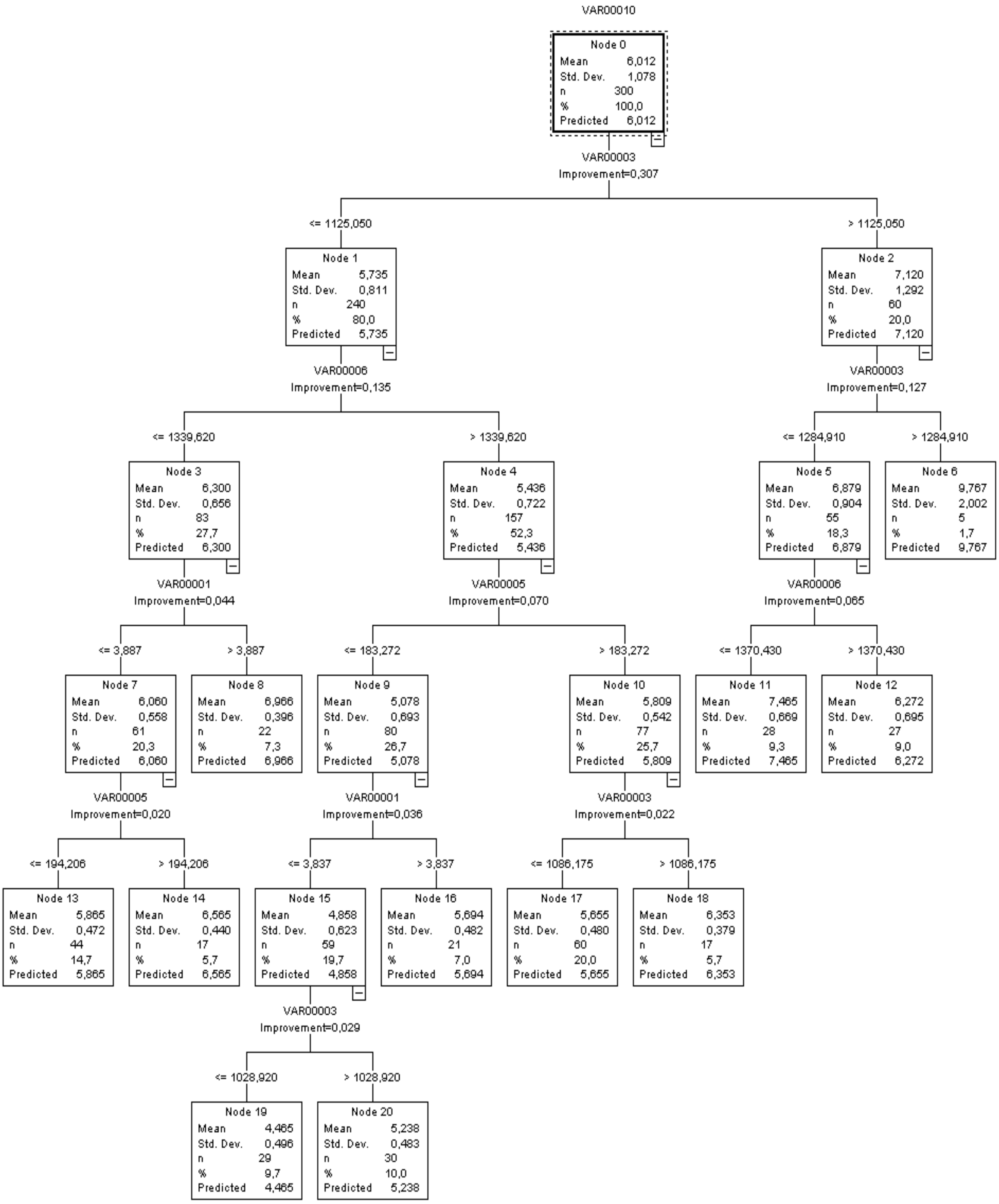
131	3,89074	51,6274	962,63	68,866	222,521	1320,24	22,8559	1,59485	6,943502
132	3,69964	50,8373	1058,36	74,6556	192,897	1372,4	26,3507	1,91831	5,75181
133	3,5437	53,3869	894,81	65,1523	207,225	1388,45	25,7223	2,01521	5,289759
134	3,95924	52,6248	979,94	54,7277	170,072	1305,24	27,0405	1,99049	6,596747
135	3,56895	53,5514	1074,64	74,736	171,796	1375,04	23,9154	2,22427	4,85544
136	3,63051	52,0142	1110,47	60,7629	193,108	1372,07	23,1009	1,93281	6,124328
137	3,63973	54,0996	1057,78	56,8654	170,414	1392,17	29,1664	1,50768	4,951645
138	3,90236	54,8741	1060,73	67,3774	201,2	1375,33	24,4167	2,80595	5,691074
139	3,69834	53,2764	1118,37	64,3362	164,712	1303,51	23,414	2,62811	6,574304
140	3,73683	50,9303	979,89	68,4141	181,381	1335,68	21,4521	1,87487	5,787117
141	3,73248	52,7729	855,47	61,8912	203,84	1334,29	25,0694	1,99575	6,236315
142	3,98316	54,0618	1118,07	79,2688	158,488	1326,53	25,4611	1,83267	6,75404
143	3,62613	53,9174	977,1	63,8125	208,913	1312,36	24,1317	2,44419	6,296634
144	4,02563	55,5505	1149,32	77,7145	164,742	1380,44	22,9964	2,41119	6,261911
145	3,49064	52,7591	1148,03	59,4801	165,978	1381,58	24,3735	1,43757	5,498093
146	3,68169	52,1088	1090,56	64,5002	175,026	1391,73	23,9753	1,65971	5,483152
147	3,90461	53,9947	1150,66	43,1502	110,734	1404,85	24,0639	2,12969	6,568531
148	3,96094	50,6502	1198,06	69,0502	192,007	1407,01	22,3063	2,19228	7,162971
149	3,77353	53,3646	1183,85	53,2308	180,22	1349,73	20,4816	1,75625	7,312721
150	3,88717	53,7044	992,47	39,8665	163,595	1293,07	22,1348	1,18439	6,664941
151	3,56331	55,3184	1232,45	47,0375	200,216	1372,66	27,3381	2,01059	6,977147
152	3,63725	51,3169	1061,91	69,0342	178,538	1325,82	26,2079	2,18994	6,026842
153	3,71337	54,9831	1146,94	74,4262	178,996	1472,13	26,842	2,34525	4,588051
154	3,79613	50,7149	1125,16	58,5189	174,14	1303,67	27,5995	2,24585	7,726561
155	3,61821	53,3434	942,65	62,5525	197,361	1351,05	20,4158	1,93822	5,529283
156	3,73724	51,1448	1117,01	62,6723	194,221	1353,91	21,777	2,49713	6,72887
157	4,15476	53,8086	1109,1	58,2095	159,026	1386,46	22,813	1,90353	6,964322
158	3,89246	51,6767	984,9	77,0215	185,409	1367,33	27,2501	1,7928	5,537328
159	3,8801	53,487	933,87	63,2155	187,451	1418,72	30,6892	1,90437	4,914641
160	3,5941	52,1313	1064,68	76,6706	192,927	1367,49	29,9784	1,72101	5,439338
161	3,96482	50,7001	1103,85	82,3831	243,883	1343,24	21,4869	1,87683	6,621435
162	3,99946	52,9063	880,45	65,9594	196,688	1379,08	30,9313	2,10978	5,690869
163	3,49729	52,1552	991,62	63,6329	208,539	1313,59	25,0303	0,96209	6,428002
164	3,79685	51,1735	1062,63	76,7373	183,026	1429,25	25,1892	2,8727	5,099396
165	3,98746	50,961	1045,65	57,8525	186,475	1285,41	20,8905	2,11064	7,843112
166	3,74815	51,5109	917,23	55,4662	202,876	1372,89	28,1747	1,545	6,006886
167	3,92968	54,5265	1022,63	73,0251	189,967	1349,81	26,5206	1,64388	5,706656
168	3,88457	53,129	1049,33	89,8622	172,231	1369,12	25,7715	1,81491	5,254677
169	3,75194	52,5202	1121,65	58,9957	210,822	1367,79	26,4835	1,92575	6,612452
170	3,64287	51,7226	1081,08	86,6527	165,741	1346,34	18,9532	1,72116	5,326029
171	3,74855	52,4161	1157,56	63,6904	232,024	1413,4	19,3321	1,97283	6,229504
172	4,10993	53,3329	1031,26	66,0669	196,138	1316,59	27,2048	1,74972	6,90284
173	3,92677	49,9262	941,03	73,9268	160,203	1360,29	27,6951	2,18832	5,422069
174	3,46453	53,4032	934,11	47,768	157,36	1365,83	19,2216	1,30711	4,099064
175	3,8506	51,9272	862,62	57,9505	193,6	1361,22	24,2149	2,00575	5,912894
176	3,45109	49,7353	892,67	62,5628	182,591	1428,08	17,4106	2,04383	4,34267

177	3,9202	52,9263	1132,09	70,2829	218,75	1401,37	19,1118	1,89389	5,999983
178	3,65841	54,3182	1060,4	90,668	182,696	1333,51	24,2291	1,55701	5,14956
179	3,35047	49,9834	1212,36	67,3058	178,321	1342,89	24,9469	2,37881	6,925957
180	3,6954	51,7432	1054,56	53,1805	175,334	1329,23	24,5287	1,87358	6,306502
181	3,69072	50,0085	1080,71	64,12	157,322	1315,37	22,5759	2,72067	6,4382
182	4,01398	51,7171	1197,07	68,4165	182,654	1365,37	24,8896	1,83891	7,846211
183	3,64166	51,6718	1039,91	64,7507	179,706	1318,89	26,7658	1,80355	6,037397
184	3,45357	54,4001	947,65	53,943	217,721	1374,88	20,0406	2,25846	5,879856
185	3,61361	50,6935	946,55	58,2117	147,727	1270,63	25,2546	1,97843	5,352694
186	3,74956	52,5557	903,37	63,6042	181,504	1272,86	22,9879	1,7622	6,246185
187	3,84418	53,1358	1080,43	69,7735	169,767	1323,48	27,5883	2,11623	6,331155
188	3,64611	52,7091	970,12	71,3999	175,33	1365,58	25,03	2,39101	4,808994
189	3,79886	53,221	970,22	64,9747	186,482	1334,51	23,3686	1,76143	5,76434
190	3,59398	51,3842	1055,03	73,5716	182,175	1321,31	23,9782	2,06273	5,895427
191	3,69906	52,3296	1147,42	63,6378	185,507	1371,51	24,4219	1,99066	6,364977
192	3,48572	50,7974	967,76	60,1203	172,392	1398,61	21,3737	2,28186	4,484745
193	3,77621	54,7006	1024,34	65,1438	150,728	1324,16	20,6878	2,73864	5,277814
194	3,68111	53,1147	1064,49	55,7047	186,261	1366,01	23,4188	1,69705	5,814038
195	3,947	51,8424	979,96	57,5967	198,701	1343,05	23,555	1,93412	6,565164
196	3,77434	53,1609	1186,93	65,5265	190,061	1320,55	28,3158	2,188	7,50498
197	3,73638	53,1451	899,04	82,3916	221,005	1492,25	22,9392	1,84947	4,407358
198	3,62789	52,4563	1133,4	76,174	219,715	1259,4	20,3515	1,6375	7,759275
199	3,99453	51,5795	1130,66	77,5342	194,336	1327,2	22,9384	1,83321	7,231439
200	3,62505	53,9109	1108,13	70,7799	168,757	1399,44	22,967	2,28843	4,953834
201	3,44379	54,0442	954,47	64,4549	197,507	1371,47	26,125	1,95528	4,96739
202	3,89514	52,0962	1064,21	49,9163	203,313	1336,54	26,5813	1,98945	7,167103
203	3,57983	51,7977	1250,88	64,5965	209,926	1328,88	22,263	1,8673	8,219472
204	3,53943	53,823	1076,47	60,2784	171,399	1352,16	22,7899	1,98669	5,259677
205	3,73141	52,4472	946,2	69,0662	133,596	1365,07	21,406	2,03344	4,131652
206	3,52349	53,1214	1124,94	64,6934	133,672	1387,4	20,9489	1,40576	4,668482
207	4,02069	53,1295	990,45	67,6962	189,128	1301,93	28,5997	1,64562	6,700415
208	3,63788	52,7949	1292,39	67,3547	211,268	1393,89	24,6184	1,83416	7,458706
209	4,16408	54,38	916,93	73,1227	163,164	1348,54	23,9473	1,61234	5,63762
210	3,6982	52,19	1324,93	65,9409	159,925	1390,6	25,0013	2,36122	9,094168
211	3,70596	49,6188	1079,6	60,7064	162,531	1378,62	25,6542	1,82946	5,884322
212	3,85831	50,9415	958,59	81,7575	189,953	1378,67	24,8304	2,31819	5,325528
213	3,66493	53,069	951,42	71,1056	178,85	1335,29	24,1856	1,7963	5,144071
214	3,81161	52,6499	950,61	56,6	195,029	1333,22	22,6843	2,17491	6,230492
215	3,82877	52,9879	1157,33	52,3327	192,688	1404,93	29,8494	1,41157	6,48651
216	3,69115	52,9357	1017,8	82,1283	179,787	1292,66	25,8341	1,99175	5,769657
217	3,65232	48,595	1167,75	60,9518	207,528	1349,59	23,4719	2,04238	7,843147
218	3,99882	51,9528	965,53	69,752	173,922	1281,56	21,8439	2,21339	6,766185
219	3,80962	53,0178	1188,97	64,1239	189,143	1364,65	27,7772	1,90521	7,017196
220	3,7573	51,5072	922,97	63,2794	165,161	1378,77	28,7091	2,04159	4,798744
221	3,74957	50,8847	1018,84	58,9863	205,385	1338,11	25,5937	2,38648	6,714134
222	3,78797	53,0172	1004	82,9291	206,813	1368,48	19,2166	2,59051	5,418582

223	3,56491	53,7366	860,37	61,6356	170,472	1363,83	24,0654	2,30362	4,333249
224	3,78924	54,9084	1021,7	44,1702	176,346	1322,88	25,1678	1,60505	6,136573
225	3,46859	52,2123	1104,21	72,3901	185,69	1323,4	24,7751	2,28039	5,928421
226	3,77783	53,3212	883,7	75,6839	148,866	1343,37	26,1701	1,73714	4,319231
227	3,70306	54,4925	1131,68	70,6021	195,372	1431,91	24,6445	2,137	5,106573
228	3,60441	52,6843	961,95	47,5412	190,484	1331,68	23,9256	1,97747	5,993297
229	3,78116	50,4389	923,23	74,8496	202,654	1394,39	22,5166	2,26523	5,454534
230	3,8614	50,5154	1023,94	54,723	197,881	1374,17	20,3046	2,56	6,444312
231	3,78099	51,2762	999,02	81,271	146,908	1356,52	20,2013	1,83985	4,886385
232	3,90047	54,0777	1009,72	75,5008	145,432	1339,71	22,5538	2,36952	5,257007
233	3,73064	51,444	1012,9	85,8847	198,315	1366,61	24,4543	1,6708	5,407764
234	3,94207	50,0019	991,71	76,1552	204,471	1301,26	19,3859	1,75361	7,036437
235	3,78067	51,9304	1038,26	62,0275	179,888	1427,59	19,6	1,86244	5,099156
236	3,52671	49,7474	1106,16	66,3616	168,265	1383,07	24,305	1,63306	5,534567
237	3,71467	52,3368	1123,14	74,0815	223,923	1396,25	21,2375	2,08638	5,944652
238	3,8564	50,2584	989,58	59,912	134,889	1321,92	22,6164	1,5637	5,743961
239	3,57322	55,0687	929,58	54,4614	197,516	1317,62	19,986	1,92711	5,817226
240	3,99101	53,3653	975,21	65,4405	160,438	1342,71	26,8674	1,99945	5,718801
241	3,72032	51,3517	946,31	62,6172	236,466	1431,44	28,8148	1,4738	6,047646
242	3,79972	51,4069	1123,73	65,8844	217,108	1386,98	23,9773	1,83221	6,451065
243	3,92854	53,7629	1052,74	52,6557	219,469	1316,08	23,8386	2,27899	7,235827
244	3,55239	51,611	1083,23	74,3073	170,206	1318,13	26,6112	1,87493	5,755566
245	3,82069	54,4611	925,44	75,3472	169,892	1383,9	21,7354	1,59413	4,48968
246	3,88346	53,6632	911,05	49,5011	187,507	1331,32	24,8323	2,0114	6,162787
247	3,50272	48,5365	1205,73	57,0903	225,255	1360,46	25,3666	1,88644	8,316421
248	3,4699	52,4391	1049,48	67,3781	190,102	1297,67	25,0317	1,71409	6,079607
249	3,52451	51,1472	1038,67	55,726	212,964	1441,51	23,2675	2,25051	5,479709
250	3,92048	53,4099	1042,45	89,5696	165,769	1349,27	24,5669	1,85265	5,4527
251	3,62424	50,1942	965,38	56,6801	184,787	1370,11	22,2463	1,95637	5,535273
252	3,78334	54,713	1314,04	66,6365	191,11	1350,72	20,5419	1,78351	8,580524
253	3,43605	53,063	990,8	62,3132	197,737	1344,9	28,0958	2,22595	5,489678
254	3,58886	51,6003	824,8	62,1557	226,316	1351,17	25,8545	2,52658	7,228417
255	3,77448	51,5411	1110,8	57,4814	193,61	1370,43	25,9132	1,79843	6,581893
256	3,55243	50,1875	964,64	61,0076	175,936	1357,53	24,0888	1,75739	5,178405
257	4,19583	50,855	1287,39	71,4199	166,545	1326,32	25,3613	2,23027	12,12165
258	4,03919	53,2819	1132,58	61,5616	185,955	1387,4	23,8139	2,3152	6,649991
259	3,56209	51,419	1197,95	60,033	178,003	1407,72	22,5907	2,35302	6,303965
260	3,88637	52,0955	867,5	79,1498	173,631	1342,96	20,6594	2,09866	5,186982
261	3,73362	49,574	935,09	77,2297	189,065	1345,57	23,747	2,25932	5,684208
262	3,62878	55,1331	991,13	58,0767	204,391	1343,07	26,367	2,16372	5,778015
263	3,87455	51,6549	1037,73	71,439	158,972	1325,48	24,508	2,36761	6,124722
264	3,30304	52,5624	920,43	57,3963	144,158	1342,28	26,4398	2,06727	3,431083
265	3,96677	53,9913	1012,87	63,1212	146,134	1366,17	23,7537	2,15847	5,439067
266	3,78988	55,8361	1104,02	59,5951	211,514	1335,9	23,0148	2,07612	6,384676
267	3,35403	55,2068	828,06	49,7122	192,409	1434,55	22,5745	2,78045	4,247451
268	3,71838	51,8529	1168,56	68,4674	153,491	1410,08	21,1632	1,90038	5,950643

269	3,98475	51,2886	1153,27	67,0296	210,837	1303,54	26,6274	1,72266	8,078174
270	3,52126	50,3649	982,11	69,7983	208,427	1379,33	21,2645	2,0477	5,703711
271	3,75229	52,0842	855,81	67,8118	195,228	1417,79	27,1917	2,15925	4,948738
272	3,74581	52,2404	1195,47	59,4753	143,181	1306,79	25,0105	2,66104	8,0927
273	3,61854	50,09	1118,15	50,9284	222,003	1370,94	23,5553	1,81301	7,325807
274	3,70441	53,1781	958,71	68,4182	156,154	1326,4	21,8467	2,11532	4,865509
275	3,67601	52,7991	980,54	57,5547	161,518	1388,09	22,2213	2,34724	4,620685
276	3,69305	56,3365	1008,62	42,866	191,611	1316,42	26,886	2,07915	6,108545
277	3,98141	53,5172	1028,95	63,2416	212,98	1392,87	23,2839	2,356	5,846269
278	3,62408	51,9296	1102,72	75,9885	169,561	1410,46	27,278	2,16119	4,979728
279	3,72272	50,6972	1072,13	59,1432	200,518	1311,39	26,0595	2,55578	7,259382
280	3,62474	52,7053	973,7	73,3393	221,906	1290,03	21,1434	1,8181	6,918388
281	3,91003	52,8171	1103,55	70,601	201,253	1402,65	28,3724	1,48541	5,824398
282	3,90957	52,6125	902,79	61,0379	153,163	1343,49	23,6581	2,43617	5,152414
283	3,90732	51,4935	1038	65,7383	149,515	1365,84	30,7802	1,86641	5,783613
284	3,82833	54,459	1073,08	66,5606	110,184	1431,52	23,891	2,28351	4,423894
285	3,7672	52,9684	1098,2	71,911	228,703	1382,48	24,4578	1,88788	6,035049
286	3,8756	52,4158	1105,82	61,007	198,528	1374,69	28,7556	2,28215	6,448793
287	3,55799	53,6029	1058,75	69,8715	172,227	1367,51	22,441	2,34255	4,892811
288	3,74734	50,8888	1022,72	67,5813	183,954	1364,07	22,8725	1,95418	5,752508
289	3,93282	50,1627	1042,55	51,2035	237,533	1336,42	22,7925	1,98106	7,855014
290	3,91268	51,1971	1050,88	61,1447	173,624	1323,51	22,7101	2,35891	6,844546
291	3,74326	52,3663	1007,56	61,9729	194,684	1344,94	25,2522	1,7419	6,029825
292	3,82144	52,3129	957,84	67,5634	147,464	1308,12	27,4291	1,59625	5,353323
293	3,67955	49,7423	924,49	56,8324	177,579	1350,59	27,2234	2,07129	5,582249
294	3,87512	52,7918	841,58	79,9492	193,396	1307,24	22,3634	1,65937	5,99886
295	3,74228	51,8176	1083,78	75,5079	217,732	1332,7	27,0394	1,97352	6,599137
296	3,81406	50,7591	898,91	61,6726	212,864	1388,63	23,0859	2,00597	6,129048
297	3,493	49,9378	1031,97	66,8314	226,951	1422,05	23,7682	2,32359	5,946986
298	3,60399	50,2409	991,87	69,1045	195,956	1397,51	25,1342	2,28141	5,304431
299	3,7433	52,7971	1191,52	67,2707	172,555	1364,46	23,7911	2,00426	6,846989
300	3,75131	52,3717	1127,41	82,7542	183,702	1298,63	23,4535	2,12466	6,77769

APPENDIX C Tree of percentages of casting defect



APPENDIX D REDUCED DATA SET

A: Moisture content (%)
B: Sand particle size (AFS)
C: Green compression strength (g/cm^2)
D: Mold hardness (nu)
E: Permeability (nu)
G: Pouring time (sec)
H: Pressure test (Mpa)
F: Pouring temperature (deg c)

	A	B	C	D	E	F	G	H	Defect (%)
1	3,84504	53,3897	1014,05	57,0487	219,23	1320,52	23,4263	1,90251	6,95741283
2	3,91024	55,7114	1058,42	79,7555	195,654	1343,54	21,809	2,39604	5,61845505
3	3,74821	54,1944	1209,67	61,6602	158,631	1375,68	27,7944	2,47723	6,82035661
4	3,7089	55,0156	1053,3	60,841	174,006	1406,68	22,9397	2,28699	4,80040912
5	3,81246	52,7062	925,75	65,1701	211,057	1364,47	25,0945	2,35473	5,99737572
6	3,62737	52,0983	1019,71	53,5456	135,224	1362,38	23,3668	2,06555	4,57673701
7	4,1012	52,6842	1004,94	72,7971	161,898	1355,18	22,8834	2,359	6,06789103
8	3,73734	53,0634	1006,47	43,2738	182,468	1330,09	17,9356	1,68536	6,27402198
9	3,70469	52,7685	1017,41	72,1029	145,181	1307,53	22,3594	1,98741	5,2163695
10	3,47565	51,8759	1154,42	64,0033	186,121	1447,93	20,5012	2,31421	5,14989726
11	3,83582	53,8396	1193,98	70,6063	204,22	1413,82	29,9019	1,17089	6,06712672
12	3,51242	52,7892	919,48	68,899	153,949	1367,57	26,8068	1,69302	3,83238606
13	3,34046	53,1818	1060,84	76,9485	176,482	1343,98	23,0628	1,62953	4,71062252
14	3,62518	52,2072	860,02	61,6728	197,242	1355,89	20,4718	1,59127	5,63473672
15	4,1439	54,2517	1015,06	72,9929	244,916	1307,12	24,0597	1,45685	6,68367923
16	3,59619	53,2219	1122,25	61,0726	177,177	1400,98	21,5957	2,11392	5,37169209
17	3,89078	52,3138	902,3	69,6259	174,855	1367,72	25,5815	1,86474	5,17455563
18	3,89866	52,1856	1194,04	72,4672	208,951	1380,41	20,335	1,56057	6,8179823
19	3,92915	50,2508	1002,22	69,3984	168,765	1326,09	20,8542	2,13391	6,38656645
20	3,69808	53,5131	1118,71	72,6739	162,67	1445,28	22,1795	2,71474	4,71556934
21	3,68665	51,1221	1035,8	63,8751	186,086	1376,22	28,1591	2,4503	5,64558073
22	3,61959	52,4077	939,1	53,6799	206,655	1366,22	28,0453	1,87199	5,99038585
23	4,2131	54,173	1025,13	70,2592	196,926	1325,92	21,5291	2,72707	6,66475487
24	3,80961	54,2794	918,79	75,5891	202,107	1364,24	22,3822	2,12174	5,32811736
25	3,84513	53,3708	1082,54	62,6384	169,104	1364,48	24,1496	2,51926	5,9424652
26	4,02887	51,5981	1019,45	72,5864	196,248	1365,03	21,466	2,27262	6,16361003
27	3,9684	54,6291	1113,08	70,7918	163,678	1320,89	20,9552	1,83291	6,79282226
28	3,84186	53,83	1075,92	79,6761	135,842	1320,15	24,5077	1,31672	5,77135796
29	3,69884	52,426	1087,37	74,0295	176,454	1278,73	20,6209	1,9689	6,67714555
30	3,79644	54,0878	1076,28	59,3248	141,218	1351,78	21,2458	2,22551	5,56386084
31	3,52646	53,1982	994,14	69,7141	209,936	1354,66	27,0469	1,60248	5,67743789
32	3,63822	52,1787	794,63	41,5402	175,579	1301,02	16,2517	2,23713	5,87772902

33	3,84368	52,4947	976,57	62,7702	192,959	1334,81	21,2648	2,24137	6,15115291
34	4,10412	53,2292	1063,12	58,293	226,505	1332,52	22,5451	2,19035	7,03379403
35	3,80221	52,1456	1081,98	77,7395	159,037	1345,39	29,0392	1,72338	5,84615863
36	3,70135	53,5169	1107,29	75,7266	164,583	1403,8	20,2155	1,92709	5,01228087
37	3,70185	51,8551	1124,48	67,0985	150,688	1345,15	21,6933	1,99542	6,14662311
38	3,73633	49,8634	1100,12	54,4803	181,659	1369,11	23,0187	1,85414	6,66205644
39	3,65457	49,6594	1098,44	65,1148	220,156	1431,11	24,2523	1,93915	6,02217645
40	3,79477	52,7513	1049,17	62,3842	192,801	1361,2	23,7839	2,00164	6,00049982
41	3,94758	52,2294	1157,36	73,8602	139,633	1387,53	24,1421	1,86078	6,869736
42	3,54718	52,9232	1013,03	60,3269	217,116	1322,99	29,0551	1,69703	6,65128512
43	3,49304	52,9182	1088,5	68,2855	183,137	1333,75	26,2141	2,15768	5,66517499
44	3,36881	53,2482	969,94	60,3925	169,263	1422,34	16,8393	2,55201	3,74325431
45	4,06082	51,837	989,62	59,6349	175,772	1367,76	25,1559	2,07825	6,18747084
46	3,85936	53,5336	1162,36	67,6876	192,869	1393,05	24,3478	1,95	6,2528725
47	3,82549	55,2962	1128,57	66,1204	196,088	1371,26	22,7541	2,20027	5,94329274
48	3,75273	55,6531	1014,65	65,5245	191,397	1391,41	23,9693	2,49786	4,95764277
49	3,62272	50,5926	1117,81	69,6973	131,227	1352,98	26,3299	2,08593	5,58104658
50	3,70286	52,1592	1176,86	61,3303	187,683	1387,36	25,4416	1,69333	6,56737035
51	3,61836	52,8825	1083,63	72,5378	188,789	1371,44	21,4082	1,74495	5,45540469
52	3,44635	53,1449	1087,76	52,1536	174,354	1358,73	23,0651	1,95567	5,36830099
53	3,77575	52,7446	1025,48	84,0433	140,227	1378,78	26,591	2,19925	4,5510014
54	3,88878	50,1065	922,56	62,2174	197,094	1392,86	25,7294	2,20726	5,82646246
55	3,641	50,1895	1073,31	60,5658	198,485	1377,2	21,1401	1,34731	6,22754857
56	3,78615	53,2513	1032,36	65,9422	164,244	1356,26	24,7201	1,57427	5,38732379
57	3,81825	53,0738	1080,55	52,9316	226,661	1333,26	23,366	1,9396	7,22081835
58	3,70234	53,4964	957,72	66,5482	195,017	1221,11	29,5828	1,49711	7,20042387
59	3,79658	50,0241	1088,72	73,1065	199,464	1374,73	19,2221	1,76438	6,30572342
60	3,40164	51,9537	1093,93	69,6525	187,915	1333,04	20,7915	1,79713	5,76046852
61	3,86472	54,8349	868,89	71,7799	214,832	1414,59	24,1365	2,81053	5,22215399
62	3,82853	52,1095	1003,63	51,5265	127,142	1384,54	22,6366	1,62654	4,83285259
63	3,73337	51,675	1028,72	67,0288	220,992	1424,82	23,9408	2,08144	5,58462107
64	3,72657	52,5904	1071,94	67,847	178,985	1328,43	19,0077	2,66606	6,11711606
65	3,56267	51,586	1133,93	49,885	214,806	1420,68	21,878	2,28536	6,29772287
66	3,93646	51,4178	1032,7	42,0861	142,278	1363,59	15,9897	1,43541	6,24168942
67	3,71447	53,4958	1253,21	46,1399	153,559	1385,14	27,2798	2,33073	7,84906688
68	3,73001	54,1357	1023,63	57,2804	225,283	1392,23	20,0169	2,24733	5,95349223
69	3,88687	54,4817	1060,52	58,1508	180,161	1320,86	31,799	1,74363	6,45947823
70	3,66312	53,1473	898,48	66,7469	153,951	1442,74	24,9103	1,66914	3,5192496
71	3,93232	53,3496	1044,13	65,2454	168,899	1368,47	23,3834	1,65065	5,77987924
72	3,98216	52,5041	1065,1	73,3483	200,088	1322,69	23,9342	1,86994	6,72282248
73	3,76019	54,3159	995,07	57,8714	192,951	1391,12	25,9141	1,81453	5,26514871
74	3,76133	52,6364	988,09	69,4887	163,224	1379,44	22,9334	2,03058	4,81332197
75	3,88353	56,5924	964,74	64,707	172,474	1355,31	20,6905	2,45933	5,01581969
76	3,74506	54,1935	857,83	72,6166	198,834	1339,82	23,7418	1,99769	5,5611769
77	3,88972	50,7579	943,88	56,3527	168,228	1357,44	18,814	2,0905	5,74015242
78	3,97928	53,4957	896,73	56,755	204,707	1452,7	26,9998	2,58447	5,12792032

79	3,41091	49,5488	1034,01	59,3325	139,44	1327,61	20,1471	1,7773	4,62646824
80	3,52405	53,1709	1074,29	56,0905	149,218	1371,13	22,3387	1,72548	4,72075456
81	3,48995	53,8944	894,22	71,1186	179,94	1349,87	29,3987	2,06045	4,49409756
82	3,80455	53,7653	913,55	48,515	166,437	1381,52	28,894	1,94401	4,88772627
83	4,08244	52,7794	956,84	72,3199	188,575	1351,37	22,5213	1,77408	5,99291007
84	3,59433	51,8516	1058,15	78,4814	196,464	1336,28	24,1081	1,78294	5,83666977
85	3,68932	50,8891	1074,83	77,6133	170,512	1313,59	24,688	1,92621	6,1642621
86	3,76668	52,9136	1050,72	57,2647	145,722	1332,41	26,0004	1,94149	5,68437611
87	3,68294	53,0699	1119,34	68,2261	144,746	1364,07	23,5005	1,79752	5,51221935
88	4,06796	53,6305	1047,88	73,2624	176,475	1379,57	23,9872	2,16313	5,84103634
89	3,87193	52,7743	902,98	83,5304	164,487	1333,47	23,7166	1,97137	4,98278155
90	3,52077	49,9842	971,52	81,1459	136,864	1382,09	20,4475	2,24127	3,68878409
91	3,97034	51,0495	931,54	46,8918	176,019	1351,03	23,8589	1,83687	6,31477909
92	3,73055	49,5623	1110,47	70,4475	186,728	1388,43	26,6949	1,72144	6,19928059
93	3,66945	50,7207	1050,09	72,2481	170,147	1378,76	27,1997	2,5043	5,27353312
94	3,89717	50,8292	905,54	55,6493	218,28	1303,5	25,8521	2,59135	7,74934432
95	3,78902	54,5164	926,27	80,648	147,283	1345,01	23,9181	1,6033	4,28182589
96	3,66856	54,6497	1161,96	65,4834	169,827	1380,61	26,5258	2,40171	5,76219819
97	3,75029	52,6307	1090,2	57,7521	199,641	1352,22	21,4283	2,38699	6,51194776
98	3,67159	50,6484	1110,29	58,9478	193,693	1420,65	22,551	1,76836	5,86391059
99	3,6152	50,92	1079,55	57,9924	199,947	1398,36	27,7698	1,69474	5,93582286
100	4,00361	52,4981	958,08	76,9381	183,518	1372,41	29,2812	1,90245	5,4753144
101	4,05889	52,1494	1049,04	68,5748	199,039	1326,89	27,8026	1,9148	6,89618366
102	3,66344	50,1976	916,71	70,036	183,982	1331,88	24,14	1,49245	5,60489646
103	4,02313	46,778	1158,52	74,0614	191,199	1438,92	24,5769	2,03562	7,01500778
104	3,66073	53,974	1147,76	78,3103	210,249	1377,7	28,5245	1,72116	5,77863503
105	3,7991	54,972	980,98	75,1817	182,958	1429,47	26,0306	1,77627	4,33943407
106	3,80645	52,7891	992,99	64,3922	181,154	1411,9	22,2813	1,55336	4,97001068
107	3,69488	53,3913	1082,78	62,7045	188,658	1339,53	24,7211	2,08691	6,11943947
108	3,72084	51,9739	1116,29	64,1986	187,842	1356,88	19,7089	2,23183	6,39298307
109	4,09215	53,3077	1090,84	76,2319	154,551	1331,31	25,3785	1,73211	7,01081083
110	3,30109	52,5892	955,79	57,1057	182,977	1342,69	31,1814	2,18988	4,83957413
111	3,61395	50,7194	987,93	71,9563	145,107	1340,94	24,096	2,25562	4,61637008
112	3,73262	47,8356	1078,38	70,9451	162,024	1339,02	28,4822	1,89849	6,53721085
113	3,85688	51,2072	1000,46	67,4131	206,169	1352,39	23,6606	1,93085	6,32348331
114	3,48982	53,7649	1121,91	66,1679	180,895	1397,44	22,0582	2,00533	5,0678394
115	3,87786	52,1769	908,84	65,4483	207,329	1331,94	21,0962	1,6525	6,4647333
116	3,8414	53,0372	953,63	51,2692	198,61	1337,98	21,3151	2,13722	6,39355951
117	3,89074	51,6274	962,63	68,866	222,521	1320,24	22,8559	1,59485	6,9435018
118	3,69964	50,8373	1058,36	74,6556	192,897	1372,4	26,3507	1,91831	5,75181047
119	3,5437	53,3869	894,81	65,1523	207,225	1388,45	25,7223	2,01521	5,28975859
120	3,95924	52,6248	979,94	54,7277	170,072	1305,24	27,0405	1,99049	6,59674668
121	3,56895	53,5514	1074,64	74,736	171,796	1375,04	23,9154	2,22427	4,85544041
122	3,63051	52,0142	1110,47	60,7629	193,108	1372,07	23,1009	1,93281	6,12432812
123	3,63973	54,0996	1057,78	56,8654	170,414	1392,17	29,1664	1,50768	4,95164521
124	3,90236	54,8741	1060,73	67,3774	201,2	1375,33	24,4167	2,80595	5,69107352

125	3,69834	53,2764	1118,37	64,3362	164,712	1303,51	23,414	2,62811	6,57430357
126	3,73683	50,9303	979,89	68,4141	181,381	1335,68	21,4521	1,87487	5,78711682
127	3,73248	52,7729	855,47	61,8912	203,84	1334,29	25,0694	1,99575	6,23631468
128	3,98316	54,0618	1118,07	79,2688	158,488	1326,53	25,4611	1,83267	6,75403996
129	3,62613	53,9174	977,1	63,8125	208,913	1312,36	24,1317	2,44419	6,29663395
130	4,02563	55,5505	1149,32	77,7145	164,742	1380,44	22,9964	2,41119	6,26191064
131	3,49064	52,7591	1148,03	59,4801	165,978	1381,58	24,3735	1,43757	5,49809336
132	3,68169	52,1088	1090,56	64,5002	175,026	1391,73	23,9753	1,65971	5,48315244
133	3,90461	53,9947	1150,66	43,1502	110,734	1404,85	24,0639	2,12969	6,5685307
134	3,96094	50,6502	1198,06	69,0502	192,007	1407,01	22,3063	2,19228	7,16297085
135	3,88717	53,7044	992,47	39,8665	163,595	1293,07	22,1348	1,18439	6,66494076
136	3,56331	55,3184	1232,45	47,0375	200,216	1372,66	27,3381	2,01059	6,97714665
137	3,63725	51,3169	1061,91	69,0342	178,538	1325,82	26,2079	2,18994	6,02684178
138	3,71337	54,9831	1146,94	74,4262	178,996	1472,13	26,842	2,34525	4,58805051
139	3,61821	53,3434	942,65	62,5525	197,361	1351,05	20,4158	1,93822	5,52928327
140	3,73724	51,1448	1117,01	62,6723	194,221	1353,91	21,777	2,49713	6,72886985
141	4,15476	53,8086	1109,1	58,2095	159,026	1386,46	22,813	1,90353	6,96432163
142	3,89246	51,6767	984,9	77,0215	185,409	1367,33	27,2501	1,7928	5,53732773
143	3,8801	53,487	933,87	63,2155	187,451	1418,72	30,6892	1,90437	4,91464086
144	3,5941	52,1313	1064,68	76,6706	192,927	1367,49	29,9784	1,72101	5,43933843
145	3,96482	50,7001	1103,85	82,3831	243,883	1343,24	21,4869	1,87683	6,6214349
146	3,99946	52,9063	880,45	65,9594	196,688	1379,08	30,9313	2,10978	5,69086937
147	3,49729	52,1552	991,62	63,6329	208,539	1313,59	25,0303	0,96209	6,42800195
148	3,79685	51,1735	1062,63	76,7373	183,026	1429,25	25,1892	2,8727	5,09939593
149	3,98746	50,961	1045,65	57,8525	186,475	1285,41	20,8905	2,11064	7,84311213
150	3,74815	51,5109	917,23	55,4662	202,876	1372,89	28,1747	1,545	6,00688552
151	3,92968	54,5265	1022,63	73,0251	189,967	1349,81	26,5206	1,64388	5,70665628
152	3,88457	53,129	1049,33	89,8622	172,231	1369,12	25,7715	1,81491	5,254677
153	3,75194	52,5202	1121,65	58,9957	210,822	1367,79	26,4835	1,92575	6,61245165
154	3,64287	51,7226	1081,08	86,6527	165,741	1346,34	18,9532	1,72116	5,32602943
155	3,74855	52,4161	1157,56	63,6904	232,024	1413,4	19,3321	1,97283	6,22950364
156	4,10993	53,3329	1031,26	66,0669	196,138	1316,59	27,2048	1,74972	6,90283963
157	3,92677	49,9262	941,03	73,9268	160,203	1360,29	27,6951	2,18832	5,42206885
158	3,46453	53,4032	934,11	47,768	157,36	1365,83	19,2216	1,30711	4,09906363
159	3,8506	51,9272	862,62	57,9505	193,6	1361,22	24,2149	2,00575	5,91289429
160	3,45109	49,7353	892,67	62,5628	182,591	1428,08	17,4106	2,04383	4,34267026
161	3,9202	52,9263	1132,09	70,2829	218,75	1401,37	19,1118	1,89389	5,99998293
162	3,65841	54,3182	1060,4	90,668	182,696	1333,51	24,2291	1,55701	5,14956017
163	3,6954	51,7432	1054,56	53,1805	175,334	1329,23	24,5287	1,87358	6,30650224
164	3,69072	50,0085	1080,71	64,12	157,322	1315,37	22,5759	2,72067	6,43820043
165	4,01398	51,7171	1197,07	68,4165	182,654	1365,37	24,8896	1,83891	7,84621116
166	3,64166	51,6718	1039,91	64,7507	179,706	1318,89	26,7658	1,80355	6,03739724
167	3,45357	54,4001	947,65	53,943	217,721	1374,88	20,0406	2,25846	5,87985593
168	3,61361	50,6935	946,55	58,2117	147,727	1270,63	25,2546	1,97843	5,35269377
169	3,74956	52,5557	903,37	63,6042	181,504	1272,86	22,9879	1,7622	6,24618455
170	3,84418	53,1358	1080,43	69,7735	169,767	1323,48	27,5883	2,11623	6,33115548

171	3,64611	52,7091	970,12	71,3999	175,33	1365,58	25,03	2,39101	4,80899355
172	3,79886	53,221	970,22	64,9747	186,482	1334,51	23,3686	1,76143	5,76433973
173	3,59398	51,3842	1055,03	73,5716	182,175	1321,31	23,9782	2,06273	5,89542712
174	3,69906	52,3296	1147,42	63,6378	185,507	1371,51	24,4219	1,99066	6,36497719
175	3,48572	50,7974	967,76	60,1203	172,392	1398,61	21,3737	2,28186	4,48474525
176	3,77621	54,7006	1024,34	65,1438	150,728	1324,16	20,6878	2,73864	5,27781354
177	3,68111	53,1147	1064,49	55,7047	186,261	1366,01	23,4188	1,69705	5,81403844
178	3,947	51,8424	979,96	57,5967	198,701	1343,05	23,555	1,93412	6,56516369
179	3,77434	53,1609	1186,93	65,5265	190,061	1320,55	28,3158	2,188	7,50497965
180	3,73638	53,1451	899,04	82,3916	221,005	1492,25	22,9392	1,84947	4,4073582
181	3,62505	53,9109	1108,13	70,7799	168,757	1399,44	22,967	2,28843	4,95383395
182	3,44379	54,0442	954,47	64,4549	197,507	1371,47	26,125	1,95528	4,96739009
183	3,89514	52,0962	1064,21	49,9163	203,313	1336,54	26,5813	1,98945	7,16710282
184	3,53943	53,823	1076,47	60,2784	171,399	1352,16	22,7899	1,98669	5,25967654
185	3,73141	52,4472	946,2	69,0662	133,596	1365,07	21,406	2,03344	4,13165182
186	3,52349	53,1214	1124,94	64,6934	133,672	1387,4	20,9489	1,40576	4,66848237
187	4,02069	53,1295	990,45	67,6962	189,128	1301,93	28,5997	1,64562	6,70041536
188	4,16408	54,38	916,93	73,1227	163,164	1348,54	23,9473	1,61234	5,63762028
189	3,70596	49,6188	1079,6	60,7064	162,531	1378,62	25,6542	1,82946	5,8843221
190	3,85831	50,9415	958,59	81,7575	189,953	1378,67	24,8304	2,31819	5,32552756
191	3,66493	53,069	951,42	71,1056	178,85	1335,29	24,1856	1,7963	5,14407107
192	3,81161	52,6499	950,61	56,6	195,029	1333,22	22,6843	2,17491	6,23049246
193	3,82877	52,9879	1157,33	52,3327	192,688	1404,93	29,8494	1,41157	6,48651009
194	3,69115	52,9357	1017,8	82,1283	179,787	1292,66	25,8341	1,99175	5,76965698
195	3,99882	51,9528	965,53	69,752	173,922	1281,56	21,8439	2,21339	6,7661852
196	3,7573	51,5072	922,97	63,2794	165,161	1378,77	28,7091	2,04159	4,79874352
197	3,74957	50,8847	1018,84	58,9863	205,385	1338,11	25,5937	2,38648	6,71413373
198	3,78797	53,0172	1004	82,9291	206,813	1368,48	19,2166	2,59051	5,41858161
199	3,56491	53,7366	860,37	61,6356	170,472	1363,83	24,0654	2,30362	4,33324941
200	3,78924	54,9084	1021,7	44,1702	176,346	1322,88	25,1678	1,60505	6,13657316
201	3,46859	52,2123	1104,21	72,3901	185,69	1323,4	24,7751	2,28039	5,92842094
202	3,77783	53,3212	883,7	75,6839	148,866	1343,37	26,1701	1,73714	4,31923063
203	3,70306	54,4925	1131,68	70,6021	195,372	1431,91	24,6445	2,137	5,10657348
204	3,60441	52,6843	961,95	47,5412	190,484	1331,68	23,9256	1,97747	5,99329705
205	3,78116	50,4389	923,23	74,8496	202,654	1394,39	22,5166	2,26523	5,45453408
206	3,8614	50,5154	1023,94	54,723	197,881	1374,17	20,3046	2,56	6,44431218
207	3,78099	51,2762	999,02	81,271	146,908	1356,52	20,2013	1,83985	4,88638472
208	3,90047	54,0777	1009,72	75,5008	145,432	1339,71	22,5538	2,36952	5,25700742
209	3,73064	51,444	1012,9	85,8847	198,315	1366,61	24,4543	1,6708	5,40776389
210	3,94207	50,0019	991,71	76,1552	204,471	1301,26	19,3859	1,75361	7,03643705
211	3,78067	51,9304	1038,26	62,0275	179,888	1427,59	19,6	1,86244	5,09915625
212	3,52671	49,7474	1106,16	66,3616	168,265	1383,07	24,305	1,63306	5,53456738
213	3,71467	52,3368	1123,14	74,0815	223,923	1396,25	21,2375	2,08638	5,94465238
214	3,8564	50,2584	989,58	59,912	134,889	1321,92	22,6164	1,5637	5,74396104
215	3,57322	55,0687	929,58	54,4614	197,516	1317,62	19,986	1,92711	5,81722643
216	3,99101	53,3653	975,21	65,4405	160,438	1342,71	26,8674	1,99945	5,71880114

217	3,72032	51,3517	946,31	62,6172	236,466	1431,44	28,8148	1,4738	6,04764613
218	3,79972	51,4069	1123,73	65,8844	217,108	1386,98	23,9773	1,83221	6,45106502
219	3,92854	53,7629	1052,74	52,6557	219,469	1316,08	23,8386	2,27899	7,23582735
220	3,55239	51,611	1083,23	74,3073	170,206	1318,13	26,6112	1,87493	5,75556628
221	3,82069	54,4611	925,44	75,3472	169,892	1383,9	21,7354	1,59413	4,4896798
222	3,88346	53,6632	911,05	49,5011	187,507	1331,32	24,8323	2,0114	6,16278707
223	3,52451	51,1472	1038,67	55,726	212,964	1441,51	23,2675	2,25051	5,47970941
224	3,92048	53,4099	1042,45	89,5696	165,769	1349,27	24,5669	1,85265	5,45270045
225	3,62424	50,1942	965,38	56,6801	184,787	1370,11	22,2463	1,95637	5,53527281
226	3,43605	53,063	990,8	62,3132	197,737	1344,9	28,0958	2,22595	5,48967832
227	3,58886	51,6003	824,8	62,1557	226,316	1351,17	25,8545	2,52658	7,22841741
228	3,77448	51,5411	1110,8	57,4814	193,61	1370,43	25,9132	1,79843	6,58189264
229	3,55243	50,1875	964,64	61,0076	175,936	1357,53	24,0888	1,75739	5,17840466
230	3,56209	51,419	1197,95	60,033	178,003	1407,72	22,5907	2,35302	6,30396457
231	3,88637	52,0955	867,5	79,1498	173,631	1342,96	20,6594	2,09866	5,18698233
232	3,73362	49,574	935,09	77,2297	189,065	1345,57	23,747	2,25932	5,68420847
233	3,62878	55,1331	991,13	58,0767	204,391	1343,07	26,367	2,16372	5,7780149
234	3,87455	51,6549	1037,73	71,439	158,972	1325,48	24,508	2,36761	6,12472242
235	3,30304	52,5624	920,43	57,3963	144,158	1342,28	26,4398	2,06727	3,43108261
236	3,96677	53,9913	1012,87	63,1212	146,134	1366,17	23,7537	2,15847	5,43906682
237	3,78988	55,8361	1104,02	59,5951	211,514	1335,9	23,0148	2,07612	6,38467591
238	3,35403	55,2068	828,06	49,7122	192,409	1434,55	22,5745	2,78045	4,24745109
239	3,71838	51,8529	1168,56	68,4674	153,491	1410,08	21,1632	1,90038	5,95064283
240	3,52126	50,3649	982,11	69,7983	208,427	1379,33	21,2645	2,0477	5,70371059
241	3,75229	52,0842	855,81	67,8118	195,228	1417,79	27,1917	2,15925	4,94873777
242	3,61854	50,09	1118,15	50,9284	222,003	1370,94	23,5553	1,81301	7,32580705
243	3,70441	53,1781	958,71	68,4182	156,154	1326,4	21,8467	2,11532	4,86550869
244	3,67601	52,7991	980,54	57,5547	161,518	1388,09	22,2213	2,34724	4,62068528
245	3,69305	56,3365	1008,62	42,866	191,611	1316,42	26,886	2,07915	6,10854455
246	3,98141	53,5172	1028,95	63,2416	212,98	1392,87	23,2839	2,356	5,84626936
247	3,62408	51,9296	1102,72	75,9885	169,561	1410,46	27,278	2,16119	4,97972768
248	3,72272	50,6972	1072,13	59,1432	200,518	1311,39	26,0595	2,55578	7,25938224
249	3,62474	52,7053	973,7	73,3393	221,906	1290,03	21,1434	1,8181	6,91838824
250	3,91003	52,8171	1103,55	70,601	201,253	1402,65	28,3724	1,48541	5,82439838
251	3,90957	52,6125	902,79	61,0379	153,163	1343,49	23,6581	2,43617	5,15241422
252	3,90732	51,4935	1038	65,7383	149,515	1365,84	30,7802	1,86641	5,78361292
253	3,82833	54,459	1073,08	66,5606	110,184	1431,52	23,891	2,28351	4,42389356
254	3,7672	52,9684	1098,2	71,911	228,703	1382,48	24,4578	1,88788	6,03504889
255	3,8756	52,4158	1105,82	61,007	198,528	1374,69	28,7556	2,28215	6,4487926
256	3,55799	53,6029	1058,75	69,8715	172,227	1367,51	22,441	2,34255	4,89281087
257	3,74734	50,8888	1022,72	67,5813	183,954	1364,07	22,8725	1,95418	5,75250789
258	3,93282	50,1627	1042,55	51,2035	237,533	1336,42	22,7925	1,98106	7,85501383
259	3,91268	51,1971	1050,88	61,1447	173,624	1323,51	22,7101	2,35891	6,84454607
260	3,74326	52,3663	1007,56	61,9729	194,684	1344,94	25,2522	1,7419	6,02982525
261	3,82144	52,3129	957,84	67,5634	147,464	1308,12	27,4291	1,59625	5,35332271
262	3,67955	49,7423	924,49	56,8324	177,579	1350,59	27,2234	2,07129	5,58224888

263	3,87512	52,7918	841,58	79,9492	193,396	1307,24	22,3634	1,65937	5,9988596
264	3,74228	51,8176	1083,78	75,5079	217,732	1332,7	27,0394	1,97352	6,59913653
265	3,81406	50,7591	898,91	61,6726	212,864	1388,63	23,0859	2,00597	6,12904799
266	3,493	49,9378	1031,97	66,8314	226,951	1422,05	23,7682	2,32359	5,94698581
267	3,60399	50,2409	991,87	69,1045	195,956	1397,51	25,1342	2,28141	5,30443095