Optimization of Castings by using Surrogate Models

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Cover:
Residual stresses in a stress lattice. The colors indicating different stress levels along the direction of the legs.

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To Jennie and our lovely daughter Tindra
Preface

There are many people I would like to thank for supporting and helping me to get to this stage but first I would like to thank my employer SweCast AB for giving me the opportunity to become an industry graduate student.

Among the persons I would like to thank, the first one to mention is my supervisor, Associate Professor Niclas Strömberg at JTH. Without his support and encouragement this work would not have been where it is today.

Thanks to my graduate student colleague at JTH, Magnus Hofwing, for great discussions regarding residual stress analysis and also all very nice discussions about soccer and sports in general.

Thanks to my colleagues at SweCast for great input regarding the casting process. Magnus Wihed for performing tensile testing, Ulf Gotthardsson and Ulla Ledell for help with questions regarding and testing of mold material, Jörgen Blom for help with forming of molds, Martin Risberg for introduction to HyperMesh, Ola Björk for help with some CAD and finally Stefan Gustafsson Ledell and Lars-Erik Björkegren for their support in general.

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Finally, thanks to my fiance Jennie and our lovely daughter Tindra for your endless support and thanks to my parents for helping out with various things when there just isn’t time enough to deal with everything.

Erik Gustafsson
Aneby, September 2007
Abstract

In this thesis structural optimization of castings and thermomechanical analysis of castings are studied.

In paper I an optimization algorithm is created by using Matlab. The algorithm is linked to the commercial FE solver Abaqus by using Python script. The optimization algorithm uses the successive response surfaces methodology (SRSM) to create global response surfaces. It is shown that including residual stresses in structural optimization of castings yields an optimal shape that differs significantly from the one obtained when residual stresses are excluded.

In paper II the optimization algorithm is expanded by using neural networks. It is tested on some typical bench mark problems and shows very promising results.

Combining paper I and II the response surfaces can be either analytical functions, both linear and non-linear, or neural networks. The optimization is then performed by using either sequential linear programming or by using a zero-order method called Complex. This is all gathered in a package called StuG-OPT.

In paper III and IV focus is on the thermomechanical problem when residual stresses are calculated. In paper III a literature review is performed and some numerical simulations are performed to see where numerical simulations can be used in the industry today. In paper IV simulations are compared to real tests. Several stress lattices are casted and the residual stresses are measured. Simulations are performed by using Magmasoft and Abaqus. In Magmasoft a $J_2$-plasticity model is used and in Abaqus two simulations are performed using either $J_2$-plasticity or the "Cast Iron Plasticity" available in Abaqus that takes into account the different behavior in tension and compression for grey cast iron.
List of Papers

This thesis is based on the following four papers, which will be referred to by their Roman numerals:

I. E. Gustafsson, N. Strömberg, Optimization of Castings by using Successive Response Surface Methodology, Accepted for publication in Structural and Multidisciplinary Optimization, 2006.

II. E. Gustafsson, N. Strömberg, Successive Response Surface Methodology by using Neural Networks, Presented at 7th World Congress on Structural and Multidisciplinary Optimization, 2007.

III. E. Gustafsson, Residual Stresses in Castings - ’a literature review’, to be published as SweCast report.


Articles have been reformatted to fit the layout of the thesis.
## Contents

Preface v

Abstract vii

List of Papers ix

Contents xi

1 Introduction 1

2 Structural Optimization 3
   2.1 Surrogate Models .............................................. 3
      2.1.1 Analytical Response Surface ............................. 5
      2.1.2 Neural Networks .......................................... 6
      2.1.3 Radial Basis Function Network ........................... 7
      2.1.4 Kriging .................................................. 8

3 Residual Stresses in Castings 11

4 Results 13

5 Summary of Appended Papers 17
   5.1 Paper I ....................................................... 17
   5.2 Paper II ....................................................... 17
   5.3 Paper III ..................................................... 17
   5.4 Paper IV ...................................................... 18

Bibliography 19

Paper I 29

Paper II 63

xii
<table>
<thead>
<tr>
<th>CONTENTS</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Paper III</td>
<td>87</td>
</tr>
<tr>
<td>Paper IV</td>
<td>115</td>
</tr>
</tbody>
</table>
Introduction

There are higher and higher demands on casted components in modern products. They should withstand higher loads and at the same time be as light as possible. In the automotive industry there is also emission regulations and this also put high demands on casted components in engines since emission for example can be reduced by increasing the pressure or temperature in the engine. These regulations were originally introduced in [1] followed by a number of amendments. In 2005, the regulations were re-cast and consolidated by [2]. The emission regulations are often referred to as Euro I … V. In short these regulations drastically reduce the allowed NO\textsubscript{x} and particles from the engine. This is summarized in Table 1. It should be noted that the actual date for Euro IV and Euro V are 2006.09 and 2009.09 respectively, i.e. the introduction of these regulations are a little behind schedule.

<table>
<thead>
<tr>
<th>Gate</th>
<th>Date</th>
<th>NO\textsubscript{x}</th>
<th>Particles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euro I</td>
<td>1992</td>
<td>8.0</td>
<td>0.36</td>
</tr>
<tr>
<td>Euro II</td>
<td>1998.10</td>
<td>7.0</td>
<td>0.15</td>
</tr>
<tr>
<td>Euro III</td>
<td>2000.10</td>
<td>5.0</td>
<td>0.10</td>
</tr>
<tr>
<td>Euro IV</td>
<td>2005.10</td>
<td>3.5</td>
<td>0.02</td>
</tr>
<tr>
<td>Euro V</td>
<td>2008.10</td>
<td>2.0</td>
<td>0.02</td>
</tr>
</tbody>
</table>

In order to be able to solve the problem of higher loads on casted components there is a need to include properties from the casting process into the structural stress calculations and further on perform structural optimization on these components while including casting constraints. An easy to use and correct methodology where casting simulation and structural stress analysis are combined should therefore be very useful. Casting simulation is though a wide name of several simulation disciplines within the casting process. There are fluid flow simulation to determine the filling of the mould, solidification analysis from a metallurgical point of view where the location and size of pores and local material properties are
determined and finally thermo-mechanical solidification analysis where residual stresses, shape distortions and hot tear are determined. Since the casting simulation covers all these disciplines it is hard (impossible??) to cover all this in one project and the focus in this thesis therefore lies in combining thermo-mechanical solidification analysis with structural stress analysis. There are though ongoing projects, for example VIKTOR, in Sweden today where research groups consisting of people representing several disciplines are working together to combine more disciplines from casting simulation with structural stress analysis.

Today there are a couple of leading softwares on the market for casting simulation like Magmasoft, NovaFlow & Solid and ProCast. The two first, Magmasoft and NovaFlow & Solid uses the Finite Difference Method (FDM) and ProCast uses Finite Element Method (FEM). All of these softwares are capable of simulating the complete casting process from filling to solidified material.

The casting constraint from the casting process that we would like to include is residual stresses and in order to do this the FE software Abaqus was used because it is easily handled by scripts and since the FE calculations are done in Abaqus it is convenient to have the residual stress calculation done in the same software. The scripts for Abaqus are written in the program language Python and the residual stresses from the casting process are then easily included in the structural stress analysis.

By doing structural optimization on casted components in trucks a significant weight saving can be achieved since casted components approximately represents a 10-15 % [3] of the total weight of the vehicle.
Structural Optimization

Structural optimization is today a well known method for designing components that are optimized according to some objective function such as for example minimization of weight or stresses. Within the industry today this is a useful tool. Structural optimization of castings when taking into account the residual stresses from the casting process or other information from the casting process such as location or size of pores has not reach an industry standard yet. Suggested in this thesis is to use surrogate models when performing structural optimization on castings since it is a non-linear problem with perhaps many local minima.

The optimization problem that we would like to solve is to minimize some function \( g_0(x) \) where \( x = (x_1, x_2, \ldots, x_n) \) is a vector containing the design variables. \( g_0(x) \) can be any non-linear function subjected to constraint functions \( g_j(x) \). The optimization problem can be written as

\[
\begin{align*}
\text{SO} \quad & \min \quad g_0(x) \\
\text{s.t.} \quad & g_j(x) \leq 0 \quad j = 1, 2, \ldots, m, \\
& x_{\text{lower}} \leq x_i \leq x_{\text{upper}}
\end{align*}
\]

where \( x_{\text{lower}} \) and \( x_{\text{upper}} \) are lower and upper bounds respectively for the variable \( x_i \) and \( m \) are the number of constraint equations.

2.1 Surrogate Models

Surrogate models or response surface methodology is an established method for optimization of various non-linear optimization problems. Let us consider a response \( y \) dependent of a set of variables \( x \). The exact functional relationship then reads

\[
y = g_0(x).
\]  

(1)

We would then like to approximate the unknown function \( g_0 \) with a surrogate function (response surface) \( f \) that we know

\[
g_0(x) \approx f(x)
\]  

(2)
over some region of interest (RoI) $\Omega_0$. The response is then evaluated at $N$ points within the RoI so we at our experimental points have $\mathbf{y} = (y_1, y_2, \ldots, y_N)^T$ and $\mathbf{f}(\mathbf{x}) = (f(x_1), f(x_2), \ldots, f(x_N))^T$. The model can now be written as

$$\mathbf{y} = \mathbf{f}(\mathbf{x}) + \mathbf{\delta}(\mathbf{x}), \quad (3)$$

where $\mathbf{\delta}(\mathbf{x})$ are the modeling errors. If physical experiments are performed a random error is also present in (3).

The method then works such that the response surface is approximated to number of simulations that are made and the optimization is then performed on these surfaces. These responses can e.g. be analytical functions, Kriging or neural networks. Roux, Stander and Haftka were among the first to use RSM for structural optimization in 1998 [4]. Since then the method have been used for optimization of crashworthiness [5], optimization of multibody-systems [6] and optimization of sheet metal forming [7]. Other useful and interesting references are [8, 9, 10] and references therein. For more basic theory regarding RSM read [11] that gives a good introduction to RSM. In [12] there is an extensive list of various RSM activities from 1989.

An extension of RSM is the successive response surface methodology (SRSM) as proposed by Stander and Craig [13] where the region of interest (RoI) is gradually decreased around an optimal point. SRSM has been used successfully in for example [14, 15, 16] and [17].

In this thesis SRSM using both analytical response surfaces and neural networks have been performed. Two other ways of representing response surfaces, radial basis function network and Kriging, are also described in coming subchapters.
2.1. SURROGATE MODELS

2.1.1 Analytical Response Surface

The response surfaces can as mentioned earlier be approximated by different analytical functions. The most common form of these analytical functions are linear, parabolic and quadratic. The general analytical function for linear, parabolic and quadratic surface approximation will be as follows

\[ y^i = \beta_0 + \sum_j \beta_j x_j^i + \varepsilon^i, \quad i = 1, 2, \ldots, N, \]
\[ j = 1, 2, \ldots, M, \quad (4) \]

\[ y^i = \beta_0 + \sum_j \beta_j x_j^i + \sum_{jk} \beta_{jk} x_j^i x_k^i + \varepsilon^i, \quad i = 1, 2, \ldots, N, \]
\[ j = 1, 2, \ldots, M, \quad (5) \]

\[ y^i = \beta_0 + \sum_j \beta_j x_j^i + \sum_{jk} \beta_{jk} x_j^i x_k^i + \varepsilon^i, \quad j = 1, 2, \ldots, M, \]
\[ k = 1, 2, \ldots, M, \quad (6) \]

where \( x^i \) are the design points in the region of interest (RoI), \( \varepsilon^i \) is the error including both modeling (bias) and random errors, \( N \) is the number of evaluations and \( M \) are the number of parameters. The bias error is the difference between the response approximation function and the exact evaluated response.

In order to determine the unknown variables \( \beta \), the analytical function is written in matrix notation as

\[ y = X(x)\beta + \varepsilon. \]

\( \beta \) is then found by minimizing the error \( \varepsilon \) in a least square sense where this specific value for \( \beta \) denoted \( \beta^* \) is given by

\[ \beta^* = \left( X^T(x) X(x) \right)^{-1} X^T(x) y. \]

(8)

To determine the value of the parameters \( \beta \) a minimum number of simulations, \( N_{\text{min}} \), is needed. For the different analytical approximations the value of \( N_{\text{min}} \) are determined by the following equations gathered in Table 2. It has through been shown in [4] and [9] that 1.5 · \( N_{\text{min}} \) simulations in every iteration might be used to get an efficient coverage of the design domain.
Table 2: Minimum number of simulations needed for different D-optimal selections.

<table>
<thead>
<tr>
<th>Surface</th>
<th>( N_{min} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>( N + 1 )</td>
</tr>
<tr>
<td>Parabolic</td>
<td>( 2N + 1 )</td>
</tr>
<tr>
<td>Quadratic</td>
<td>( \frac{(N + 1)(N + 2)}{2} )</td>
</tr>
</tbody>
</table>

### 2.1.2 Neural Networks

In addition to the more traditional way to represent the response surfaces by using analytical functions neural networks can be used. An artificial neural network might be seen as a mathematical model of a human brain. A human brain is a complex biological system of \( 10^{11} \) neurons. A neuron consists of a cell body, an axon and dendrites. Incoming signals are first interpreted by the cell body, which in turn sends the interpretation as a new signal by the axon to a network of dendrites. Here, the signal is captured by new neurons through synapses. In the artificial network the first step is modeled by a summation and a transfer function. The output is weighted and linked to layers of new transfer functions. This step represents the axon, dendrites and synapses. A brain is learned by adjusting the synapses. In a similar manner, the artificial neural network is trained by finding optimal weights. Neural networks were introduced in 1943 by McCulloch and Pitts [18] where a single neuron was modeled. An example of a single neuron is shown in Figure 1 where \( x_i \) are the inputs, \( w_i \) are the weights and \( b \) is the bias. The expression for \( v \) is then calculated as

\[
v = b + \sum w_i x_i ,
\]

which is feed forward to the transfer function \( f \). The transfer function might have several formats, e.g. see [19, 20]. The final output from the neuron is then

\[
y = f(v) .
\]

Further information regarding neural networks can for example be found in [19, 20, 21]. In this work we use a feed-forward multi-layer network with back-propagation developed in [22]. The network consists of two hidden layers and one output layer. The transfer functions in the hidden layers are log-sigmoid functions and a linear function is used in the output layer. A principle sketch of the network is shown in Figure 2.
2.1. SURROGATE MODELS

![Figure 1: A single neuron with n input variables.](image1)

![Figure 2: The neural network used in this work.](image2)

2.1.3 Radial Basis Function Network

Another similar type of network is the Radial Basis Function Network. In [23] an introduction to this methodology is given. The response $f$ from such a network is given by

$$ f(x) = \sum_{j=1}^{m} w_j h_j(x) $$

(11)

where $x$ are the design variables, $w_j$ are the weights to be determined, $h_j$ are basis functions and $m$ is the number of basis function one would like to use. Any set of function can be used as basis function but it is preferred if it is a differentiable equation. A simple example is the straight line

$$ f(x) = ax + b, $$

(12)

which is a linear model whose two basis functions are

$$ h_1(x) = 1, $$

(13)

$$ h_2(x) = x, $$

(14)

and whose weights are $w_1 = b$ and $w_2 = a$. To make it more general the radial basis functions are used, that have the special feature that their response is affected
CHAPTER 2. STRUCTURAL OPTIMIZATION

by the distance from a central point. An example is the Gaussian function which for the case of a input \( x \) looks like

\[
h(x) = e^{-\frac{(x-c)^T(x-c)}{2r^2}}
\]

Its parameters are the center \( c \) and the radius \( r \). These functions can then be gathered in a network. An example of a network is shown in figure 3.

![Network Example](image)

Figure 3: Example of a radial basis function network. [23]

Further and recent information regarding this method is found in e.g. [24] and [25].

2.1.4 Kriging

Kriging is when the response \( y(x) \) is a combination of a global linear regression model \( f^T(x)\beta \) and a random process \( Z(x) \)

\[
y(x) = f^T(x)\beta + Z(x) \tag{16}
\]

By doing this a local correction of the global model is obtained and an exact representation of the responses at all training points can be achieved. The values of \( \beta \) and \( Z(x) \) in (16) are then obtained by the following procedure as explained in [26]. After performing \( N \) simulations we have the following system of equations

\[
y = X\beta + Z \tag{17}
\]

This is similar to (7) but now the residuals \( Z \) are correlated according to a correlation function \( R(x, w) \) where \( x \) and \( w \) are different training points.

\[
\text{cov}(Z) = \sigma^2 \begin{pmatrix} R(x_1, x_1) & \cdots & R(x_1, x_N) \\ \vdots & \ddots & \vdots \\ R(x_N, x_1) & \cdots & R(x_N, x_N) \end{pmatrix} - \sigma^2 R_D \tag{18}
\]
where \( R(x_k, x_l) = e^{-\theta(x_k-x_l)^2} \), and \( k, l \in [1, 2, \ldots, N] \), is the correlation function and \( \sigma^2 \) is the product of the process variance. Other types of correlation functions can also be used. \( \theta \) is known as the correlation function parameter.

Since the residuals are correlated (17) is multiplied by a weighting matrix \( W \) and the following is obtained

\[
W y = WX\beta + WZ \Rightarrow y^* = X^*\beta + Z^*.
\]  

(19)

\( W \) is defined as

\[
W = (\text{cov}(Z))^{-1} = \sigma^{-2} R_D^{-1}.
\]  

(20)

The coefficients \( \beta \) can now be found in a least square sense. This specific value of \( \beta \) denoted \( \beta^* \) is given by

\[
\beta^* = (X^T R_D^{-1} X)^{-1} X^T R_D^{-1} y,
\]  

(21)

and we can also determine \( \theta \) by maximizing the log-likelihood function

\[
L(\theta) = -(N \ln(s^2) + \ln(\det(R_D))),
\]  

(22)

where

\[
s^2 = \frac{1}{N} (y - X\beta^*)^T R_D^{-1} (y - X\beta^*).
\]  

(23)

Our actual expression for the response at a point \( x_0 \) can then be written as

\[
y(x_0) = f^T(x)\beta^* + r^T(x_0)R_D^{-1} Z_D,
\]  

(24)

where

\[
r(x_0) = \begin{pmatrix}
R(x_0, x_1) \\
\vdots \\
R(x_0, x_N)
\end{pmatrix}
\]  

(25)

is the vector of residuals and \( Z_D \) represents the residuals for the training designs

\[
Z_D = y - X\beta^*.
\]  

(26)

In (24) the second term is an interpolation of the residuals of the regression model \( f^T(x_0)\beta^* \). This results in a correct prediction if the response surface at the training points.

More information regarding Kriging can be found in [27]. How Kriging is being used in structural optimization are shown in for example [28] and [29].
Residual Stresses in Castings

Residual stresses in castings has been studied for approximately 45 years. One of the first to study this was Weiner and Boley that in 1963 published a paper where they analytically determined the stresses in a solidifying slab [30]. Tien and Koump [31] also solved this analytically but introduced some temperature dependent material properties. Around this time Perzyna presented his theory regarding visco-plasticity [32] that could be very useful for thermomechanical solidification analysis. This was implemented by Zienkiewicz and Cormeau, [33]. In [34] viscoplasticity was used for thermal stress calculations in castings. In [35] there is good overview of research field of residual stresses in castings until 1995. Among the work done in recent years there are for example [36, 37, 38, 39] and references therein.

Regarding residual stress analysis on casted components for the automotive industry there are a few interesting papers like [40] but here they only study stresses caused by quenching since a stress relieving process has removed all stresses caused by the casting process. The same questions are studied in [41]. In [42] the software MagmaSoft is used to determine the thermal history in a gray iron casting and the following thermo-mechanical analysis is done in Abaqus. In [42] the fact that gray iron is behaving different in tension and compression is considered by using the material model ”Cast Iron Plasticity” that is available in Abaqus. A material model for gray iron similar to the one available in Abaqus is the one presented by Hjelm [43, 44, 45]. Wiese and Dantzig [46] has proposed another constitutive model for cast iron plasticity and showed how it can be used in solidification analysis.

The use of Abaqus for residual stress calculations is well known. Some examples are [47] where Abaqus is used to determine residual stresses in cast iron calender rolls and [48] where the coupled thermal-stress model in Abaqus is used to calculate temperature, strain, and stress fields in an aluminium alloy. In [49] and [50] the work in Abaqus has been focused on developing new sand surface elements to reduce calculation time.

In this thesis residual stresses has been calculated by using either Abaqus or Magmasoft. The $J_2$-plasticity model in Abaqus has been used when structural
CHAPTER 3. RESIDUAL STRESSES IN CASTINGS

optimization has been performed on a simple casted component. The residual stress calculations in Abaqus and Magmasoft have also been compared to real tests. In Magmasoft a $J_2$-plasticity model has been used and in Abaqus both $J_2$-plasticity and "Cast Iron Plasticity" have been used for comparisons.
Results

The developments in this thesis is that an optimization algorithm is written in Matlab and an investigation of the capabilities of simulating residual stresses in casting has been performed. The optimization algorithm uses the SRSM which has proven to work very good for non-linear structural optimization problems. The response surfaces can be either analytical functions, linear and non-linear, as well as neural networks. The optimization code has today been used together with Abaqus and an in-house FEM-software called TriLab and can by very easy manipulations be used with any FEM-software that can be run via scripts.

Regarding the residual stress simulations, several stress lattices have been casted and the residual stresses have been measured and compared to simulation results from the two softwares Magmasoft and Abaqus. Some numerical examples of how residual stress simulations can be used in the product development process is also shown. Next follows some of the most important results obtained in this thesis.

The developed optimization routines has been gathered in a package called StuG-OPT and the optimization code has been tested on several problems. In paper I the SRSM algorithm with analytical non-linear response surfaces has been tested on a beam where the objective is to minimize the weight of the beam under a constraint on the maximum von Mises stress in the beam. The optimization is performed while both including and excluding residual stresses from the casting process. In Figure 4 the optimized geometries can be seen.
CHAPTER 4. RESULTS

(a) Optimal shape obtained for pure mechanical problem, SRSM optimization. (b) Optimal shape obtained for thermomechanical problem, SRSM optimization.

Figure 4: Comparison of obtained optimal shapes.

In paper II neural networks is added to the SRSM and this will increase the capabilities of the response surface to capture more non-linearities. The optimization is tested on some typical benchmark problems like an elastic plate with a hole in the center and a rivet through a plate [51]. For the plate with the hole the objective is to minimize the von Mises stress in the plate under a constraint on volume when it is subjected to a tensile load. The von Mises stress in the plate with initial shape and the plate with optimal shape can be seen in Figure 5. The decrease in maximum von Mises stress is approximately 37%. For the rivet, the objective is to minimize maximum contact pressure between the rivet and plate under a constraint on the volume of the rivet when a tensile stress is applied to the bottom of the rivet. In Figure 6(a) the optimal shape of the rivet is seen and in Figure 6(b) the contact pressure for initial and optimal design is shown.

(a) Initial geometry, \( \sigma = 414 \) MPa. (b) Optimal geometry, \( \sigma = 262 \) MPa.

Figure 5: Von Mises stress in plate with hole.
In paper IV the two softwares Magmasoft and Abaqus are compared to real tests on stress lattices. In Magmasoft, the residual stresses are simulated by using a $J_2$-plasticity model and in Abaqus two different constitutive models are used, $J_2$-plasticity and the "Cast Iron Plasticity" (CI-plasticity) mentioned in previous chapter. After casting the lattices are cut and the area of the remaining fracture surface is measured. Tensile test bars are then prepared with a cut similar to the cut that causes the lattices to fracture. The prepared test bar are then tested and the force that is needed for fracture is recorded and compared to the forces seen in the simulations. The results are summarized in Table 3. It is also possible to see how the residual stresses develop through the solidification/cooling and this is seen in Figure 7. Notice that there is a difference in the obtained results from the two softwares.

Table 3: *Simulated and the average of measured reaction forces after cutting.*

<table>
<thead>
<tr>
<th>Material model of plasticity</th>
<th>Software</th>
<th>Reaction force [kN]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J_2$</td>
<td>Abaqus</td>
<td>55.6</td>
</tr>
<tr>
<td>$J_2$</td>
<td>Magmasoft</td>
<td>39.9</td>
</tr>
<tr>
<td>CI-plasticity</td>
<td>Abaqus</td>
<td>75.0</td>
</tr>
<tr>
<td>Measured avg.</td>
<td>-</td>
<td>67.1</td>
</tr>
</tbody>
</table>
Figure 7: Stress as a function of time for three different points of the stress lattice.
Summary of Appended Papers

5.1 Paper I

In this paper an optimization algorithm is developed and used for structural optimization of a casted beam. The algorithm is written in Abaqus and linked to the FE-solver Abaqus through python scripts. The optimization algorithm uses successive response surface methodology (SRSM) and the optimization is performed using sequential linear programming. It is shown that by including residual stresses in structural optimization of casting this yields an optimal shape that might differ significantly from the optimal shape obtained when residual stresses are excluded.

5.2 Paper II

The SRSM algorithm is in this paper extended to include neural networks. By doing this the response surface is capturing non-linearities in the response more efficiently. The network used is a so called feed-forward backpropagation network with two hidden layers and one output layer. The optimization algorithm is benchend towards one classical linear elastic problem and two non-linear problems where one is including contact and the other is the thermomechanical problem studied in paper I.

5.3 Paper III

This is a survey of the research in the area of residual stress calculations. A short introduction to plasticity is given and some constitutive models that can be used for residual stress calculations are presented. Different techniques available for measuring residual stresses are also presented. Finally, two numerical examples are given to show how casting simulation can be used.
5.4 Paper IV

In this paper two commercial softwares, Magmasoft and Abaqus, are compared to real tests in order to evaluate their residual stress calculation capabilities. Several stress lattices are casted and compared to simulations. In Magmasoft a $J_2$-plasticity model is used and in Abaqus two different plasticity models are used, $J_2$-plasticity and cast iron plasticity which is a plasticity model available in Abaqus that takes into account the different behavior in tension and compression for grey cast iron.
Bibliography


