

Application of the MADMML Approach to Improve the Magnesium Alloy Quality Indicators

In this presentation we summarize our results from our joint work with Fu Yu during my stay.

/ Summary Report on the **Activities** of prof. Tontchev during the
Period **April 10 - June 9**, 2018 / in DTU, China

The approaches to improving quality indicators are subdivided into two groups [1]. MADMML belongs to the first group. It is applied after certain coefficients of an adequate regression model. In order to obtain the model, data are needed for the relation between the technological parameters and the research quantities.

Modelling Approaches

Modelling refers to the method of identifying, establishing and analyzing the input-output relationships of the physical system. Generally the modelling tools are classified into two types namely

1. Conventional modelling tools (Finite element method, Response surface methodology, Design of experiments etc.,)
2. Unconventional modelling tools (Soft computing tools like particle swarm optimization, genetic algorithm, neural networks, fuzzy logic and their different combinations)

Part 1

Predict and optimization the microstructure and mechanical properties of heat treated Mg-Zn-RE-Zr alloys with MADMML

- The data can be in a defined plan with exactly defined levels of variation -1, 0 and +1. Then we are talking about an active /ordered/ experiment. This experiment gives better results of approximation. It also requires less experimental data.
- In our case the data is unordered and this is the passive version of the experiment. With the exception of one characteristic, YS was obtained for all the studied characteristics and good results, too. Relatively high values of the determination coefficient. For all other models, Fisher verification was obtained. Models are therefore adequate and they can serve for further prediction and optimization.

➤ 1.1 Experimental data

No.	Ca	Sr	Aging temperature (°C)	Aging time (h)	D (μm)	UTS (MPa)	El. (%)	HV
1	0	0	300	0	48.4	130.2	6.2	54
2	0	0	300	4	49.08	169.3	5.34	66.64
3	0	0	300	10	49.15	163.9	4.48	67.57
4	0	0	300	32	39.29	170.7	5.11	65.48
5	0	0	325	5	45.49	170.5	5.7	67
6	0	0	325	10	34.29	189	3.8	67.57
7	0	0	325	32	40.01	168.7	3.2	64.4
8	0	0	350	6	53.14	153.3	4.86	63.22
9	0	0	350	8	47.83	158	4.63	64.25
10	0	0	350	32	46.93	168.9	4.96	61.72
11	0.2	0	300	0	36.7	131.6	5.6	59
12	0.2	0	300	4	49.59	162.7	4.77	67.1
13	0.2	0	300	12	50.09	158.7	4.67	67.65
14	0.2	0	300	32	47.64	186.1	5.3	64.39
...								
29	0.2	0.2	350	10	42.4	167.4	4.72	68.9
30	0.2	0.2	350	32	45.14	190.7	3.54	63.2

- Ca: 0, 0.2 wt.%
- Sr: 0, 0.2 wt.%
- Aging temperature: 300, 325, 350 °C
- Aging time: 0~32 h

➤ **1.2 Identify the inputs and outputs of the system**

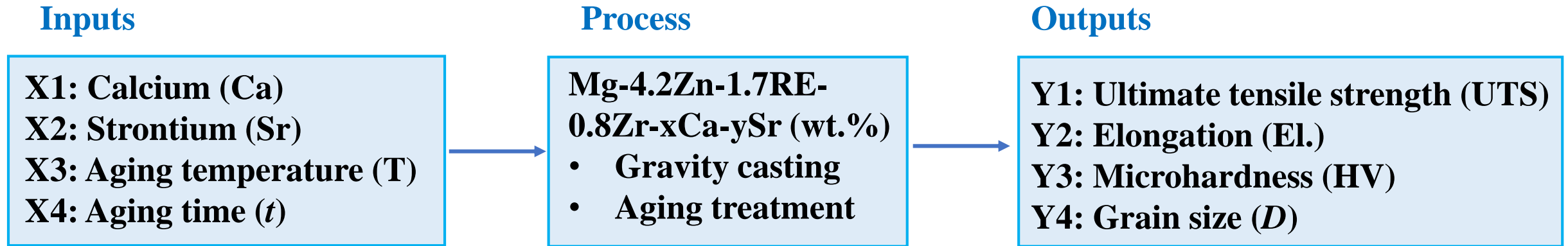


Fig. 1 Input variables and outputs of the system.

- Here the problem is defined that has been addressed. Four Input and four Output Parameters.
- In order for MADMML to be applied, the initial data needs to be encrypted.
- Coding is a Design of Experiment (DOE) operation that normalizes real data. This is a useful operation when a number of teams work on an innovation problem.
- The project manager, by encoding, locks the real data, and only when the results are transmitted decodes it. The next slide shows the encoded initial data and the coding and decoding equations.

➤ 1.3 Coding

- *Coding is done using the formula:*

$$\text{bio} := \frac{b_{\min} + b_{\max}}{2}$$

$$w := b_{\max} - \text{bio}$$

$$\text{bkod} := \frac{b - \text{bio}}{w}$$

- *Decoding is done using the formula:*

$$\text{bdekod} := w * \text{bkod} + \text{bio}$$

No	X1	X2	X3	X4	Y1	Y2	Y3	Y4
1	-1	-1	-1	-1	130,2	6,2	54	48,4
2	-1	-1	-1	-0.75	169,3	5,34	66,64	49,08
3	-1	-1	-1	-0.375	163,9	4,48	67,57	49,15
4	-1	-1	-1	1	170,7	5,11	65,48	39,29
5	-1	-1	0	-0.6875	170,5	5,7	67	45,49
6	-1	-1	0	-0.375	189	3,8	67,57	34,29
7	-1	-1	0	1	168,7	3,2	64,4	40,01
8	-1	-1	+1	-0.625	153,3	4,86	63,22	53,14
9	-1	-1	+1	-0.5	158	4,63	64,25	47,83
10	-1	-1	+1	1	168,9	4,96	61,72	46,93
11	+1	-1	-1	-1	131,6	5,6	59	36,7
12	+1	-1	-1	-0.75	162,7	4,77	67,1	49,59
13	+1	-1	-1	-0.25	158,7	4,67	67,65	50,09
14	+1	-1	-1	1	186,1	5,3	64,39	47,64
15	+1	-1	0	-0.6875	185,2	5,64	66,9	41,86
16	+1	-1	0	-0.25	194,4	3,45	74,25	32,98
17	+1	-1	0	1	170,4	3,18	63,5	51,93
18	+1	-1	+1	-0.625	171,2	4,78	63,3	48,25
19	+1	-1	+1	-0.375	175,2	5,16	64,5	53,16
20	+1	-1	+1	1	175,56	4,56	61,4	51,76
21	+1	-1	-1	-1	144,1	4,9	61	31,3
22	+1	+1	-1	-0.75	187,7	4,1	67,3	38,15
23	+1	+1	-1	-0.25	173,3	3,45	69,5	42,98
24	+1	+1	-1	1	179,3	3,08	63,9	39,39
25	+1	+1	0	-0.6875	176,2	3,49	66,9	41,19
26	+1	+1	0	-0.25	208	3,5	77,1	26,01
27	+1	+1	0	1	173,8	5,17	64,8	41,74
28	+1	+1	+1	-0.625	170,32	4,91	65,1	40,15
29	+1	+1	+1	-0.375	167,4	4,72	68,9	42,4
30	+1	+1	+1	1	190,7	3,54	63,2	45,14

- The approach I have developed is an approach to analyzing and optimizing research quantities. These quantities may be quality indicators. Once an experiment has been run or the quality parameter information is gathered, a regression model is output. The approach makes it possible to determine any desired combination of the process input parameters.
- A specific value is important for the researcher with the information provided to him/her. He/she may trust himself/herself fully after the tests of the adequacy model are positive.

➤ 1.4 Structure, coefficients and assessments of regression models

The least squares method is used to estimate the regression parameters through MathCAD software.

$$\begin{aligned} \blacklozenge \text{ UTS}(x_1, x_2, x_3, x_4) = & 193.05 + 3.23x_1 + 3.22x_2 - 2.21x_3 + 11.78x_4 + 2.93x_1 * x_3 \\ & - 3.06x_1 * x_3 - 1.58x_2 * x_4 + 0.62x_3 * x_4 - 11.14x_3^2 - 22.02x_4^2 \end{aligned}$$

$$\begin{aligned} & R=0.8002; \\ & 3.3834 > 2.3779 \\ & \text{Ft}(a=0.05, 10, 19) \end{aligned}$$

$$\begin{aligned} \blacklozenge \text{ El}(x_1, x_2, x_3, x_4) = & 3.58 - 0.069x_1 - 0.27x_2 + 0.204x_3 - 0.579x_4 + 0.233x_2 * x_3 \\ & + 0.099x_2 * x_4 - 0.204x_3 * x_4 + 0.41x_3^2 + 0.919x_4^2 \end{aligned}$$

$$\begin{aligned} & R=0.7238; \\ & 2.4451 > 2.3928 \\ & \text{Ft}(a=0.05, 9, 20) \end{aligned}$$

$$\begin{aligned} \blacklozenge \text{ HV}(x_1, x_2, x_3, x_4) = & 40.87 + 32.82x_1 - 31.78x_2 - 1.01x_3 + 2.40x_4 + 32.55x_1 * x_2 \\ & - 0.254x_1 * x_3 - 0.75x_1 * x_4 + 0.526x_2 * x_3 - 0.19x_2 * x_4 - 2.76x_3^2 - 10.01x_4^2 \end{aligned}$$

$$\begin{aligned} & R=0.9048; \\ & 7.3919 > 2.3769 \\ & \text{Ft}(a=0.05, 11, 18) \end{aligned}$$

$$\begin{aligned} \blacklozenge \text{ D}(x_1, x_2, x_3, x_4) = & 38.47 + 0.599x_1 - 3.251x_2 + 1.418x_3 - 0.448x_4 + 0.621x_1 * x_3 \\ & + 4.137x_1 * x_4 - 0.866x_2 * x_3 - 1.55x_2 * x_4 + 6.24x_3^2 - 0.617x_4^2 \end{aligned}$$

$$\begin{aligned} & R=0.7469; \\ & 2.3978 > 2.3779 \\ & \text{Ft}(a=0.05, 10, 19) \end{aligned}$$

- The next slide shows the approach that is performed when working with MADMML
- The coefficients are entered into a special editor. The step of the research is implied in the $[-1; +1]$ range with the value of 0.25. It can arbitrarily change in the domain. The step determines the discretization, and through the discretization, the addresses in the domain are determined.

In the multiparametric non-linear approximation, the software performs similar calculations, that are improved on the research. Through them, the regression coefficients are determined for a chosen structure of the model.

Multiple Regression

$$\{ (X_1, y_1), (X_2, y_2), \dots, (X_n, y_n) \}$$

Least Squares Criteria

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

$$\hat{y} = \widehat{f(X)} = X \hat{\beta}$$

- The processing of results is a statistical procedure. Our work with Fu Yu started with this procedure.
- These are matrix calculations based on the least-squares method . On the next slide, the structure, the coefficients and the assessments of all the research parameters are listed.
- The following can be said about model evaluation. The estimate depends on the structure of the model.
- The respective approximation is realized via the structure of the models.

Example

$$\hat{y} = 6.211 + 0.014x_1 + 0.383x_2 - 0.607x_3$$

variables

intercept

coefficients

Estimated Multiple Regression Equation

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3$$

$b_0, b_1, b_2, \dots, b_p$ are the estimates of $\beta_0, \beta_1, \beta_2, \dots, \beta_p$

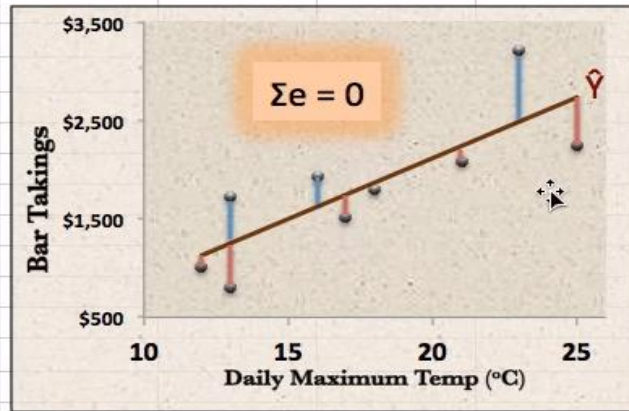
\hat{y} = predicted value of the dependent variable

The decision-maker chooses the best structure for these ratings. The structure determines the respective coefficients of the regression model. The determined coefficients define the magnitude examined. Several dimensions investigate define the criteria in the multi-criterion task, with preferences for them.

The basis of model evaluation lies with the residuals between the experimental / numerical values and those obtained through the model.

Day	Takings	Temp (°C)
3-Jun	\$3,213	23
10-Jun	\$2,089	21
17-Jun	\$2,253	25
24-Jun	\$1,801	18
1-Jul	\$801	13
8-Jul	\$1,934	16
15-Jul	\$1,720	13
22-Jul	\$1,514	17
29-Jul	\$1,017	12

SAMPLE REGRESSION LINE
 $\hat{Y} = -353.11 + 123.54X$



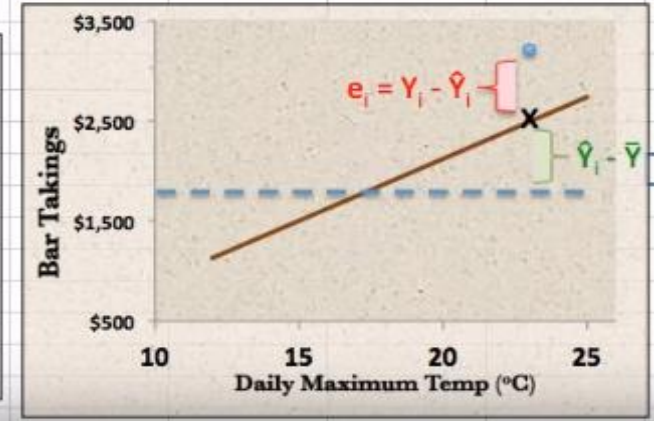
$$SSR = \Sigma(\hat{Y}_i - \bar{Y})^2$$

$$SSE = \Sigma(Y_i - \hat{Y}_i)^2$$

$$SST = SSR + SSE$$

$$SST = \Sigma(Y_i - \bar{Y})^2$$

$$R^2 = SSR/SST$$



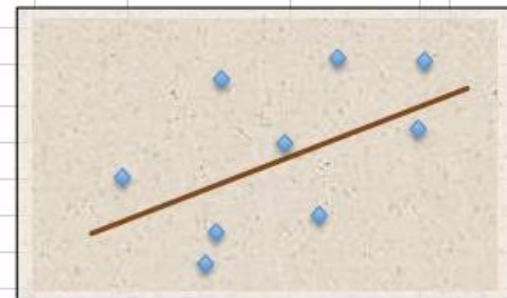
$\{(X_1, y_1), (X_2, y_2), \dots, (X_n, y_n)\}$

Residual Error of sample i :

$$e_i = y_i - \hat{y}_i$$

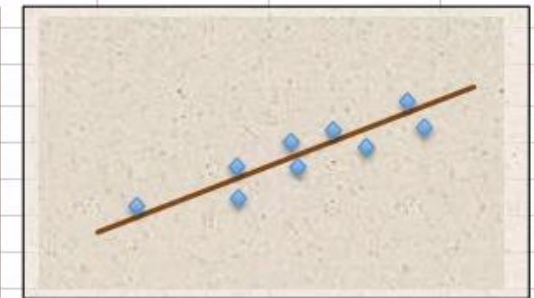
Sum of Squared Residuals (RSS):

$$RSS = \sum_{i=1}^n e_i^2$$



High SSE

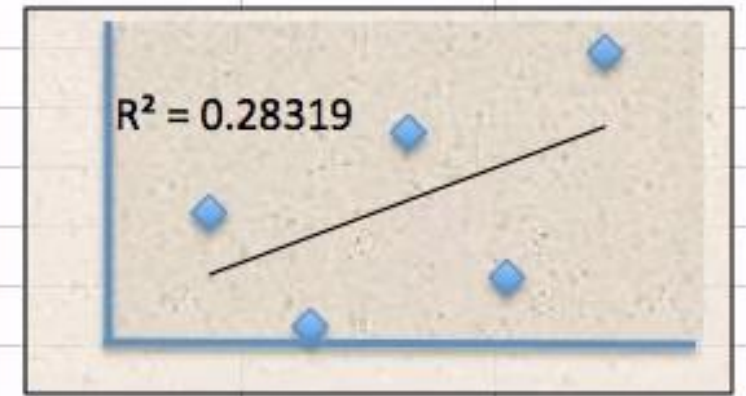
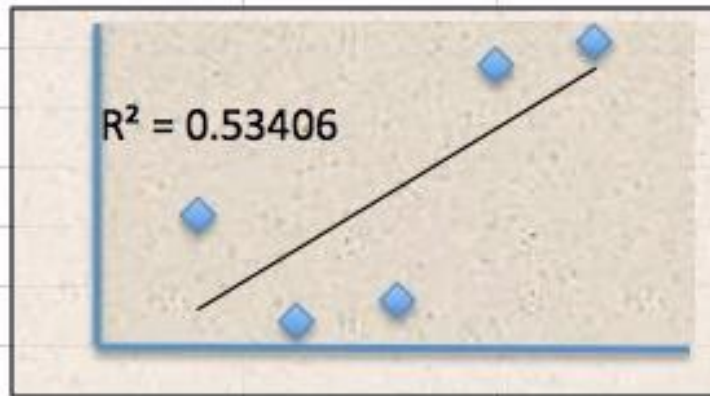
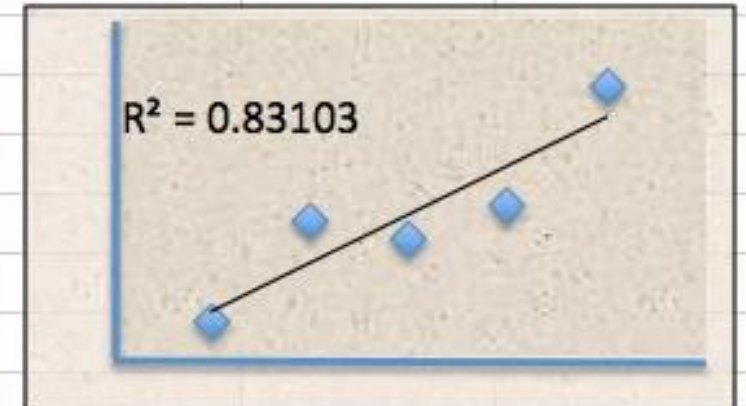
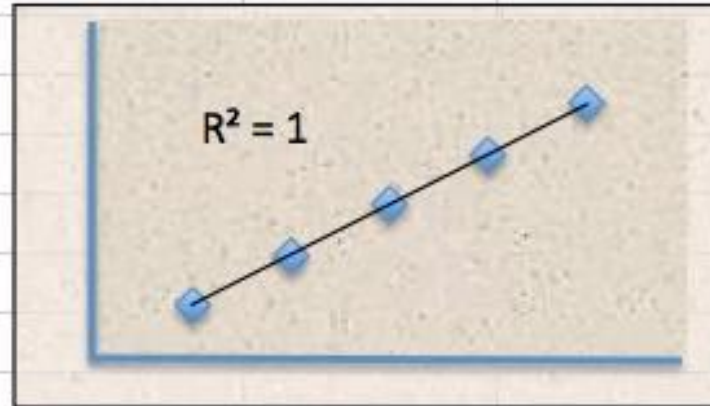
Low R^2



Low SSE

High R^2

From the scattering of the debris to the model curve, plane or hypersurface, the determination coefficient is determined. In the attached example, graphical data representations are presented for linear regression, for which the determination coefficients were defined. The software performs one more verification before giving a conclusion on adequacy.



➤ **1.5 Determine the optimal solution through *MADMMML* program**

- 1. Coefficients of regression models are written in the files for analysis, save as *.AO4 file.*
- 2. According to the requirements of decision maker, the files for optimization are edited, save as *.OO4 file.*
- 3. Through analyzing the files for optimization, the optimal combination of inputs is determined.*
- 4. Finally, return to the files for analysis and determine the corresponding outputs.*

1.5.1. Coefficients of regression models are written in the files for analysis, save as *.AO4 file.

files for analysis

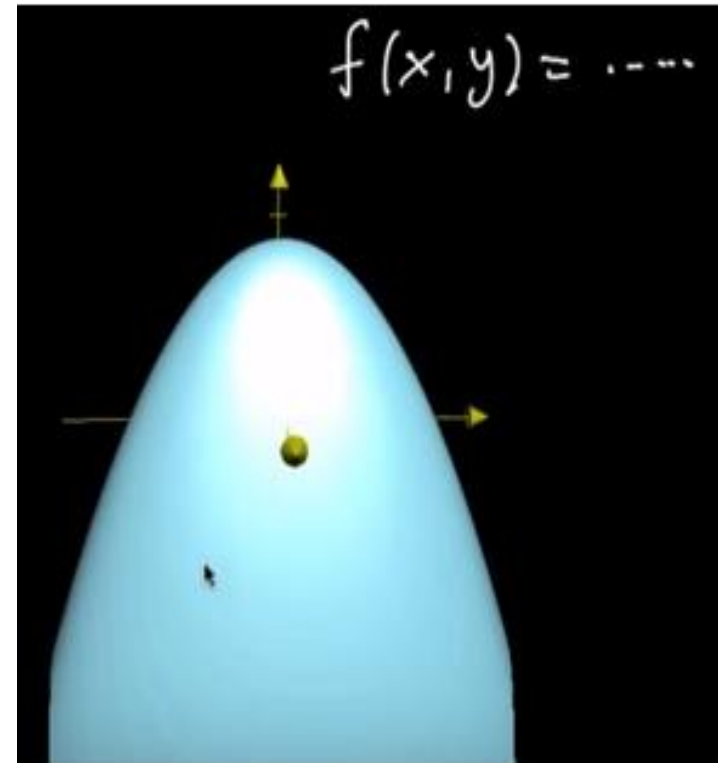
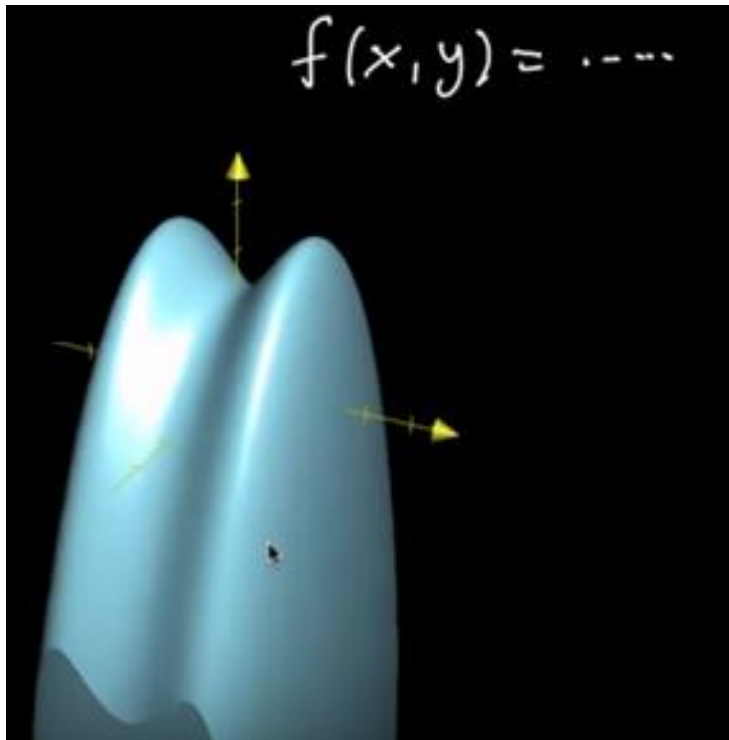
Filename	File content
3UTS.AO4	Coefficients for $UTS(x_1, x_2, x_3, x_4)$
3EL.AO4	Coefficients for $El(x_1, x_2, x_3, x_4)$
3HV.AO4	Coefficients for $HV(x_1, x_2, x_3, x_4)$
3D.AO4	Coefficients for $D(x_1, x_2, x_3, x_4)$

◆ $UTS(x_1, x_2, x_3, x_4) = 193.05 + 3.23x_1 + 3.22x_2 - 2.21x_3 + 11.78x_4 + 2.93x_1 * x_3 - 3.06x_1 * x_3 - 1.58x_2 * x_4 + 0.62x_3 * x_4 - 11.14x_3^2 - 22.02x_4^2$

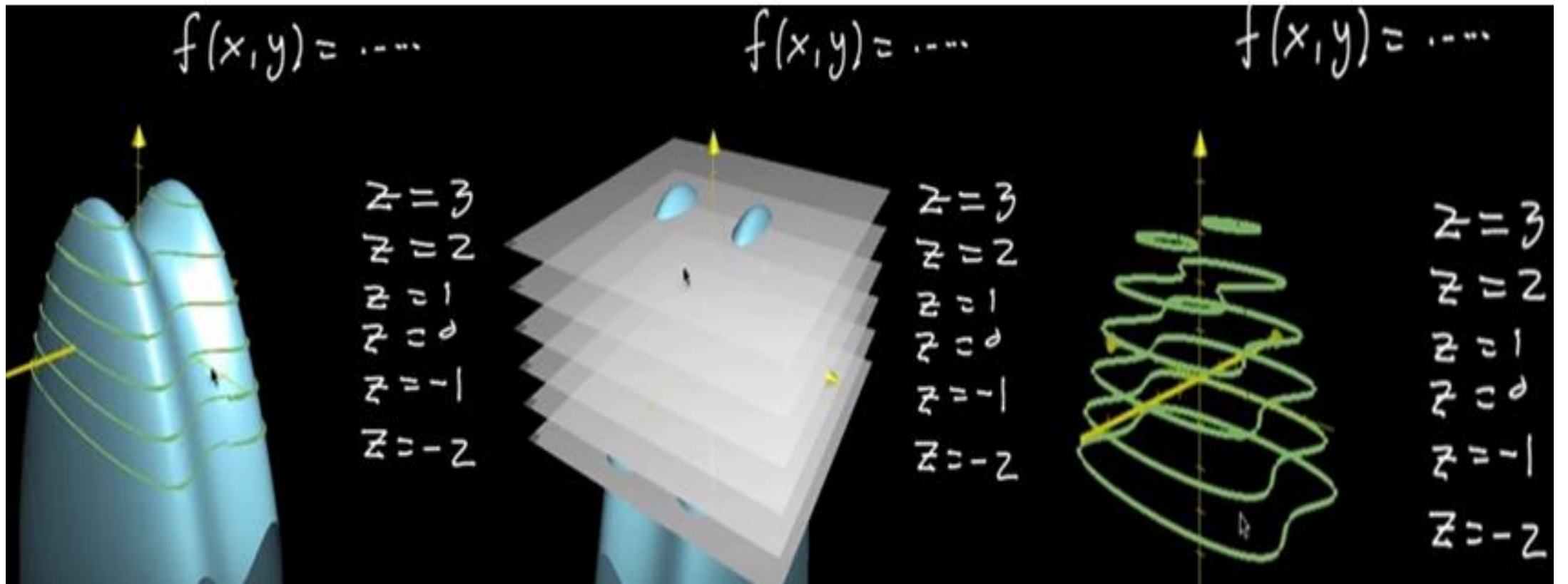


“3UTS.AO4” file

The visualization suggested in the approach uses elements of this analysis. In order to reveal the idea, the peculiarities and the differences between this method and the new one, the following example is considered. Let's look at the model represented by the images.

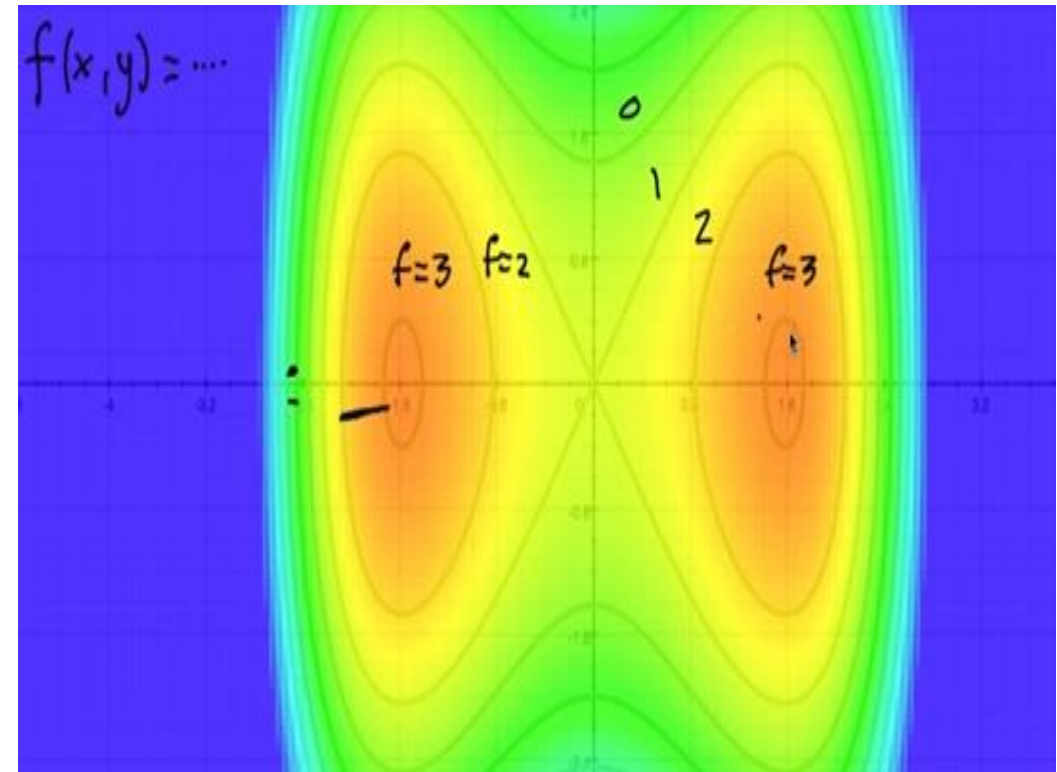
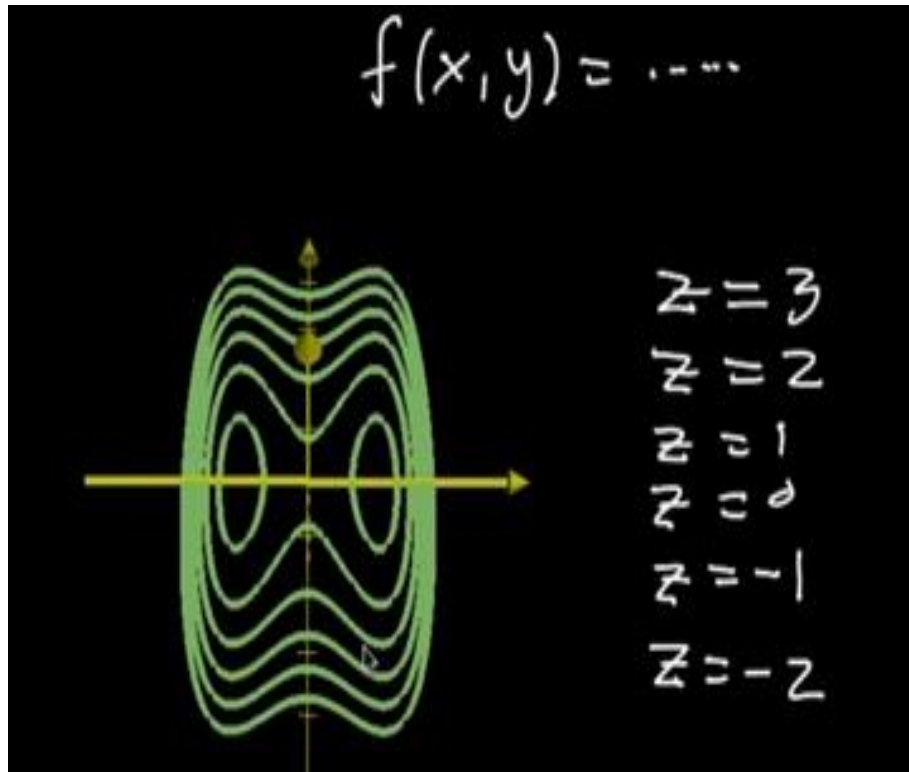


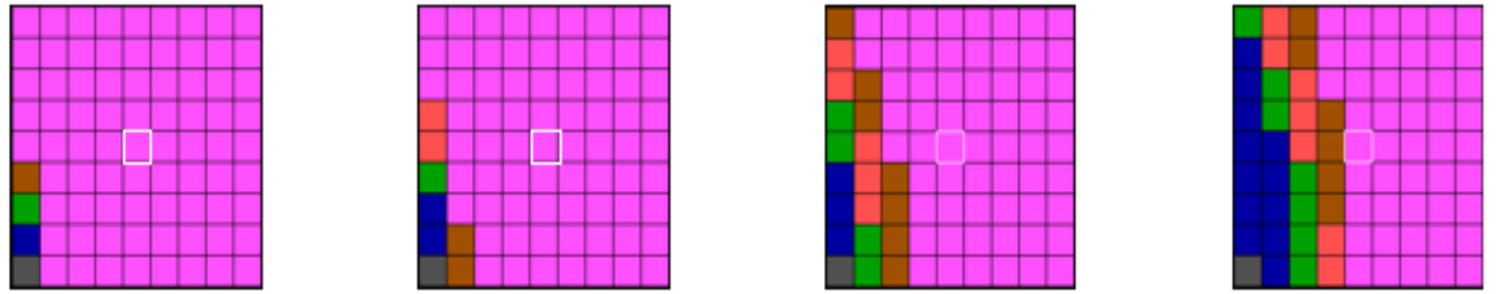
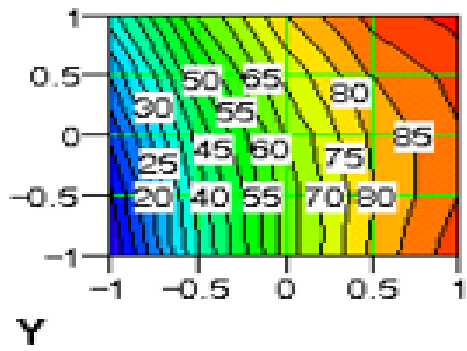
- The address is a combination of the input factor and each address corresponds to a quality indicator value. Through the projection of the response surface in the space of the technological parameters the analysis of the quality indicators is realized.
- In this design, the response surface can arbitrarily be crossed with several planes between which the research quantity is colored in a certain way. This is done within the even percentage distribution.



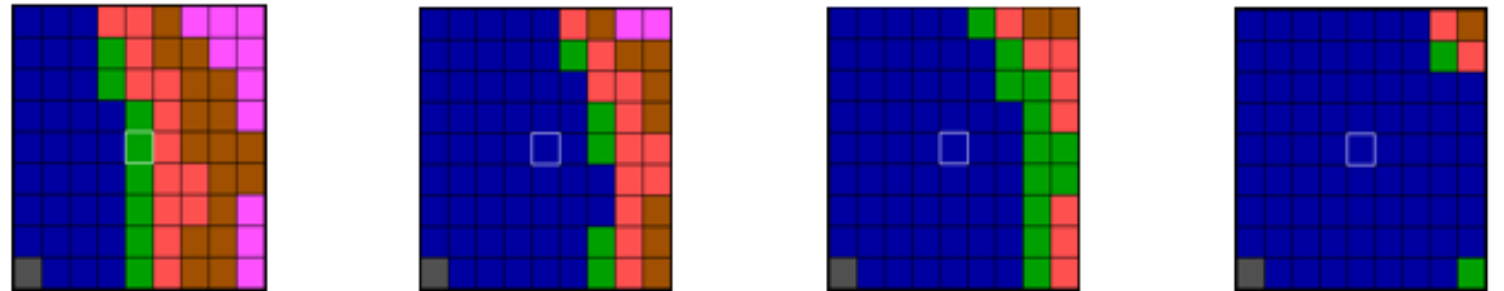
Boreholes cut the three-dimensional image of the model in height. The cut section is projected on each plane. This produces the corresponding contour line. At the last stage, the lines are gathered in a general image.

Valuable analysis of two and many parametric processes can be applied because the chosen approach takes place in the space of the variables.





Y[1]	0 .. 2 %	Y[1]	0 .. 5 %	Y[1]	0 .. 10 %	Y[1]	0 .. 30 %
Y[2]	2 .. 4 %	Y[2]	5 .. 10 %	Y[2]	10 .. 20 %	Y[2]	30 .. 40 %
Y[3]	4 .. 6 %	Y[3]	10 .. 15 %	Y[3]	20 .. 30 %	Y[3]	40 .. 50 %
Y[4]	6 .. 8 %	Y[4]	15 .. 20 %	Y[4]	30 .. 40 %	Y[4]	50 .. 60 %
Y[5]	8 .. 100 %	Y[5]	20 .. 100 %	Y[5]	40 .. 100 %	Y[5]	60 .. 100 %



Y[1]	0 .. 60 %	Y[1]	0 .. 80 %	Y[1]	0 .. 80 %	Y[1]	0 .. 92 %
Y[2]	60 .. 70 %	Y[2]	80 .. 85 %	Y[2]	85 .. 90 %	Y[2]	92 .. 94 %
Y[3]	70 .. 80 %	Y[3]	85 .. 90 %	Y[3]	90 .. 95 %	Y[3]	94 .. 96 %
Y[4]	80 .. 90 %	Y[4]	90 .. 95 %	Y[4]	95 .. 99 %	Y[4]	96 .. 98 %
Y[5]	90 .. 100 %	Y[5]	95 .. 100 %	Y[5]	99 .. 100 %	Y[5]	98 .. 100 %

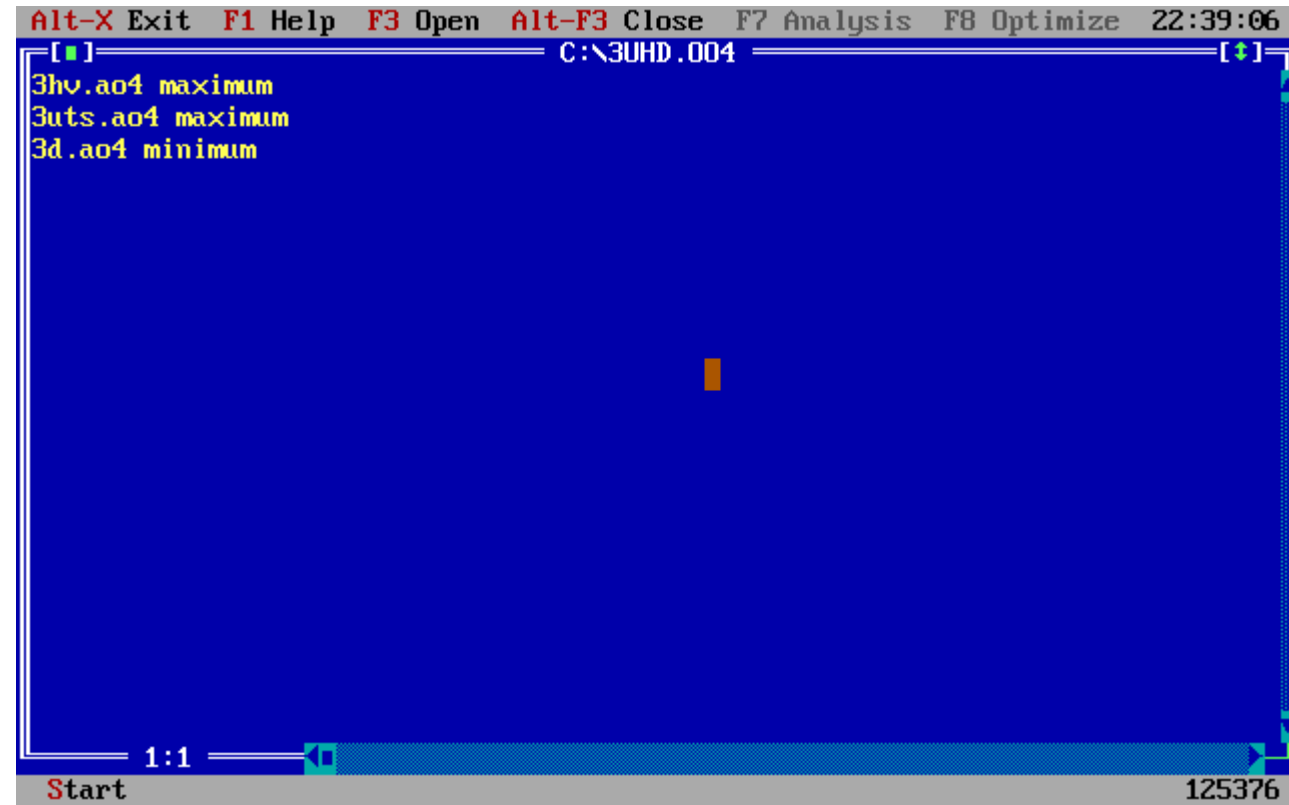
The chosen approach in our software selects the plane of the variables and normalizes the value of the research value in percentages from 0-100%. These features lead to the novelty of the proposed solution, which is the ability to vary with the number of moving planes and the variation in distance and color between them. The demonstration of this effect is indicated by movement(s) to the maximum and minimum of a two-parametric model, shown below.

- Four analysis files have been created for the four tested research quantities with MADMML. From them you can analyze the projection of the research quantity, in the way I presented them to you.
- The next slide shows the way in which the optimization problems are defined. Each specific definition has a separate solution. MADMML is used to solve optimization problems. With MADMML, the *.oo4 files are analyzed.

1.5.2. According to the requirements of decision maker, the files for optimization are edited, save as *.OO4 file.

files for optimization

Filename	File content
3UHD.OO4	3uts.ao4 maximum 3hv.ao4 maximum 3d.ao4 minimum
3UEA.OO4	3uts.ao4 maximum 3el.ao4 minimum
3UEADI.OO4	3uts.ao4 maximum 3el.ao4 maximum 3d.ao4 minimum
3HVUA.OO4	3hv.ao4 maximum 3uts.ao4 maximum
3ALL.OO4	3hv.ao4 maximum 3uts.ao4 maximum 3el.ao4 maximum 3d.ao4 minimum



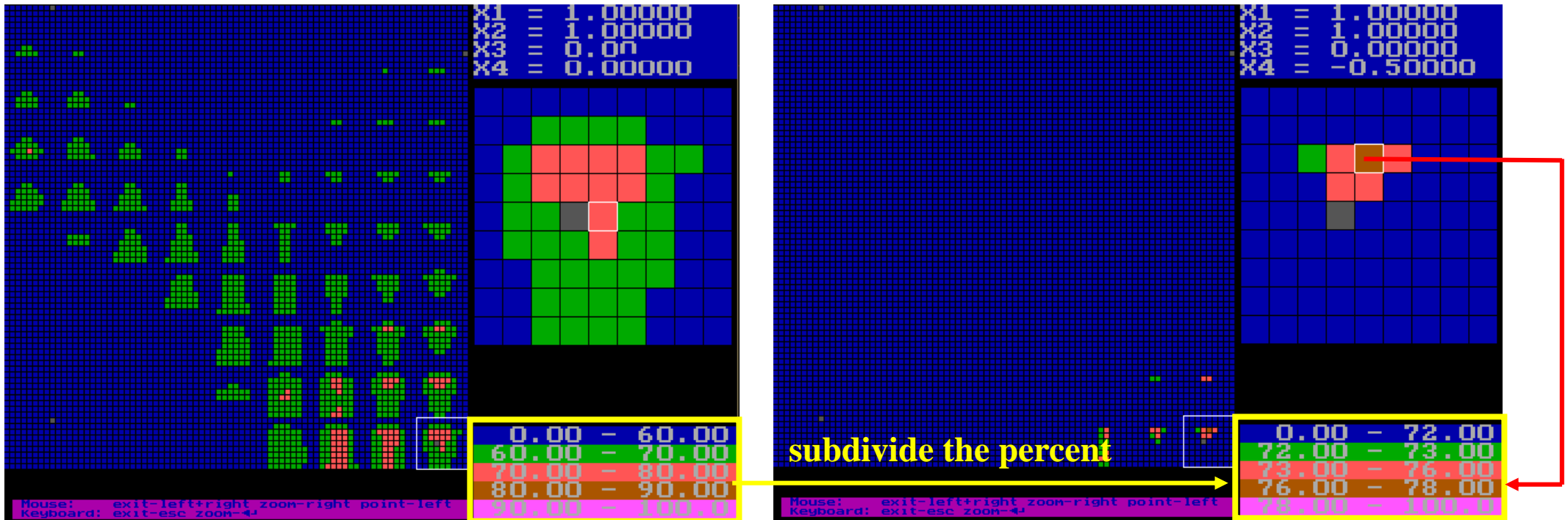
The screenshot shows a terminal window with a blue background and white text. The title bar at the top reads "Alt-X Exit F1 Help F3 Open Alt-F3 Close F7 Analysis F8 Optimize 22:39:06". The window title is "C:\3UHD.OO4". The main content area displays the following text:
3hv.ao4 maximum
3uts.ao4 maximum
3d.ao4 minimum
A cursor is visible on the line "3d.ao4 minimum". The bottom status bar shows "Start" on the left and "125376" on the right.

↓
"3UHD.OO4" file

- The next slide shows two consecutive iterations of the optimization problem, **the** relative **maxima of the** strength and **the** micro-hardness with a minimum grain size parameter.
- From the second iteration an optimal solution **is determined for which there** are shown the distributions of all the measured quantities.

1.5.3. Through analyzing the files for optimization, the optimal combination of inputs is determined.

“3UHD.004” file



□ The optimal combination of inputs is $X_1=1.0$, $X_2=1.0$, $X_3=0.0$, $X_4=-0.5$

$$UTS_n = \frac{100(UTS - UTS_{min})}{UTS_{max} - UTS_{min}}$$

This is the distribution of -

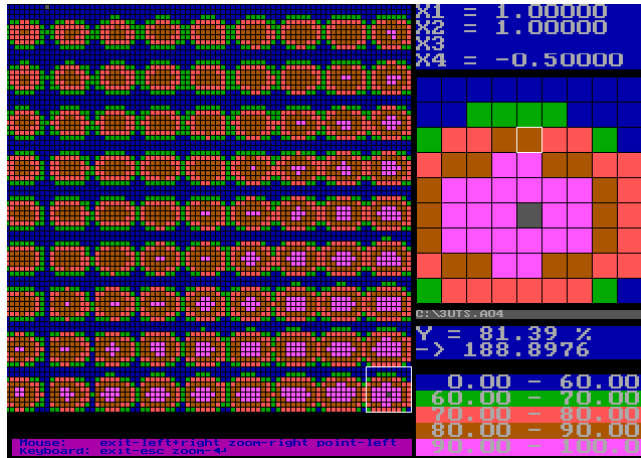
- UTS
- Elongation
- Grain size
- Micro-hardnes

from the **research** factors

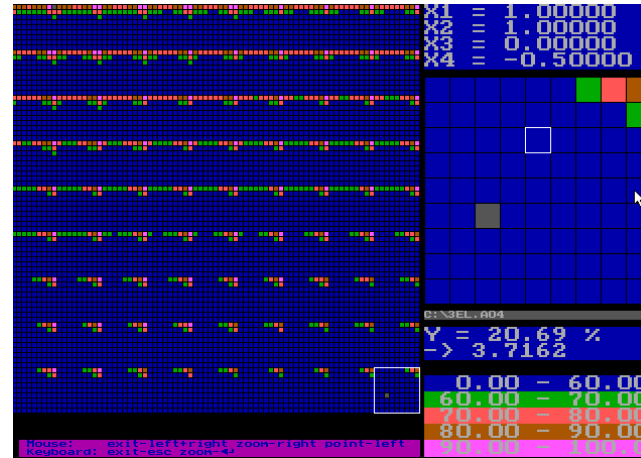
Besied the distribution, **on each graph we have the values of the four research quantities for the established optimal values of the input factors**

1.5.4. Finally, return to the files for analysis and determine the corresponding outputs.

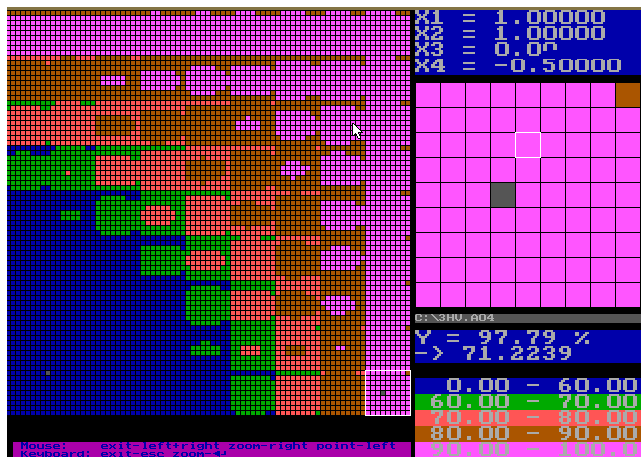
UTS(1,1,0,-0.5)



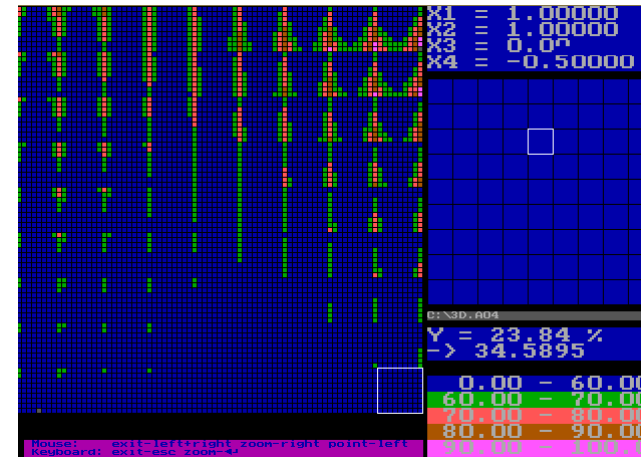
El(1,1,0,-0.5)



HV(1,1,0,-0.5)



D(1,1,0,-0.5)



Optimal solution

Parameters	Coded value	Real value
$Ca (X_1)$	1	0.2
$Sr (X_2)$	1	0.2
Aging temperature(X_3)	0	325
Aging time (X_4)	-0.5	8
$UTS (Y_1)$	81.39%	188.8976
$El. (Y_2)$	20.69%	3.7162
$HV (Y_3)$	97.79%	71.2239
$D (Y_4)$	23.84%	34.5895

1.5.4. Finally, return to the [files for analysis](#) and determine the corresponding outputs.

Other solutions

No.	Input/output parameters		I solution max UTS, max El, max HV, min d		II solution max UTS, max El,		III solution max UTS , max HV,		IV solution max UTS, max El, min d	
			code	real	code	real	code	real	code	real
1	X ₁	Ca	+1	0.2	+1	0.2	+1	0.2	+1	0.2
2	X ₂	Sr	0	0.1	-1	0	+1	0.2	-0.75	0.025
3	X ₃	Aging temperature	+0.5	337.5	+1	350	0	325	0	325
4	X ₄	Aging time	-0.75	4	-0.5	8	0	16	-0.75	4
5	Y ₁	UTS	55.33 %	172.40	56.6 %	173.21	98.15 %	199.50	54.31 %	171.76
6	Y ₂	Elongation	54.93 %	4.74	57.86 %	4.83	5.09 %	3.246	54.12 %	4.72
7	Y ₃	Grain size	37.8 %	38.53	73.79 %	48.68	28.17 %	35.81	34.21 %	37.51
8	Y ₄	HV	93.98 %	65.49	93.5 %	64.93	99.99 %	74.45	94.31 %	66.12

- With this data, an independent MADMML expertise was made via a MATLAB-based artificial neural network with the MATLAB box.
- There is a very good match of the results.
- **This is proof that all of you may use MADMML in the future.**

1.5.5. Result validation

Result comparison

<i>Parameters</i>	<i>MADMML</i>	<i>MATLAB_ANNs</i>
<i>Ca</i>	<i>0.2</i>	<i>0.2</i>
<i>Sr</i>	<i>0.2</i>	<i>0.2</i>
<i>Aging temperature</i>	<i>325</i>	<i>325</i>
<i>Aging time</i>	<i>8</i>	<i>8</i>
<i>UTS</i>	<i>188.8976</i>	<i>183.3317</i>
<i>El.</i>	<i>3.7162</i>	<i>3.9346</i>
<i>HV</i>	<i>71.2239</i>	<i>71.9053</i>
<i>D</i>	<i>34.5895</i>	<i>37.1165</i>

Part 2

Predict and optimization the of micro hardness of heat treated Mg-Zn-RE-Zr-Ca-Sr alloys by using regression model and artificial neural network

- The second problem had a similar structure with the difference that the data was more: 80 and the fourth parameter was changing to a different range. The other difference is that the research quantity is only one: the micro-hardness.
- The output again comprises approximation models, this time a regression for analysis with MADMML and neural models with MATLAB and STATISTICA 12 for comparison with the results.

➤ 2.1 Experimental data

No.	Ca	Sr	Aging temperature (°C)	Aging time (h)	HV
1	0	0	300	0.125	54.88
2	0	0	300	0.25	57.76
3	0	0	300	0.5	61.13
4	0	0	300	1	64.21
5	0	0	300	2	65.87
6	0	0	300	4	66.64
7	0	0	300	6	66.45
8	0	0	300	8	66.16
9	0	0	300	10	67.57
10	0	0	300	12	66.6
11	0	0	300	16	65.08
12	0	0	300	20	65.19
13	0	0	300	24	65.23
14	0	0	300	32	65.48
15	0	0	300	64	63.72
16	0	0	300	128	62.35
17	0	0	325	0.125	54.88
.....					
108	0.2	0.4	325	24	66.4
109	0.2	0.4	325	28	65.9
110	0.2	0.4	325	32	64.2

•Ca: 0, 0.2 wt.%

•Sr: 0, 0.2, 0.4 wt.%

•Aging temperature: 300, 325, 350 °C

•Aging time: 0~128 h

➤ **2.2 Identify the inputs and outputs of the system**

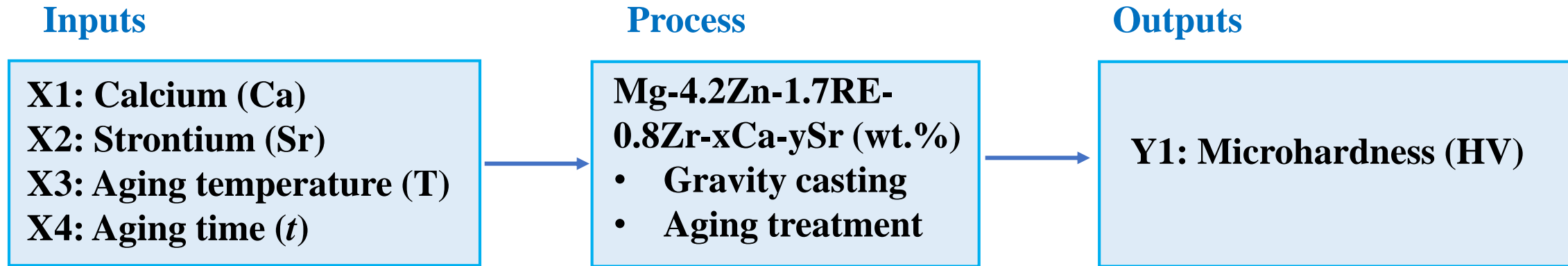


Fig. 1 Input variables and outputs of the system.

➤ 2.3 Coding

- *Coding is done using the formula:*

$$\text{bio} := \frac{b_{\min} + b_{\max}}{2}$$

$$w := b_{\max} - \text{bio}$$

$$\text{bkod} := \frac{b - \text{bio}}{w}$$

- *Decoding is done using the formula:*

$$\text{bdekod} := w * \text{bkod} + \text{bio}$$

Coded data

No	X1	X2	X3	X4	Y1
1	-1	0	-1	-1	54.88
2	-1	0	-1	-0.998	57.76
3	-1	0	-1	-0.994	61.13
4	-1	0	-1	-0.986	64.21
5	-1	0	-1	-0.971	65.87
6	-1	0	-1	-0.939	66.64
7	-1	0	-1	-0.908	66.45
8	-1	0	-1	-0.877	66.16
9	-1	0	-1	-0.846	67.57
10	-1	0	-1	-0.814	66.6
11	-1	0	-1	-0.752	65.08
12	-1	0	-1	-0.689	65.19
13	-1	0	-1	-0.627	65.23
14	-1	0	-1	-0.501	65.48
15	-1	0	-1	-0.001	63.72
16	-1	0	-1	1	62.35
17	-1	0	0	-1	54.88
18	-1	0	0	-0.998	58.39
19	-1	0	0	-0.994	61.72
.....					
108	+1	-1	+1	1	65.9
109	+1	-1	-1	-1	64.2
110	+1	+1	-1	-0.75	54.88

➤ 2.4 Regression models

The least squares method is used to estimate the regression parameters through MathCAD software.

$$\begin{aligned} \blacklozenge \quad HV(x_1, x_2, x_3, x_4) = & 65.174 + 0.304x_1 + 0.626x_2 - 1.409x_3 - 0.167x_4 - 0.497x_1 * x_4 \\ & - 0.418x_3 * x_4 - 1.837x_3^2 - 6.139 x_4^2 \end{aligned}$$

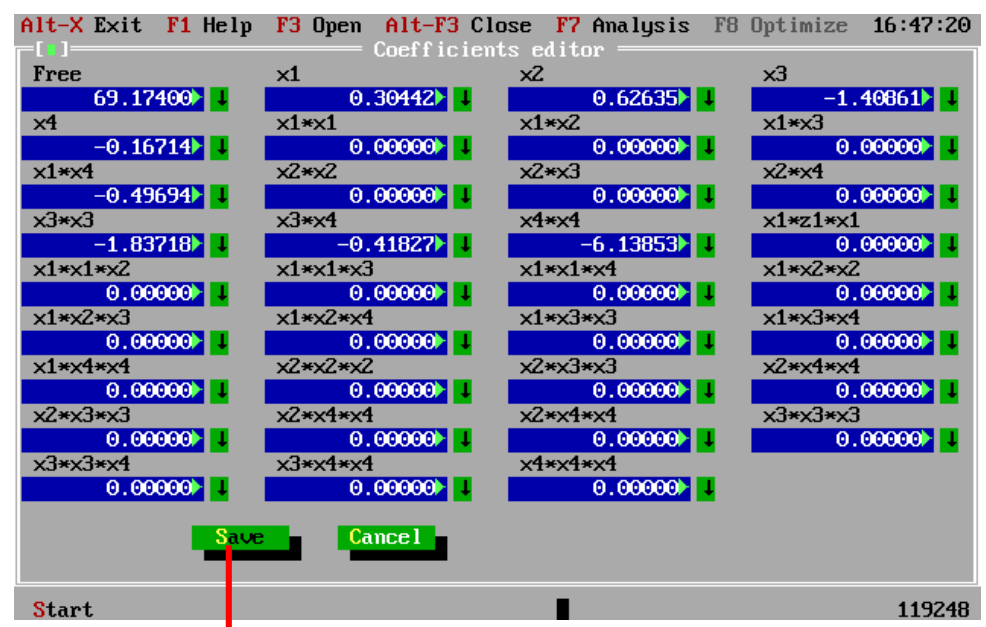
R=0.7539;

11.6889 > 2.0822

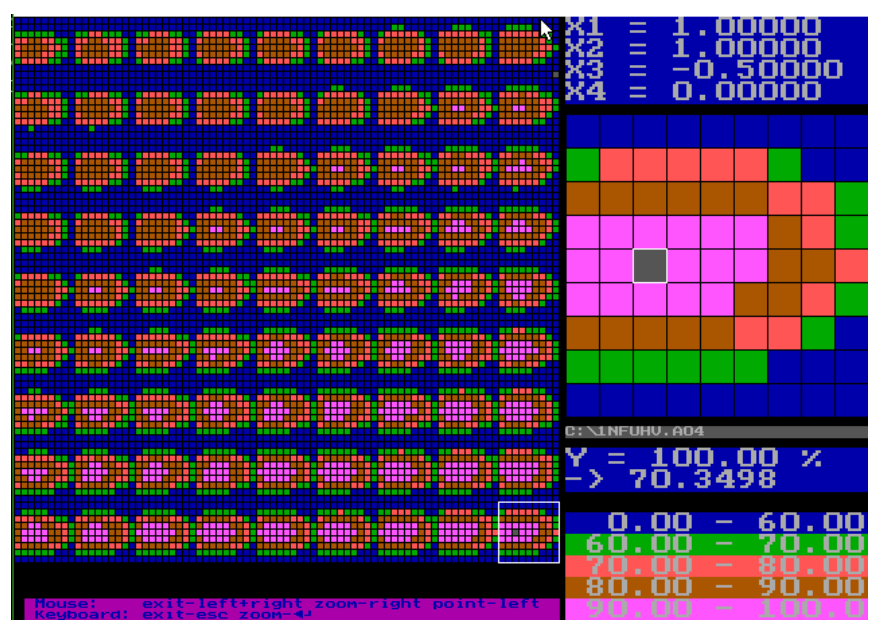
Ft(a=0.05, 8, 71)

➤ 2.5 Determine the optimal solution through **MADMML** program

1. Coefficients of regression models are written in the files for analysis, save as * **1FUHV.AO4** file.



“1NFUHV.AO4” file



Analyzing the “1NFUHV.AO4” file to determine the maximum.

- Since there is an approximation of a non-planned experiment, there are differences between the predicted **values** and the experimental values.
- During our stay we also worked with the STATISTICA 12 package.
- The next few slides are a proof of this work. They show a trained **neural** model, a table of **the** experimental **values** and **the** predicted values, and **the** response surface.
- All these results are obtained with STATISTICA 12.
- **In the future, you will have another tool in the analysis of neural models.**

2.6. Result validation

Result comparison

<i>Parameters</i>	<i>MADMML</i>		<i>Statistica Software _ANNs</i>	<i>MATLAB_AN Ns</i>
	<i>Code</i>	<i>real</i>		
<i>Ca</i>	<i>1</i>	<i>0.2</i>	<i>0.2</i>	<i>0.2</i>
<i>Sr</i>	<i>1</i>	<i>0.4</i>	<i>0.4</i>	<i>0.4</i>
<i>Aging temperatur e</i>	<i>-0.5</i>	<i>312.5</i>	<i>312.5</i>	<i>312.5</i>
<i>Aging time</i>	<i>0</i>	<i>16</i>	<i>16</i>	<i>16</i>
<i>HV</i>	<i>100%</i>	<i>70.3498</i>	<i>67.0055</i>	<i>67.4879</i>

➤ *2.7 Modeling of microhardness of heat treated Mg-Zn-RE-Zr-Ca-Sr alloys by using artificial neural network*

Inputs X1: Calcium (Ca)
 X2: Strontium (Sr)
 X3: Aging temperature (T)
 X4: Aging time (*t*)

Output Y1: Microhardness (HV)

Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
MLP 4-10-1	0.982885	0.92481	0.964745	0.27322	1.057103	0.455292	BFGS 132	SOS	Tanh	Identity

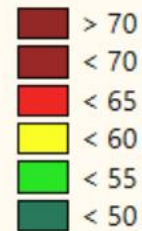
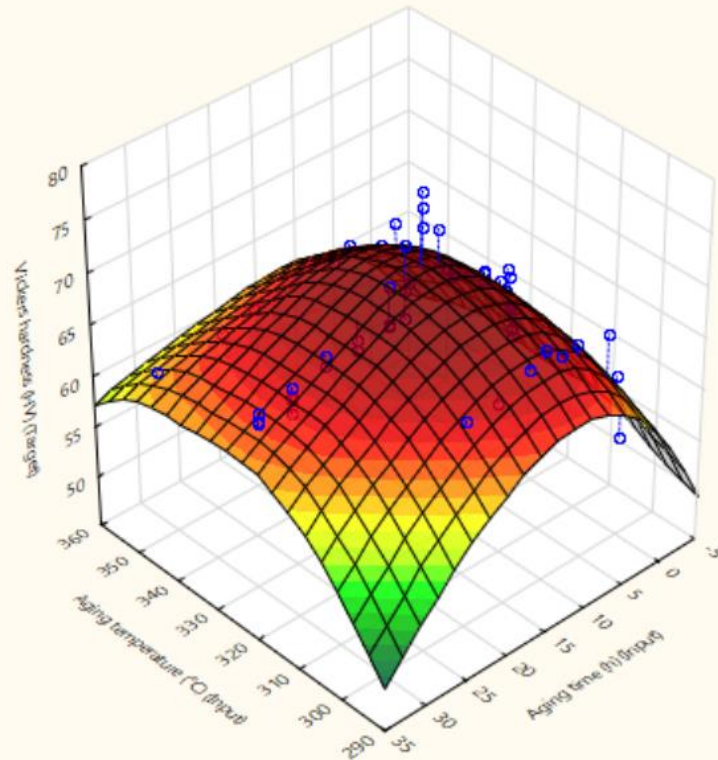
Correlation coefficients (Modified model 1 data.sta)			
	Vickers hardness (HV) Train	Vickers hardness (HV) Test	Vickers hardness (HV) Validation
1. MLP 4-10-1	0.982885	0.924841	0.964745

Predictions spreadsheet for Vickers hardness (HV). Samples: Train

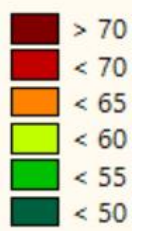
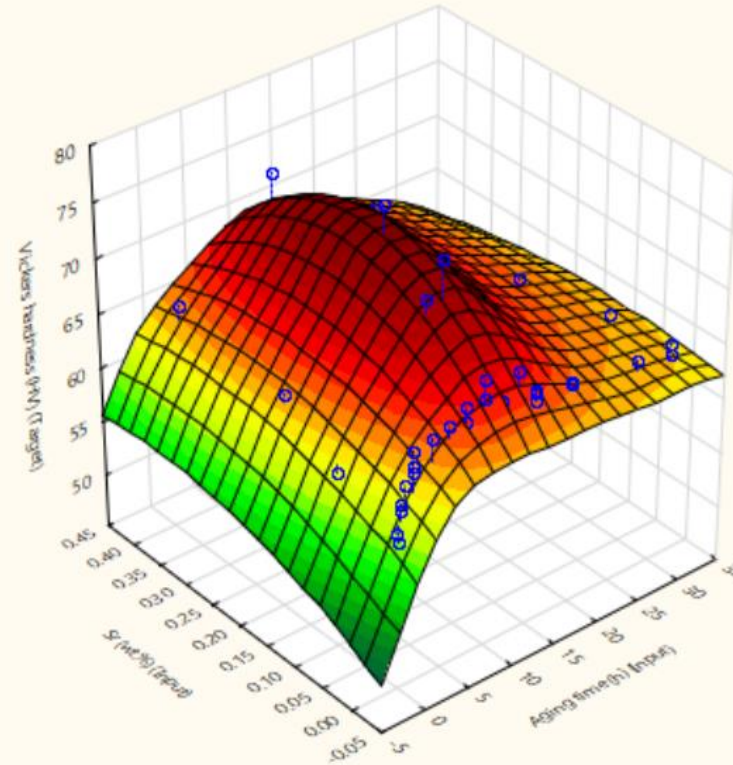
Case name	Vickers hardness (HV) Target	Vickers hardness (HV) MLP 4-10-1
1	54.88000	55.78811
2	61.13000	59.73797
4	65.87000	66.06029
5	66.45000	65.75631
6	66.16000	67.29236
7	67.57000	67.33666
8	66.60000	66.54250
9	65.08000	65.34395
10	65.19000	64.96376
12	58.39000	58.73364
13	61.72000	61.13845
14	63.12000	64.53694
19	69.23000	68.06539
20	65.80000	66.07979
21	65.91000	65.45175
23	62.70000	63.86503
24	64.40000	63.30877
26	57.37000	57.21291
28	64.01000	63.94468
.....		
74	73.70000	75.20271
76	69.80000	69.83777
78	66.40000	66.07333

➤ *2.7 Modeling of microhardness of heat treated Mg-Zn-RE-Zr-Ca-Sr alloys by using artificial neural network*

Aging temperature (°C) (Input), Aging time (h) (Input), Vickers hardness (HV) (Target)



Aging time (h) (Input), Sr (wt.%) (Input), Vickers hardness (HV) (Target)



 *Part 3*

**Solving a DOE Foundry Ph. D. student`s
problem with MATHCAD**

- This is a bidirectional research of porosity depending on the technological parameters. The porosity equations in both directions are derived with the statistical procedure depending on the technological factors.
- Due to the specificity of the data, the analysis of the models led to the conclusion that the maximum and the minimum are at the same values of the research parameters. The illustrations show the solution via MATHCAD and MADMML. The table shows the results from the solution of this problem.

3.1. Raw experimental data and coded data

№	Real value [X₁] T ° C	Code Value X₁	Real value [X₂] T ° C	Code Value X₂	Porosity z [%]	Porosity x [%]
1.	730	-1	150	-1	4.45	4.170
2.	730	-1	200	0	2.58	2.720
3.	730	-1	250	+1	2.11	1.960
4.	740	0	150	-1	2.34	2.420
5.	740	0	200	0	1.61	1.610
6.	740	0	250	+1	0.48	0.610
7.	750	+1	150	-1	1.68	1.770
8.	750	+1	200	0	0.51	0.500
9.	750	+1	250	+1	0.07	0.080

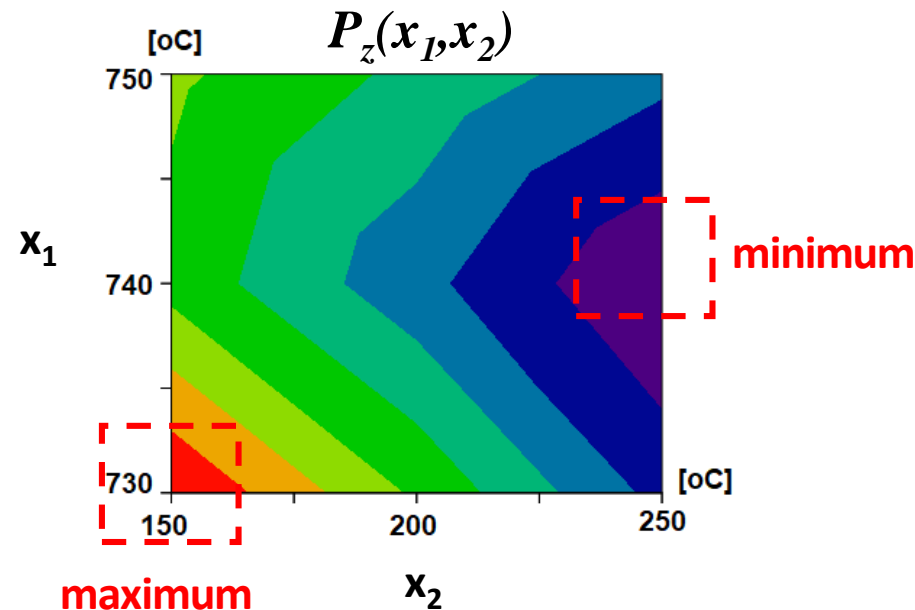
3.2. Regression model

◆ $P_z(x_1, x_2) = 1.284 - 1.147x_1 - 0.968x_2 + 0.183x_1 * x_2 + 0.423x_1^2 + 0.288 x_2^2$

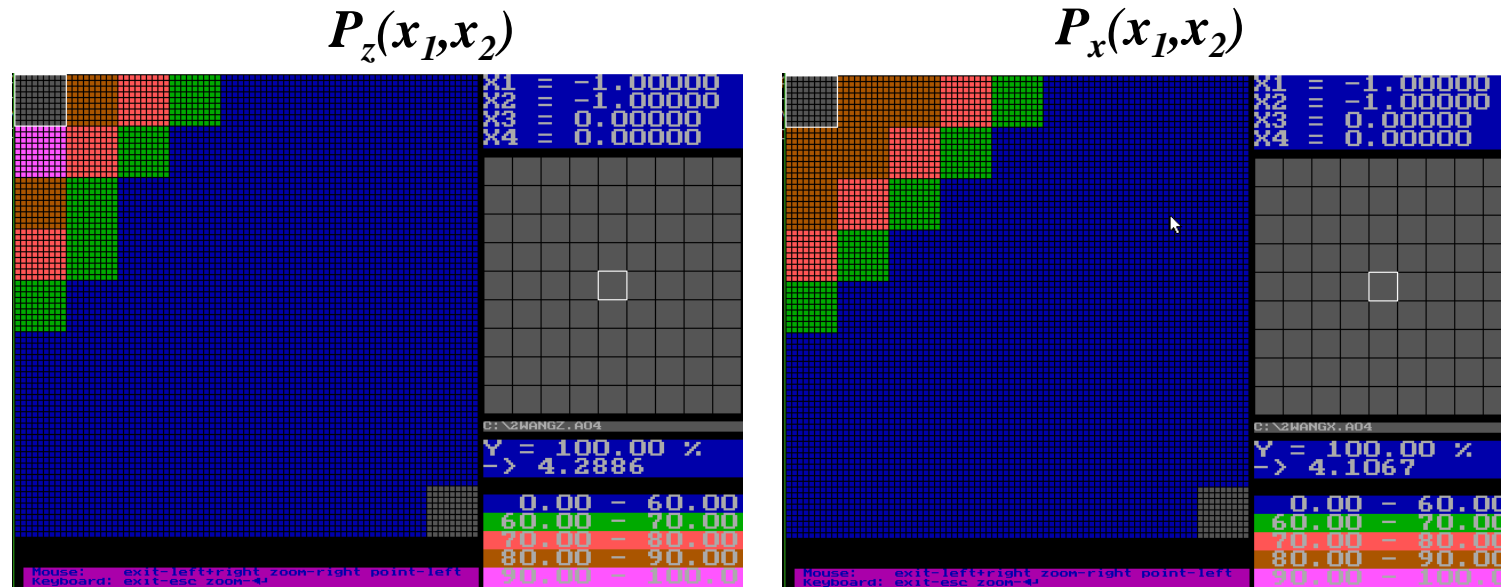
R=0.9903;
30.3397>9.0135
Ft(a=0.05,5,3)

◆ $P_x(x_1, x_2) = 1.397 - 1.083x_1 - 0.952x_2 + 0.32x_1 * x_2 + 0.13x_1^2 + 0.225x_2^2$

R=0.9957;
69.4142>9.0135
Ft(a=0.05,5,3)



3.3. Applications with the input and output parameters of the optimal solution



Properties	Porosity z, [%]		Porosity x, [%]	
	Simulation with Procast	MADMML	Simulation with Procast	MADMML
Maximum value [X ₁ =730°C; X ₂ = 150°C]	4.45	4.2886	4.17	4.1067
Minimum value [X ₁ =750°C; X ₂ = 250°C]	0.07	0.0586	0.08	0.0367

Part 4

**Resolving Mastering Problems with
High Accuracy Using and Regression
Analysis STATISTICA 12**

- The master students identified two sets of analysis data.
- The slideshows the visualization of the first problem. Product STATISTICA 12 , depending on the nature of the data and its accuracy, selects the scale /colors and their location/ for visualization.
- For the five research quantities from the two input parameters there have been derived also regression models that make possible interesting analyses based on MATHCAD.

4.1. Raw experimental data

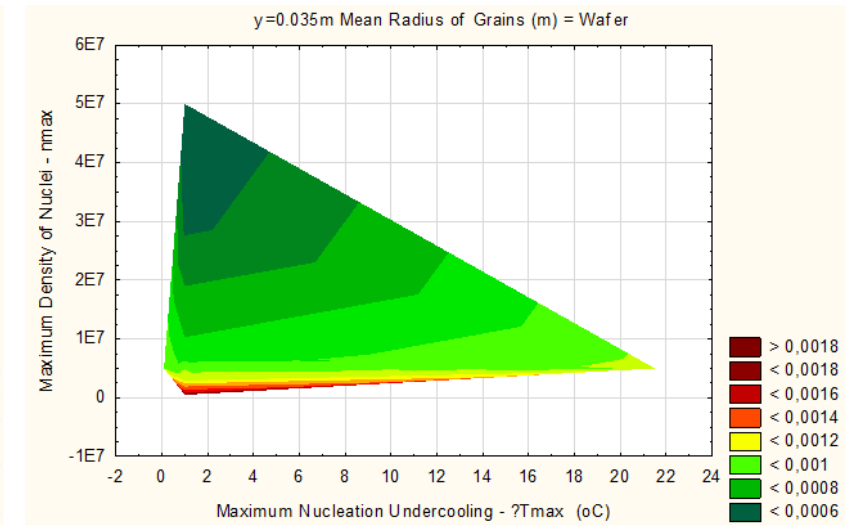
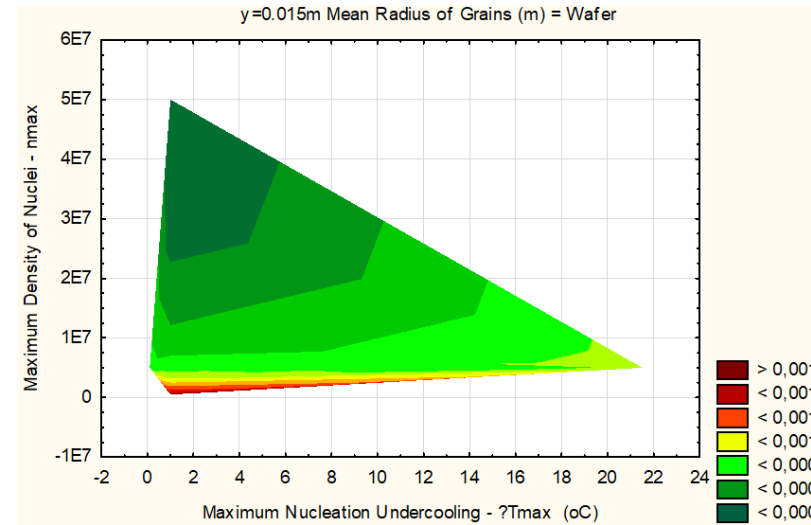
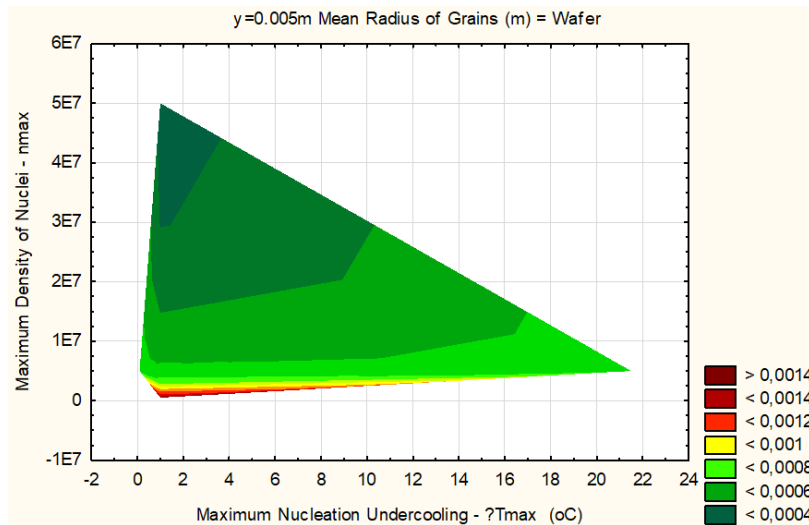
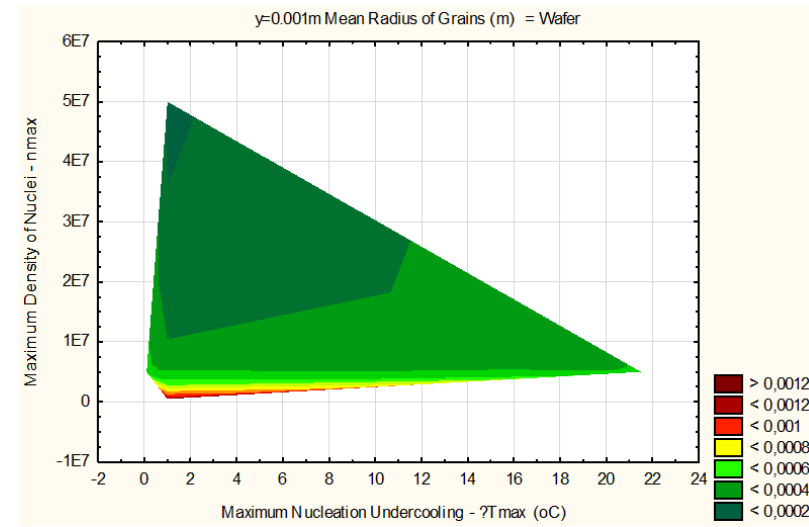
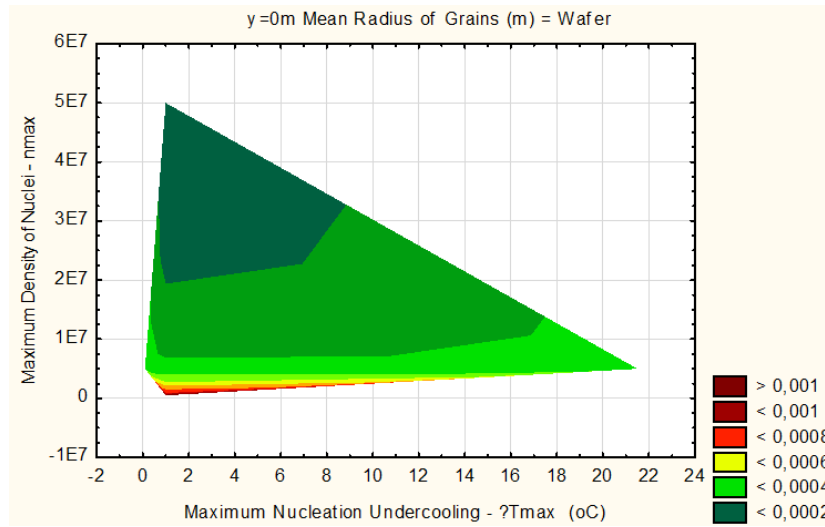
Table 1

No.	(X1) Maximum Density of Nuclei - n_{max}	(X2) Maximum Nucleation Undercooling - ΔT_{max} (°C)	(Y1) y=0m Mean Radius of Grains (m)	(Y2) y=0.001m Mean Radius of Grains (m)	(Y3) y=0.005m Mean Radius of Grains (m)	(Y4) y=0.015m Mean Radius of Grains (m)	(Y5) y=0.035m Mean Radius of Grains (m)
1	500000	1	0,00106	0,00132	0,00154	0,00166	0,00182
2	700000	1	0,00095085	0,0011	0,00139	0,00148	0,00177
3	900000	1	0,00079909	0,000982627	0,00125	0,00136	0,0015
4	3000000	1	0,000455128	0,000555854	0,000749822	0,00102	0,00109
5	5000000	1	0,000345495	0,000408482	0,000640868	0,000838531	0,000990826
.....							
21	5000000	19	0,000345354	0,000411532	0,000669229	0,000880566	0,000989495
22	5000000	21,5	0,000346578	0,000406245	0,00066771	0,000947542	0,00103

Table 2

No.	(X1) Casting Speed (m/s)	(X2) Pouring temperature (°C)	(X3) Bottom Cooling Intensity (W/m2/K)	(X4) Maximum Density of Nuclei	(X5) Maximum Nucleation Undercooling - ΔT_{max} (°C)	(Y1) Vertical Columnar Grain Zone Area (m2)
1	0.0001	1500	3000	5000000	1	0.0035464370
2	0.0003	1500	3000	5000000	1	0.0034965692
3	0.0005	1500	3000	5000000	1	0.0028353406
4	0.0008	1500	3000	5000000	1	0.0021426924
5	0.001	1500	3000	5000000	1	0.0020414520
.....						
35	0.001	1500	3000	5000000	17	0.0019891170
36	0.001	1500	3000	5000000	21.5	0.0020256631

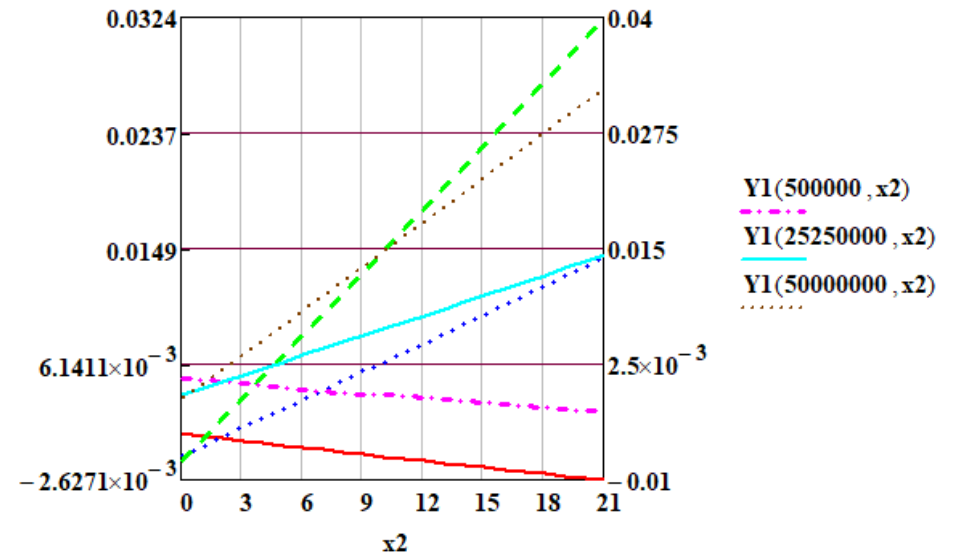
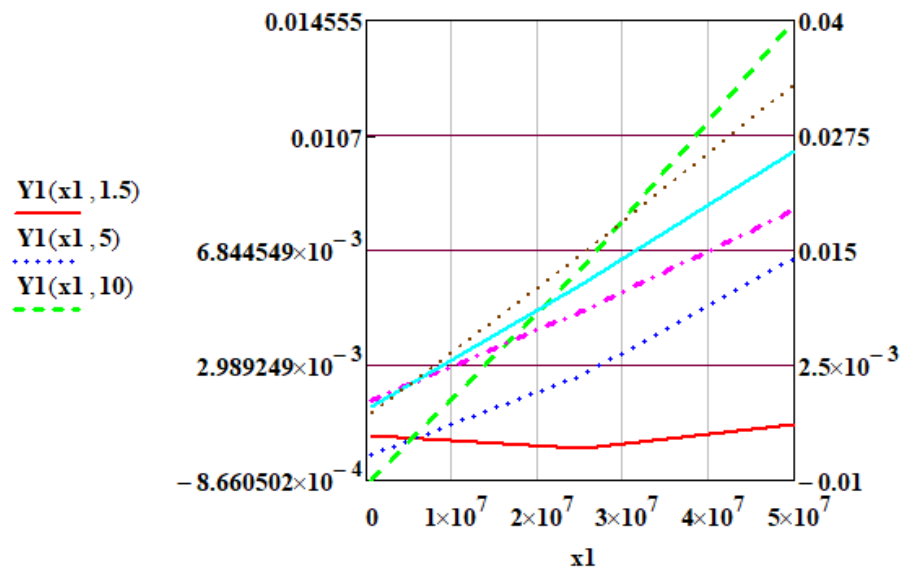
Data in Table 1—3D Wafer plots



Data in Table 1

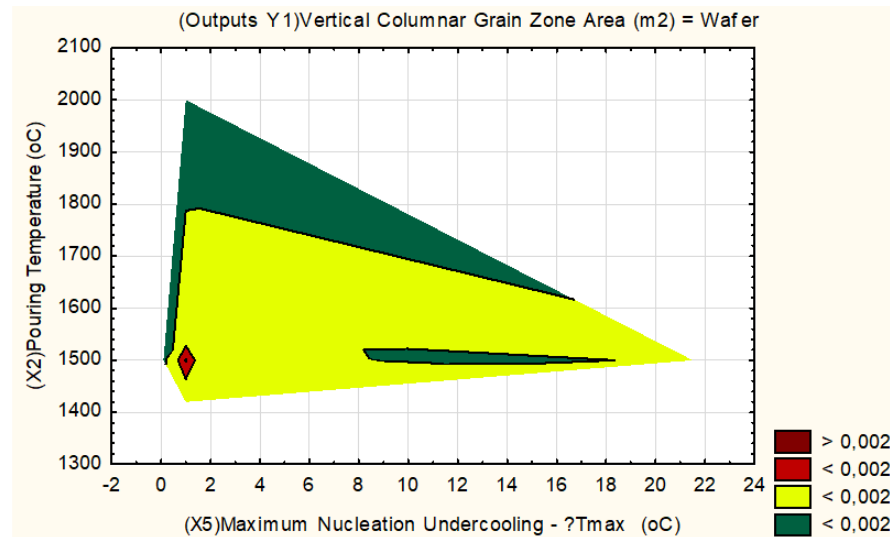
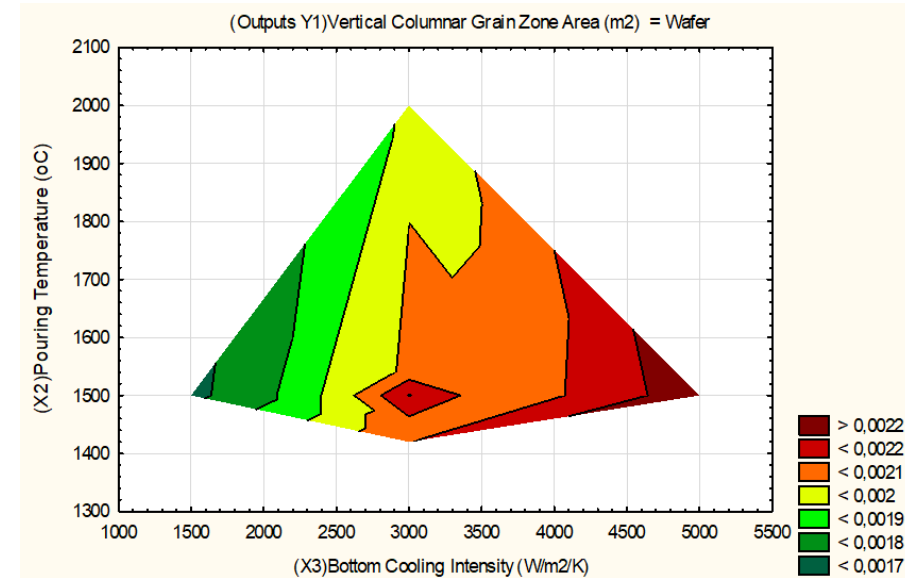
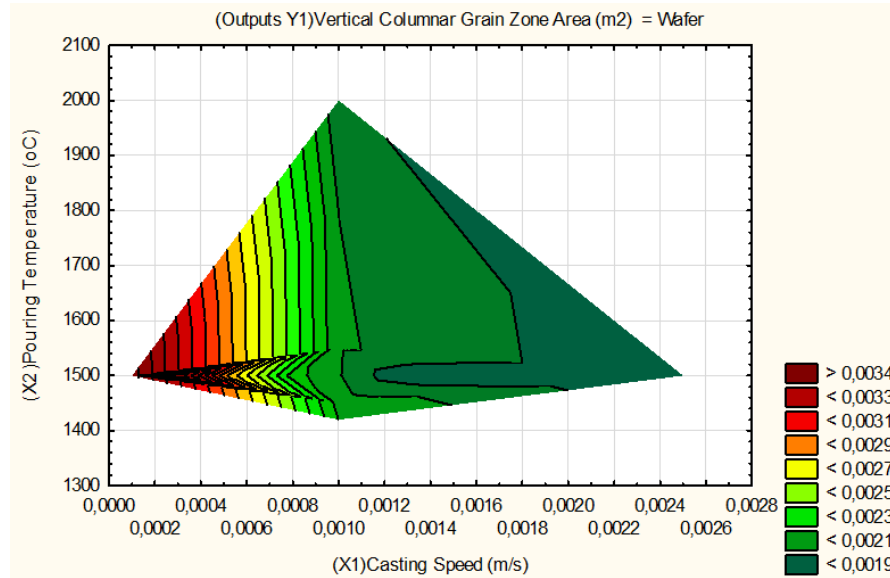
◆ $Y_1(x_1, x_2) = A_0 + A_1x_1 + A_2x_2 + A_3x_1 * x_2 + A_4x_1^2 + A_5x_2^2$

A1=9.517848E-04; A2=-9.511075E-11; A3=-2.036538E-04; A4=3.576597E-11;
 A5=9.701068E-19; A6=8.718598E-07



The second type of data has also been visualized with STATISTICA 12. Initially, they were visualized, and then a neural network was trained for them.

Data in Table 2—3D Wafer plots



Data in Table 2

Artificial neural network

Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
MLP 4-6-1	0.996886	0.814927	0.999900	0.0000	0.0000	0.0000	BFGS 93	SOS	Logistic	Logistic

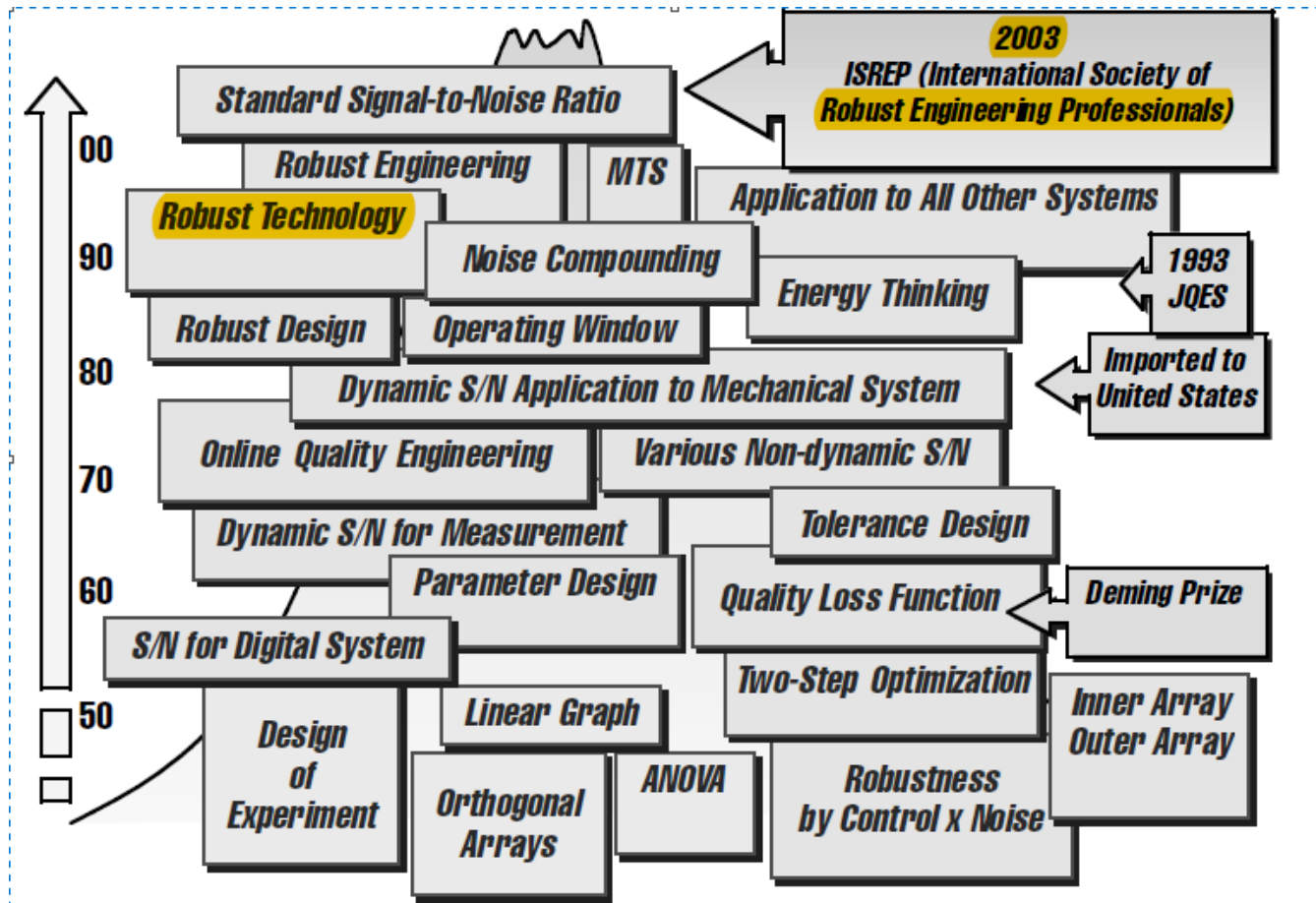
** * Part 5*
Taguchi method

The Taguchi method is an approach, which, if you wish, will be the basis for our future cooperation.

Fu Yu already knows a lot about this method.

Finally I will shortly summarize it.

Taguchi formulates the signal-to-noise ratios. For different cases, a different signal-to-noise ratio is used. When a defect is investigated, the smaller the signal-to-noise ratio, the better. We investigated the micro-hardness where we had to find that the bigger signal-to-noise ratio is the better solution.



The Taguchi method began to develop in the seventies of the previous century. Then, with the development of the original idea, different applications began to develop. In recent years, this has also been a matter of casting.

The Taguchi Design Approach

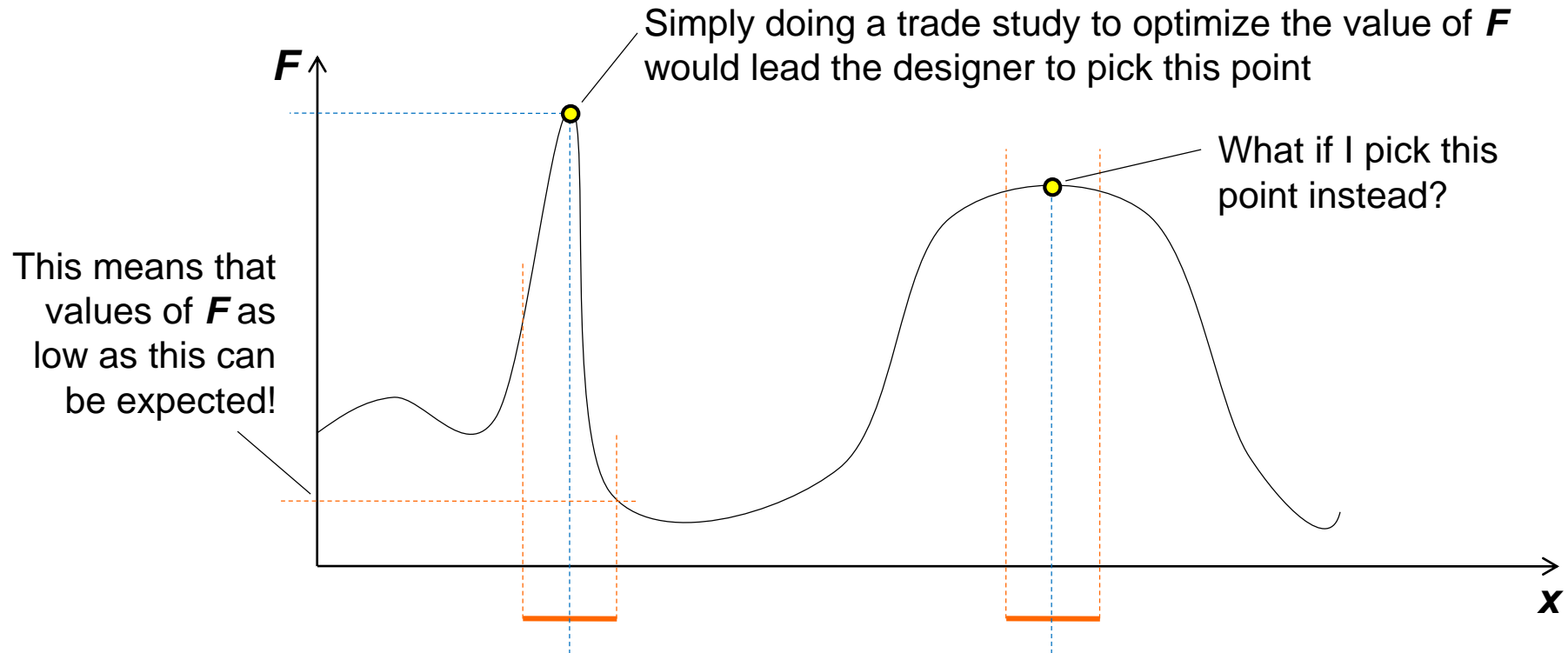
The Taguchi method defines two types of factors: control factors and noise factors. An *inner* design constructed over the control factors finds optimum settings. An *outer* design over the noise factors looks at how the response behaves for a wide range of noise conditions. The experiment is performed on all combinations of the inner and outer design runs. A performance statistic is calculated across the outer runs for each inner run. This becomes the response for a fit across the inner design runs. Table 13.1 lists the recommended performance statistics.

Table 13.1 Recommended Performance Statistics

Goal	S/N Ratio Formula
nominal is best	$\frac{S}{N} = 10 \log \left(\frac{\bar{Y}^2}{s^2} \right)$
larger-is-better (maximize)	$\frac{S}{N} = -10 \log \left(\frac{1}{n} \sum_i \frac{1}{Y_i^2} \right)$
smaller-is-better (minimize)	$\frac{S}{N} = -10 \log \left(\frac{1}{n} \sum_i Y_i^2 \right)$

Robust design: a design whose performance is insensitive to variations.

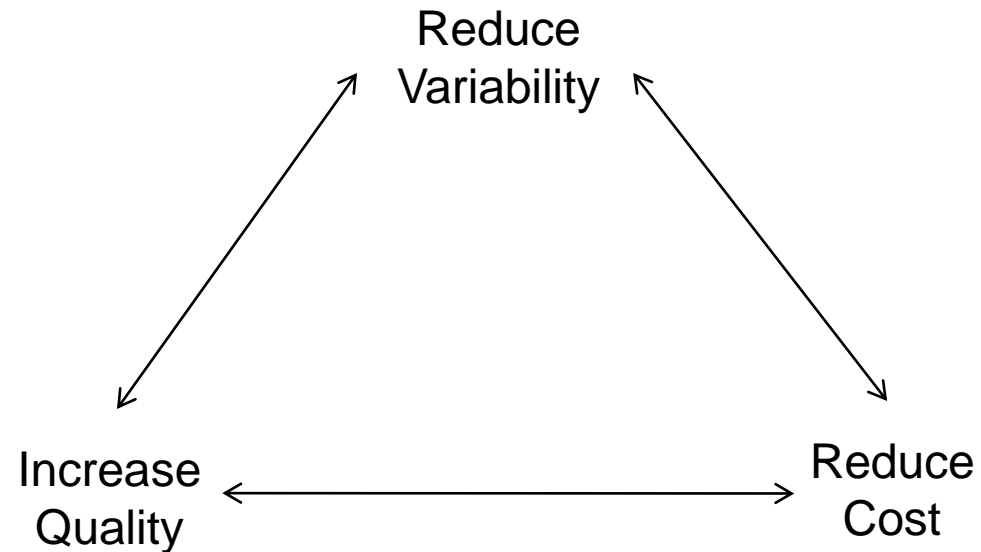
Example: We want to pick x to maximize F



The whole ideology is that this maximum is chosen, for which the qualitative parameter of the research is less sensitive to noise.

The Basic Idea Behind Robust Design

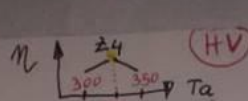
ROBUSTNESS \equiv QUALITY



- On the next slide I show the authentication of this solution from my notebook.
- This is a good educational example that, if you allow me, I will use to my students.
- The solutions from this example coincided with the MADMML **Solution.**



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$$\eta = -10 \log \left(\frac{1}{3} \sum_{i=1}^3 \frac{1}{Y_i} \right)$$

the bigger (larger) is better

	Ta	ta	z1 ca=1 sc=1	z2 ca=1 sc=1	z3 ca=1 sc=1	z4 ca=1 sc=1
1	300	4				
	-1	-0.75	62.7	-66.6	64.93	65.71
2	300	12				
	-1	-0.25	69.45	-60.17	70.85	71.44
3	300	32				
	-1	1	64.2	-65.8	63.78	63.89
4	325	4				
	0	-0.75	64.25	-64.12	65.9	67.75
5	325	12				
	0	-0.25	70.92	-57.64	71.8	73.76
6	325	32				
	0	1	65.71	-63.3	67.77	65.97
7	350	4				
	+1	-1	65.12	-67.11	61.37	64.25
8	350	12				
	+1	0	65.86	-59.26	67.27	69.86
9	350	32				
	+1	1	61.6	-66.31	60.19	62.7

- z1
- ① 36.294
- ② 36.493
- ③ 36.139
- z3
- ① 36.432
- ② 36.557
- ③ 35.947
- z4
- ① 36.494
- ② 36.754
- ③ 36.299

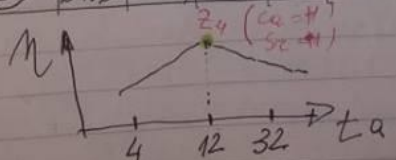
DATE



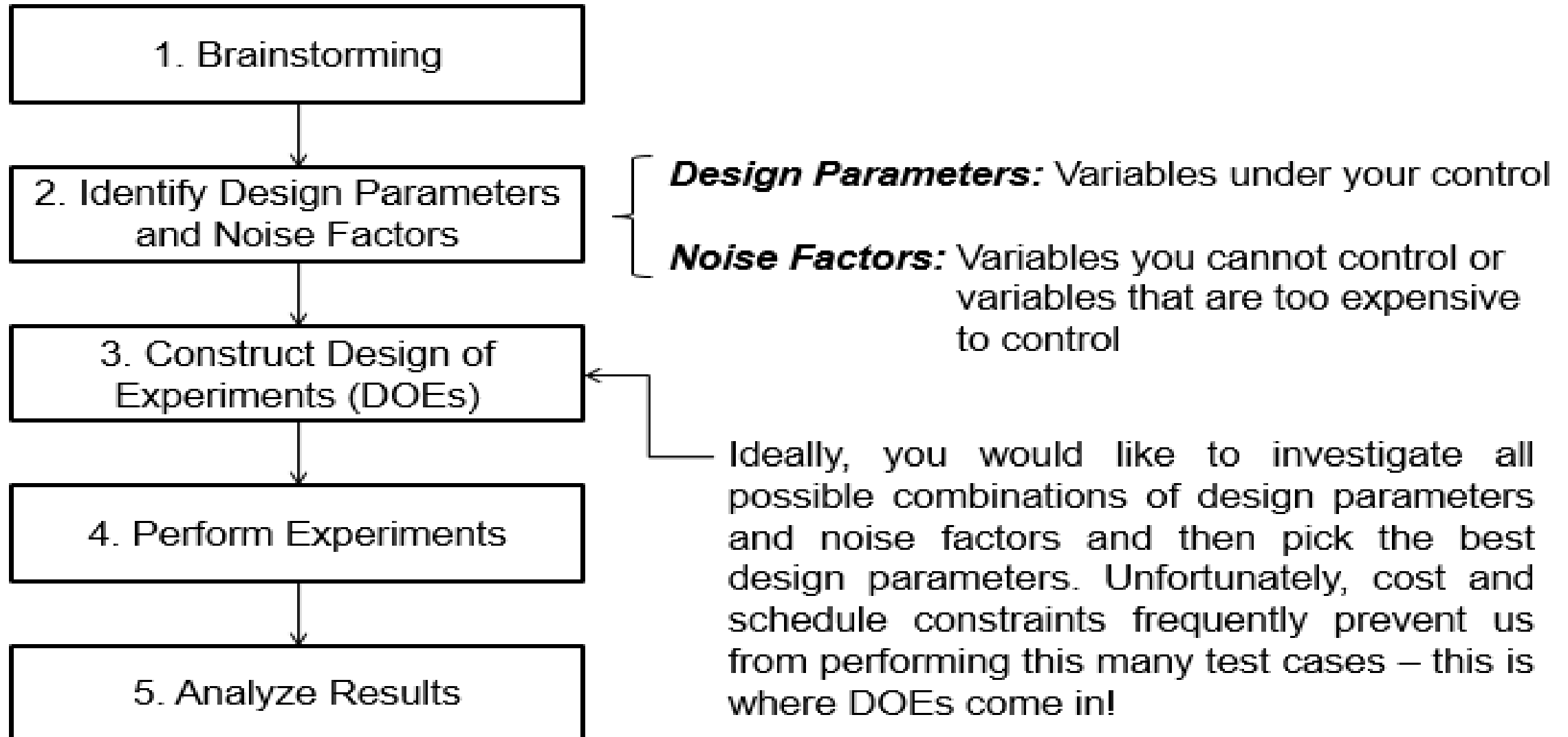
大连理工大学

	Ta	ta	z1 ca=1 sc=1	z2 ca=1 sc=1	z3 ca=1 sc=1	z4 ca=1 sc=1
1	300	4				
	-1	-0.75	62.7	-66.65	64.93	65.71
2	325	4				
	0	-0.75	64.25	-64.2	65.9	67.75
3	350	4				
	+1	-0.75	65.12	-67.11	61.37	64.25
4	300	12				
	-1	-0.25	69.45	-60.17	70.85	71.44
5	325	12				
	0	-0.25	70.92	-57.64	71.8	73.76
6	350	12				
	+1	-0.25	65.86	-59.26	67.27	69.86
7	300	32				
	-1	1	64.2	-65.8	63.78	63.89
8	325	32				
	0	1	65.71	-63.3	67.77	65.97
9	350	32				
	+1	1	61.6	-66.31	60.19	62.7

- z1
- ① 36.124
- ② 36.732
- ③ 36.092
- z3
- ① 36.119
- ② 36.888
- ③ 35.961
- z4
- ① 36.37
- ② 37.095
- ③ 36.126



Overview of Taguchi Parameter Design Method



- The part, which will be presented to you, is based entirely on publications related to foundry processes. Quality methods are related to statistical, modeling and optimization issues. In the exposition, before quoting the text from the publication, I list the title and the authors.
- Different quality indicators that can be quantified are modeled. It is also possible to analyze qualitative assessments on three-dimensional (3D) or five-dimensional (5D) scales. In quality management, only the planning of the regression analysis experiment and the Taguchi method can lead to improvement of processes and reduction of defects. The other methods related to the industrial 6 sigma method are methods for defect analysis.



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Optimization of Die casting process based on Taguchi approach

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Problem Definition and Brainstorming

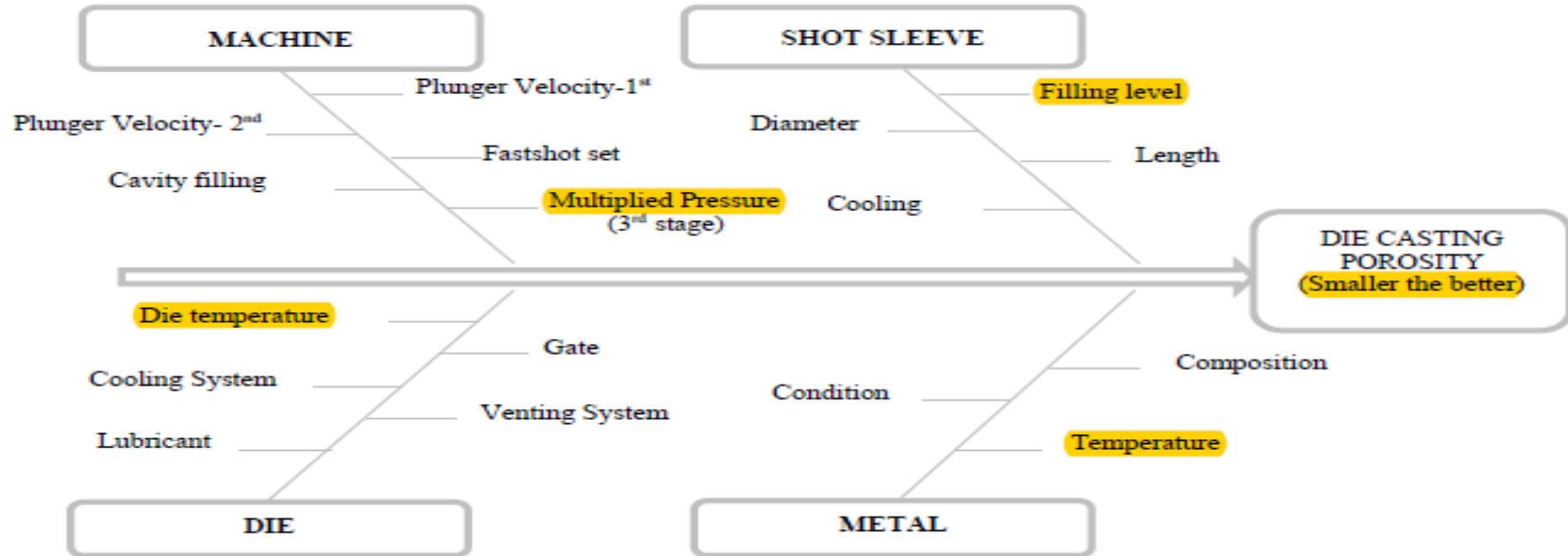


Fig. 1 Cause and effect diagram

Table 1 Process parameters with their ranges and values at three levels

Parameter destination	Process parameters	Range	Level 1	Level 2	Level 3
A	Pouring temperature(^o C)	650 - 750	650	700	750
B	Filling time (ms)	40 - 130	40	85	130
C	Die temperature(^o C)	180 - 260	180	220	260
D	Injection pressure(bar)	120 - 240	120	180	240

Run an Experiment and Summarize the Experimental Results

Table2 L₉ orthogonal array

Exp. No	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

A three level OA with 9 experimental runs has been selected for the present investigation. The assignment of casting process parameters (A to D) to columns is given in Table 2.

Table3 Casting porosity values and S/N ratios against trial numbers

Trial no	Repetition 1	Repetition 2	Repetition 3	Average	S/N ratio
1	0.538	0.502	0.466	0.5018	5.9748
2	0.466	0.573	0.538	0.5257	5.5542
3	0.323	0.358	0.394	0.3584	8.8832
4	0.394	0.358	0.394	0.3823	8.3430
5	0.538	0.502	0.430	0.4898	6.1628
6	0.430	0.430	0.394	0.4182	7.5661
7	0.394	0.358	0.430	0.3943	8.0604
8	0.251	0.215	0.287	0.2509	11.9514
9	0.394	0.358	0.323	0.3584	8.8832

Analysis of the Results

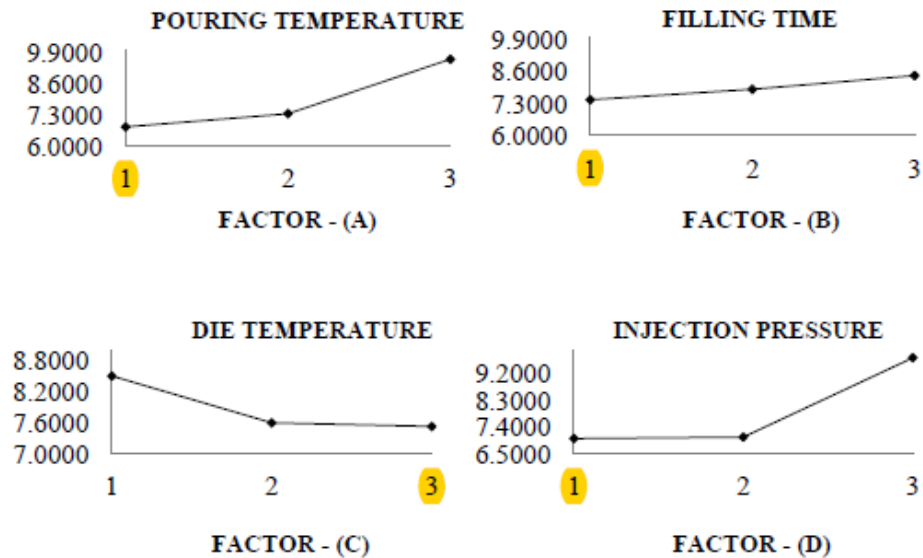


Fig.3 Average values of the S/N ratios for Al-Si8Cu3Fe aluminium alloy castings under the parameter values given in Table 1

Table 5 Average values of S/N ratios at the different levels(1-3) and their main effects

actor	Level 1	Level 2	Level 3
A	6.8041	7.3573	9.6317
B	7.4594	7.8895	8.4442
C	8.4974	7.5935	7.5233
D	7.0069	7.0602	9.7259

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Optimization of Process Parameters of Pressure Die Casting using Taguchi Methodology

Satish Kumar, Arun Kumar Gupta, Pankaj Chandna

Keywords—Aluminium Casting, Pressure Die Casting, Taguchi
Methodology, Design of Experiments

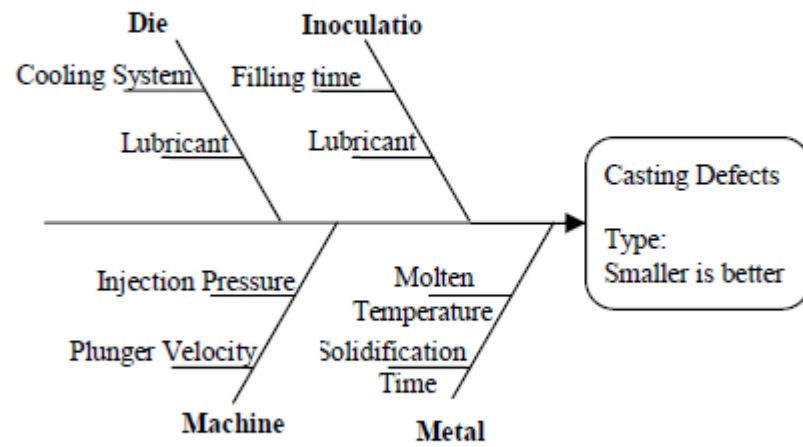


Fig. Cause effect diagram

L18 EXPERIMENTAL COMBINATIONS

S. No	Solidification Time	Molten Temperature	Pressure	Filling time	Velocity
1	3	570	300	0.50	100
2	3	570	320	0.75	110
3	3	570	340	1.00	120
4	3	595	300	0.50	110
5	3	595	320	0.75	120
6	3	595	340	1.00	100
7	3	620	300	0.75	100
8	3	620	320	1.00	110
9	3	620	340	0.50	120
10	6	570	300	1.00	120
11	6	570	320	0.50	100
12	6	570	340	0.75	110
13	6	595	300	0.75	120
14	6	595	320	1.00	100
15	6	595	340	0.50	110
16	6	620	300	1.00	110
17	6	620	320	0.50	120
18	6	620	340	0.75	100



Modelling in Squeeze Casting Process-Present State and Future Perspectives

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Abstract

The growing demand in today's competitive manufacturing environment has encouraged the researchers to develop and apply modelling tools. The development and application of modelling tools help the casting industries to considerably increase productivity and casting quality. Till date there is no universal standard available to model and optimize any of the manufacturing processes. However the present work discusses the advantages and limitations of some conventional and non-conventional modelling tools applied for various casting processes. In addition the research effort made by various authors till date in modelling and optimization of the squeeze casting process has been reported. Furthermore the necessary steps for prediction and optimization are high lightened by identifying the trends in the literature. Ultimately this research paper explores the scope for future research in online control of the process by automatically adjusting the squeeze cast process parameters through reverse prediction by utilizing the soft computing tools namely, Neural Network, Genetic Algorithms, Fuzzy-logic Controllers and their different combinations. The present work also proposed a detailed methodology, starting from the selection of process variables till the best process variable combinations for extreme values of the outputs responsible for better product quality using experimental, prediction and optimization methodology.

The explored material, the process parameters and the qualitative indicators that are controlled are specified. In the highlighted surveys the qualitative indicators are more than one. In these cases, a multicriteria procedure is sought.

The approach I have developed gives such an opportunity.

Ref.	Material	Process variables	Response	Remarks
[61]	LM24	S_p , D_T and D_p	BHN and UTS	Optimizing P_T and die lubricant can significantly improve the casting quality
[62]	LM24	S_p , D_T and D_p	BHN and UTS	GA successfully searched the process parameters that can yield maximum possible UTS and BHN of cast components
[63]	AC2A	S_p , D_T , P_T , D_p and D_M	BHN and UTS	S_p , D_T and D_p are observed as the most significant parameters contributing towards the responses
[64]	AZ80	S_p , D_T and D_p	HV, % elongation and UTS	The heuristic MM approach has been utilized to find the optimized process parameters for highest possible properties.
[65]	2017A	S_p , D_T and P_T	HV and UTS	S_p and P_T showed significant contribution towards HV and UTS of cast components
[66]	AC2A	S_p , D_T , P_T , D_p and D_M	YS	GA finds the best optimum process parameter setting using the response equation derived through taguchi method
[67]	LM6	S_p , D_T and D_M	SR	Higher surface finish can be achieved with varying P_T , D_T and S_p
[68]	LM6	S_p , D_T and D_M	SR	S_p and D_T are the critically parameters responsible for enhanced squeeze casting surface finish
[69]	AISI9Cu3	P_T , S_p , F_v and D_T	% elongation, HBS and UTS	S_p , F_v , D_T and P_T are listed in ascending order based on significant importance towards the responses
[70]	AC2A	S_p , D_T , P_T , D_p and D_M	Wear resistance	GA shown slight improvement in the wear resistance property as compared to taguchi and XL solver methods
[71]	LM20	S_p , D_T and P_T	Density and SR	The application of grey relational analysis finds the single optimal casting condition for both the responses.

Table 1: Statistical taguchi method applications in squeeze casting process.

Further, in the referred paper the capabilities of different computational methods are determined.

My approach is a way like all of those that are quoted. It is a decision support system. The system defines those conditions / technology parameters / for which the quality indicator will have the most preferred value.

It may be minimal when it concerns a metal defect defect or maximum when it is for a firming property.

- How wide the field of application of the method I propose in the casting practice I will present with a review of the survey.
- In this research, besides that it is a real experiment, it is also shown that very often simulations are analyzed that are obtained by different software. For example, this is the research

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Review of Optimization Aspects for Casting Processes

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G.P.Syrcos (2001) optimized the Die casting process using Taguchi methods. He tried to achieve optimal setting of the die **casing process** performing **Design of Experiments (DOE)** and using Taguchi technique. Piston velocity, metal temperature and filling time were the factors chosen to be varied in the process. The results concluded that the selected parameters affect the density of the material effectively and hence the porosity defect can be gradually reduced. ^[4]

Mekonnen Liben Nekere and Ajit Pal Singh (2005) conducted a study on various optimization techniques used for Aluminium Blank Sand Casting Process. During their study they came across Design of Experiments (DOE) Taguchi's technique which helped them to find out major contributing factors in the die casting process. They carried out experimental runs on two batches of blanks of aluminium casting which indicated the major factors responsible such as grain size, clay content, moisture content, ramming, sprue size, riser size, and diameter to thickness (D/t) ratio of the blank. An orthogonal array was constructed for the seven factors identified, and performed eighteen sets of experiments to generate the required data. A statistical analysis of variance (ANOVA) was also performed to see which process parameters are statistically significant. They verified the readings by performing a verification experiment in which the new data proved to be promising and hence the sand casting process was enhanced by Taguchi robust design method.^[5]

Zhizhong Sun, Henry Hu and Xiang Chen (2008) studied the numerical methods used to optimize the parameters of a gating system for a magnesium alloy casting. They used **Taguchi** technique of Design of Experiments (DOE) to find out the effect of various parameters such as height and width of ingate and dimensions of the runner which are major process parameters which influence magnesium alloy casting. The mould filling and metal solidification process was simulated on commercial Computer Aided Engineering (CAE) package MAGMAsoft. The optimized process parameters resulted in improved filling velocity, reduced porosity and increased product yield of castings made from magnesium alloy. ^[10]

Uday A. Dabade and Rahul C. Bhedasgaonkar (2013) analysed the various defects in the process of metal casting process and optimized the performance of the system using Design of Experiments (DOE). The entire process of metal casting was simulated virtually using a commercial Computer Aided Engineering (CAE) package MAGMASoft. The virtual simulation helped to narrow down on defects such as hot tears and shrinkage porosity. The Design of Experiments (DOE) model was used to improve the feeding system design and gating locations which helped them to achieve a reduction in shrinkage porosity by 15% and improved yield strength by 5%.^[19]

Finally in my lecture, I want to say that during my stay I was able to pass on my experience and my knowledge to a colleague who can solve such problems by herself. I also provided all the software I had. I am extremely satisfied with my work with her.

I consider this to be the most important during my stay.

Other problem which we decide

1. The approaches to plan the experiments/simulations, e.g. Taguchi method.....
2. Casting simulation, for example, MAGMA software.
3. The materials selection. Method`s Asby.
4. Multi-criteria optimization, for example, front Pareto
5. Activities and examples with MathCAD and statistica software.

Thank you for attention!