向更美好而变-

– Change for the better

变化的时刻 -

- Time to improve

Preliminary investigations of Prof. Prof. Nikolay TONTCHEV, D Sc., on a project:

Design, Preparation and Property Prediction of Magnesium Alloys

2018

Introduction

Statistical processing of experimental data and experiment planning as a method of optimization and research of technological processes are a powerful means of achieving the required results in the hands of the researcher.

When carrying out experimental work, there is always a scatter in the obtained results. On this occasion they say that the results of measurements are a random variable. The appearance of such random results is associated either with the random nature of the phenomenon itself, or with various random effects that can not be controlled. Mathematical statistics studies methods for processing the results of observations (measurements) of mass random phenomena that have statistical robustness, regularity, in order to reveal this pattern.

The development of a new technological process and its implementation, the creation of new modes/materials are usually preceded by the study of available theoretical and experimental data, the verification, the development of the project (new technologies, etc.) and optimization of the process conditions. Until now, a significant part of the research has traditionally been conducted according to the research scheme for the influence of individual factors.

It should be noted that modern technological processes are complex, multidimensional and they are a subject to various interference effects. Stabilization of the conditions for conducting experiments in them is often an impossible problem, and therefore the traditional scheme of research under such conditions becomes ineffective. In addition, the aggregate effect of individual factors (variables) is not always equal to their simple sum due to the phenomenon of interaction between factors.

As a rule, technological research is associated with significant energy and material costs, so they are laborious, therefore one of the most important tasks of the researcher is to achieve the desired result in an optimal way.

Design of experiments allows the researcher to choose from the types of plans or programs for their construction, the methods of processing experimental data for the various practical problems that are most acceptable.

The most common experiment is to solve the following two main problems.

The first problem is called extreme. It consists in finding the process conditions ensuring the optimal value of the selected parameter.

A feature of extremal problems is the requirement to search for an extremum of a certain function. Experiments that are put to solve optimization problems are called extreme.

The second problem is called interpolation. It consists in constructing an interpolation formula for predicting the values of the parameter being explored, depending on a number of factors.

To solve an extremal or interpolation problem, it is necessary to have a mathematical model of the explored object. In most cases, such models can be obtained using regression analysis.

Classical regression analysis is based on processing the results of passive experiments. In this case, as applied to engineering and technical problems, the researcher formulates the experiments in an arbitrary way, choosing experimental points, based, for example, on intuition or his own experience.

But, as a rule, the essence of the tactics of the researcher is to search through various conditions for the experiment. When solving such problems, it is necessary to deal with a very large number of independent variables. In this case, the method becomes extremely cumbersome, especially the difficulties with computational operations. But here it should be noted that the widespread use of personal computers and standard software products for mathematical calculations virtually eliminate the previous difficulties with computing operations.

When regression analysis is used to process the results of a passive experiment, the following circumstances should be taken into account:

• In the case of a passive multivariate experiment, it is difficult to estimate the error of the experiment and, consequently, it is impossible to strictly check the adequacy hypothesis of the chosen mathematical model from the results of the experiment;

• It is impossible to construct a criterion for discarding experiments containing gross errors;

• Independent variables are often pairwise correlated, so the corresponding effects can not be separated;

• It is not possible to separately evaluate regression coefficients with, for example, the / - criterion, even when the independent variables are weakly correlated.

Estimating the results of regression analysis, we can only talk about the existence of a statistical relationship between the variables, but one can not say anything about the nature of this relationship. It makes no sense to attach any importance to individual regression coefficients.

If we approach the regression equations as some interpolation formulas, the above disadvantages will.can be neglected.

If we need a mathematical model of an object in order to use it later to manage this object, the uncertainty in the results of the research, connected with the shortcomings of the obtained regression models, becomes decisive.

Researchers working in the field of statistical processing of experimental data consider that the results of a passive experiment occurring in a strong noise field do not contain information on the mathematical model of the process.

But in a number of cases, statistical processing of the results of passive experiments can be very useful. For example, when evaluating the quality of a product in a particular process unit or in different shops, it may be useful to construct histograms and determine at least two parameters of the distribution function, the mean and variance.

A comparative statistical analysis of these parameters allows us to compare the results obtained under different conditions and establish pair correlation relations. The results of passive observations in some cases can be used for monitoring and even forecasting.

Thus, the information obtained through passive observation can be very important for the current monitoring of certain processes (or objects), but it is completely inadequate for constructing mathematical models with which to manage the process (or the object).

Since the calculation of the regression coefficients for statistical processing of the experimental data of passive and active experiments is carried out using the same expressions, practical examples will be given mainly for active experiments carried out according to special plans.

New opportunities were opened after the experimental points began to be selected according to a special plan. Planning an experiment is a new approach to research, in which mathematical methods play an active role. There is an opportunity to actively influence the research process, to plan the experiments in such a way as to obtain maximum information at minimal cost. Such experiments are usually called active.

I. Research Capabilities Based on Proprietary Software

At present, there are a number of clearly formulated criteria for optimal planning for different situations, and algorithms have been developed for them, using which the researcher can locate experimental points in the factor space and process the results of observations. The main idea of this method is the possibility of optimal control of the experiment with incomplete knowledge.

On the basis of regression analysis, a mathematical model of the objective system is obtained, which is called the regression equation. Regression analysis methods allow choosing the most appropriate ones from several different kinds of models. Regression analysis is reduced to the determination based on the experimental data of the model coefficients (regression coefficients), the evaluation of the significance of these coefficients and the degree of adequacy of the model.

The model of the object is obtained using the results of experiments. In the research of a multifactorial process, the formulation of all possible experiments to obtain a mathematical model is associated with the enormous laboriousness of the experiment, since the number of all possible experiments is very large. Experimental planning is to establish the minimum number of experiments required.

The results of the experiment are used to obtain a mathematical model of the explored process. A mathematical model is a system of mathematical relations describing the explored process or phenomenon.

It has been proven that the support for decision-making is also an important activity in the design process. The timeliness of this activity is determined on the basis of the benefits achieved, as in any other optimization process. Unlike classical optimization, technical decision making takes place under more than one criteria, with a different number of control parameters. For this reason, our team has built several software applications to support the process of this application from engineering practice. Our development activity has been running for more than fifteen years. For this period of time, applied tasks in the field of casting, thermal and chemical-thermal processing and the restoration of worn surfaces by welding and coating are solved.

The software is extremely useful in exploring a set of quality indicators, as in the material science is the complex of properties after applied processing. Processing parameters are process input control parameters, and quality indicators are output controlled reactions. Multicriteria optimization defines these process modes of the research process, for which the user has explicitly defined certain preferences of the quality indicators.

The algorithm that is being offered is not complicated. It is related to multicriterial support for making technical decisions. The algorithm analyzes and optimizes parameters after an engineering experiment. Since actual experimental data is used, if the models obtained prove the necessary checks, it means that the models are adequate and the forecasts obtained are reliable and can be used in engineering practice. The analysis that is applied is user-friendly. This analysis is valuable because it provides solutions for multifactor processes. Various alternatives can be evaluated. So far, software has been developed for two, three and four control parameters in the study of various selected technical quality parameters. In the future, under the proposed algorithm, there is an idea to develop further with control parameters for which the total number is up to ten parameters describing the technological regime.

The number of previously developed four parameter controls can be considered as optimal. For tasks with more established influences, they can be transformed and solved in steps / parts.

The suggested analysis is valuable at the following two points:

1) Specialized software can process simulation test results and thus be used as a hybrid method in CAD / CAE systems in designing process processes.

2) It can be determined from the many determined solutions that it is acceptable in terms of economy of spent energy or raw material during the

experiment. This realized energy or raw material savings is applied after an acceptable solution has been obtained from the set quality parameters.

Indeed, how is this approach applied to energy and materials savings. Among the many technologies investigated with the software, a chemico-thermal process was developed to enhance the working properties of heat-resistant steels. Several solutions with a desired set of properties have been identified to solve the task. This is characteristic of any multi-criterion task. Each particular solution corresponds to different modes that vary considerably over the duration of the process or the pressure of the gas used. Thus, among these solutions, a mode with a shorter chemico-thermal treatment time is chosen which is more energy efficient and less gas consuming. Thus, on the one hand, a compromise solution is established that satisfies all the quality indicators and, on the other hand, provides less energy or material consumption.

The optimization of the complex of properties is accomplished through the multicriteria optimization module, which produces an effective solution. Any effective solution, by its very nature, can also be innovative. Effective solutions are Pareto's solutions. These solutions are not improving optimal solutions. Strategies for determining effective solutions can be varied: average, geometric, and so on. Our approach uses the strategy of the pessimistic option. This strategy maximizes solutions in a matrix containing the smallest value of the criteria analyzed.

In the modeling area, when the regression model is displayed, it is necessary to specify the connections between the control and the managed parameters as input data. They can be pre-planned or consecutively executed, unassigned in the so-called passive experiment. For a larger number of data processing observations, a different pattern structure can be applied. Each structure is evaluated with two estimates. 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 approach is applicable to all processes with multiple adjustable parameters that vary in range. The variable range is scaled to nine steps in which all controlled control parameters are changed. In combinations 9^4, if the parameters are four, the process under consideration fully analyzes 6541 combinations of control modes. For defined technical multi-criteria tasks this proposed accuracy is fully satisfactory.

The purpose of this section is to present the capabilities of the approach for analysis and multi-criteria optimization of quality indicators, changing from several identical **(**same**)** parameters operating in a certain interval.

The approach I present to you is appropriate for the design phase of various new, unsettled processes.

Their technological parameters change in a certain range.

Through the approach one or more sets of technological parameters can be determined to be experimentally tested when specifying the technology of the test item.

The desired complex of properties depends on certain combinations of the technological parameters.

The idea is that this complex is optimal.

Since there are several properties, the optimization procedure is a multi-criteria one.

From the set/expected values of the criteria/properties, a procedure is performed which determines the combinations of technological parameters that can realize it.

After the numerical experiment, it is determined whether the property values can be improved or reached.

Sometimes different combinations have different energy-intensive content.

This opportunity, like checking software, is very valuable in terms of energy saving.

In this way the approach can be attributed to innovative instruments.

The approach is characterized by the user friendly attitude of making the optimal decision.

The solution takes into account which optimal complex of properties to what combination of parameters corresponds.

This combination of parameters is recorded in the technological documentation and it is executed during the technological mode.

The user friendly approach is very valuable because with respect to all properties, the analyzes and the comparisons are carried out in the same dimensionless proportions (percents).

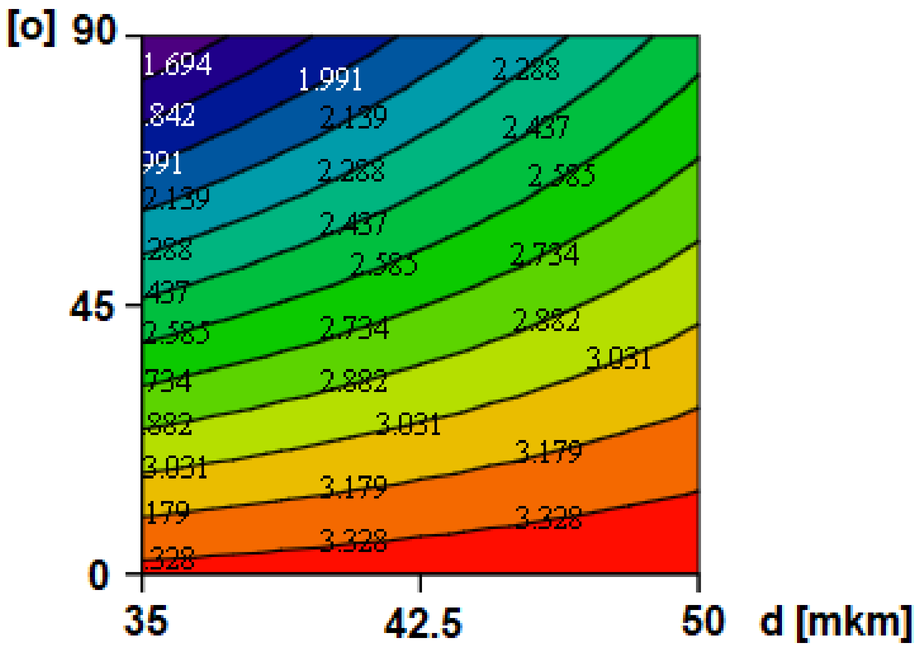
Five variable percentage ranges are available that can be expanded or narrowed, depending on the decision maker's wishes.

Through this movement to the 'top' – the 100%, the boundaries of the variables are fixed up in several iterations, thus reaching the optimal solutions.

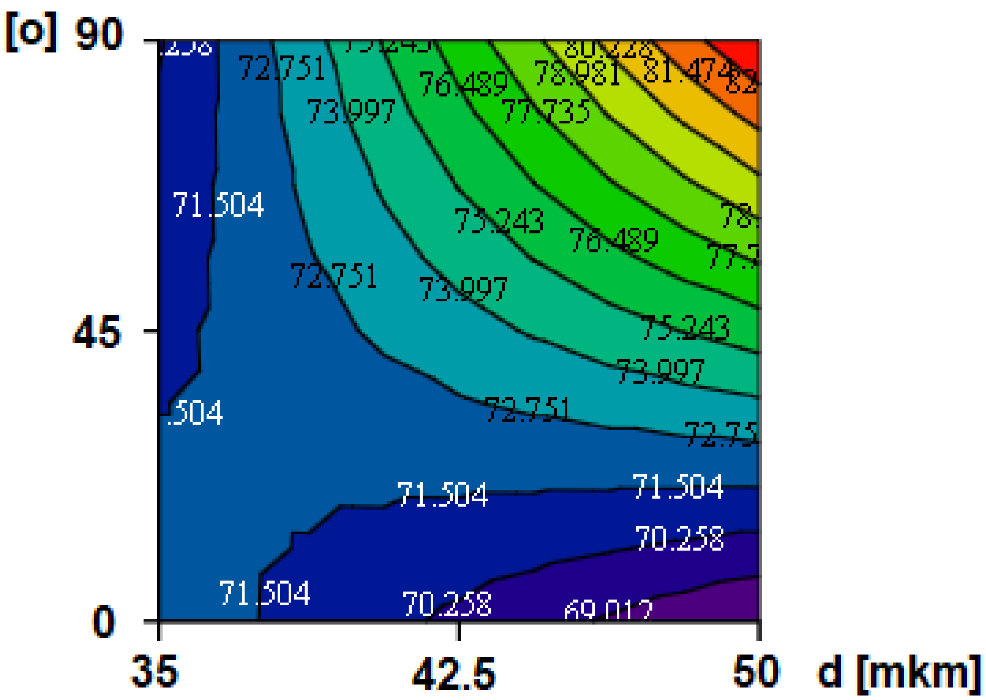
An example of how the approach works in the 2D/two-dimensional case is illustrated by the following figures.

For comparison, conventional graphical images are also shown, from which it is also possible to trace the veracity of the solution.

$$\mathbf{Grapavost}_{i,j} := 2.72833 + 0.26833 \cdot x1_i + 0.2175 \cdot x1_i \cdot x2_j - 0.6975 \cdot x2_j$$

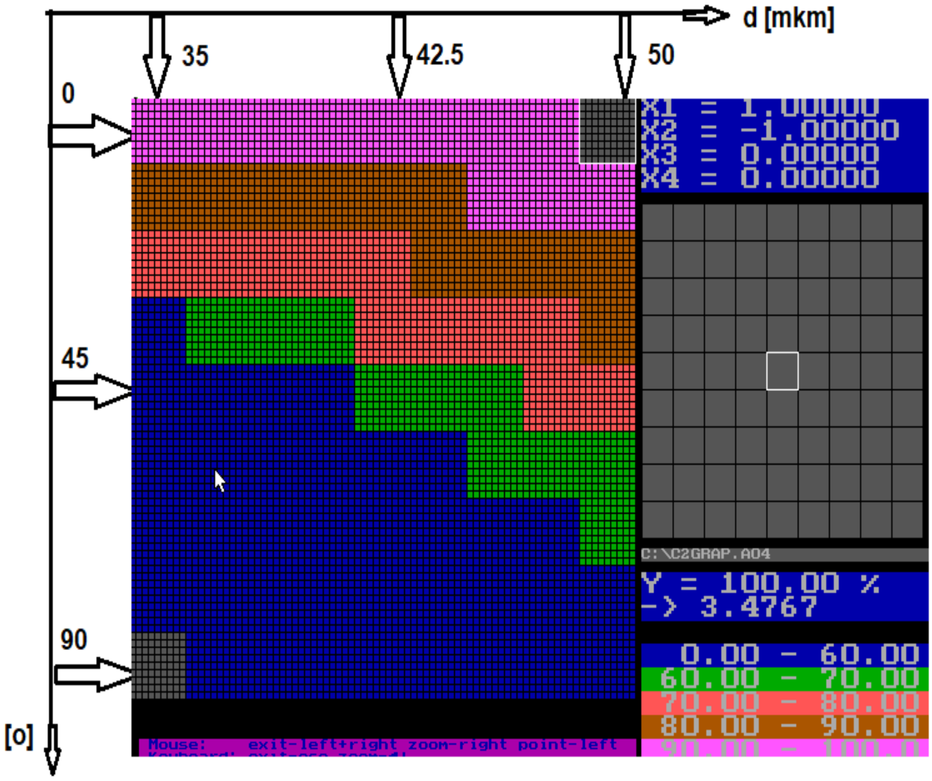


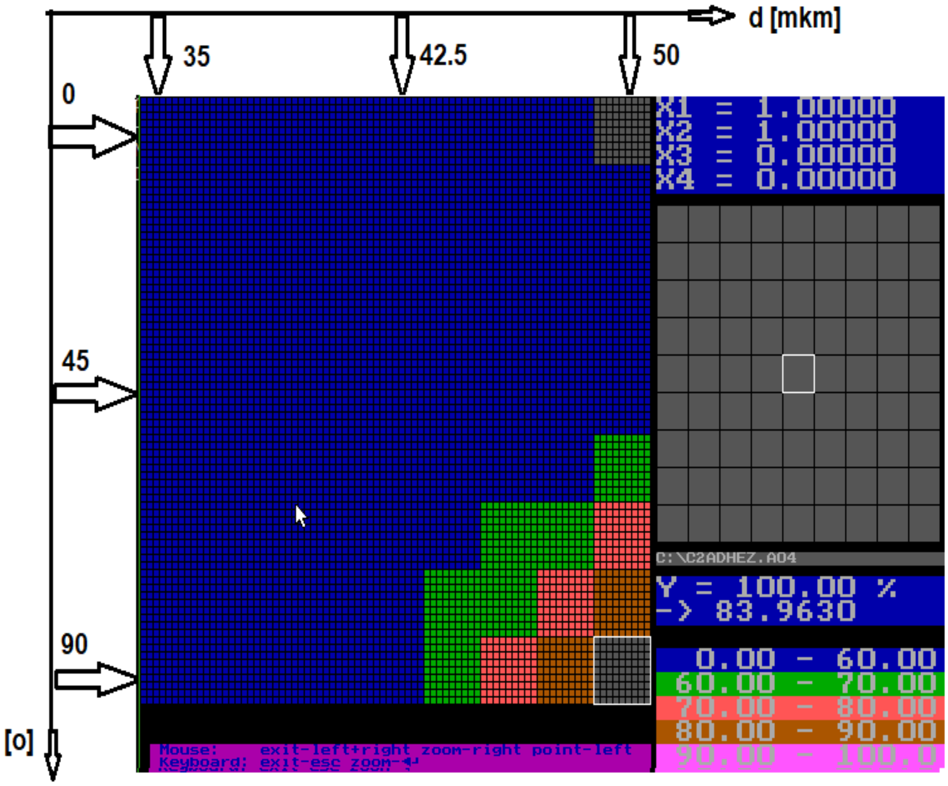
$$\mathbf{Adhezija}_{i,j} := 73.533 + 2.333 \cdot x1_i + 3.525 \cdot x2_j + 4.575 \cdot x1_i \cdot x2_j$$



There are two models and their graphical images, through countur lines with Mathcad and our author’s approach.

The selected visualization models can be multi-criterially optimized because the maxima and minima of the two models occur for different values of the control parameters that define the horizontal and vertical axis of variations.

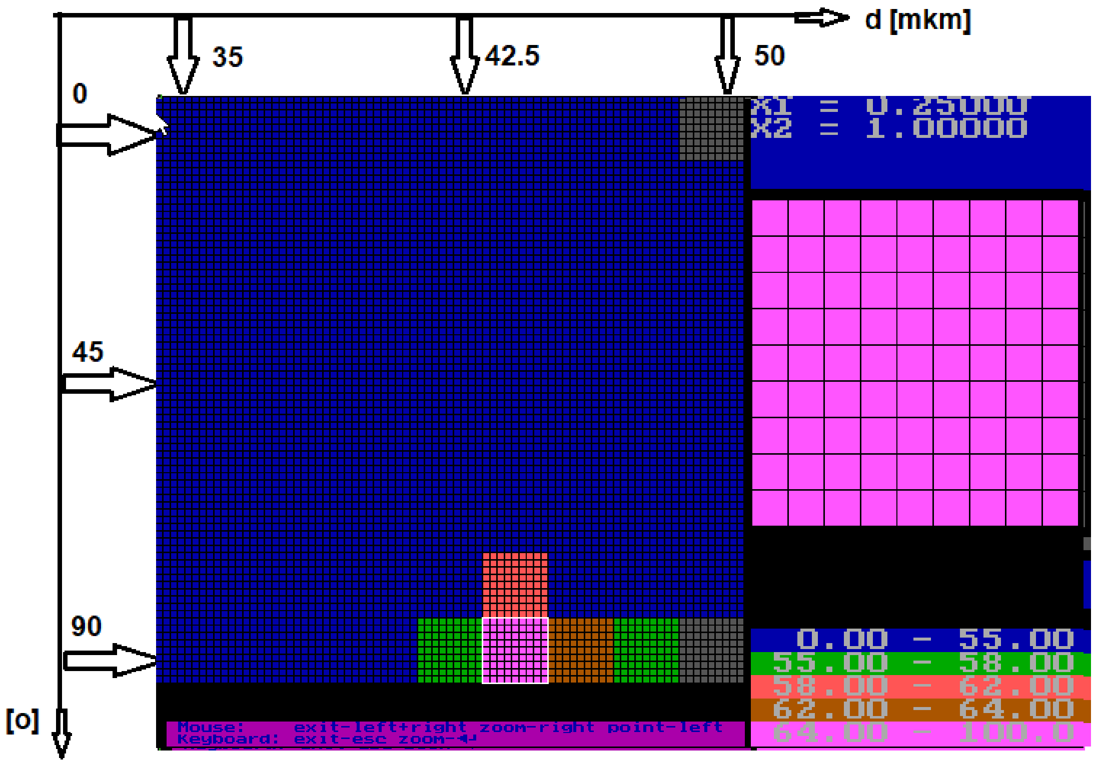




The optimization problem that is defined is to determine the control process parameters, the minimal first property and the maximal second property.

From the graph of the presented solution it is clear that the optimal solution starts at a thickness of 42.5 at 90 degrees and that it is over 64% for the two explored values.

Because the minimal value is sought for one of the properties, the solution found to be minimal is less than 36% (100-64%).

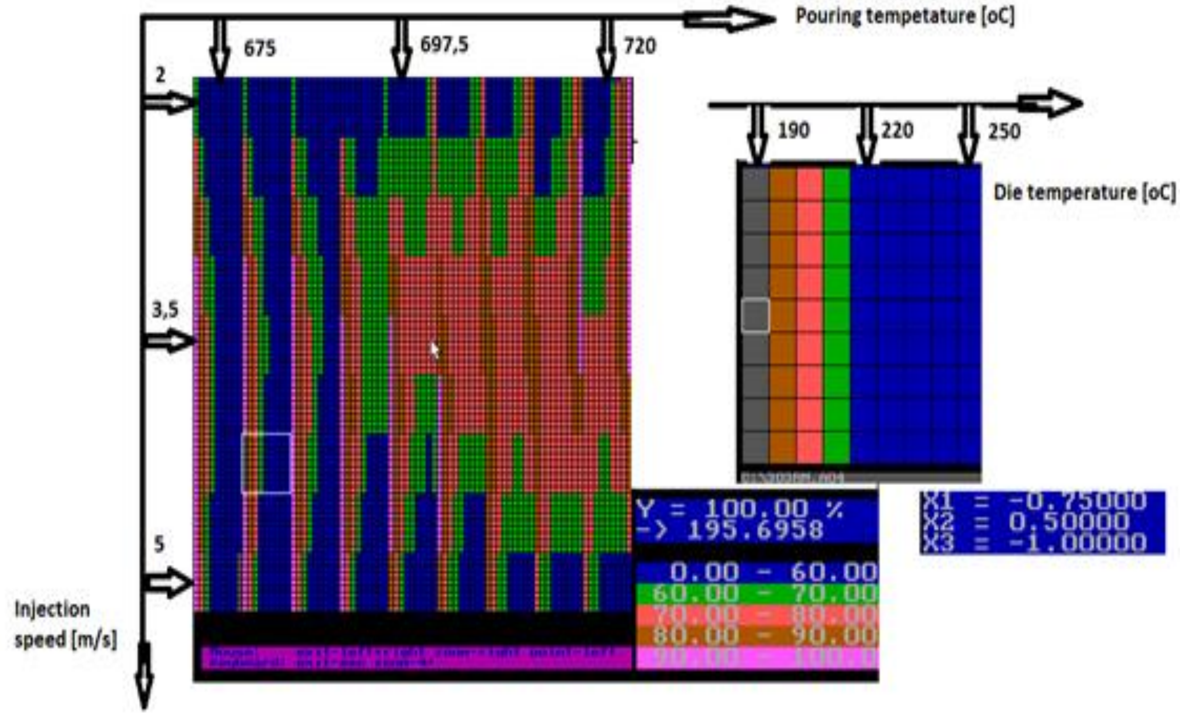


With the design adopted in the defining area defined by the control parameters, 81 states are controlled (9^2, where 2 are the parameters and 9 are the nodes in which the test parameter is controlled).

As impressed by these 81 squares, in these 81 squares there are another 81 states (9^2) in the case that the parameters are 4, not [just] 2.

Then globally in the domain there are changed: the first (horizontally) and the second (vertically); locally changes the third (horizontally) and the fourth (vertically).

An example of an image of a three-parameter model is presented as follows:

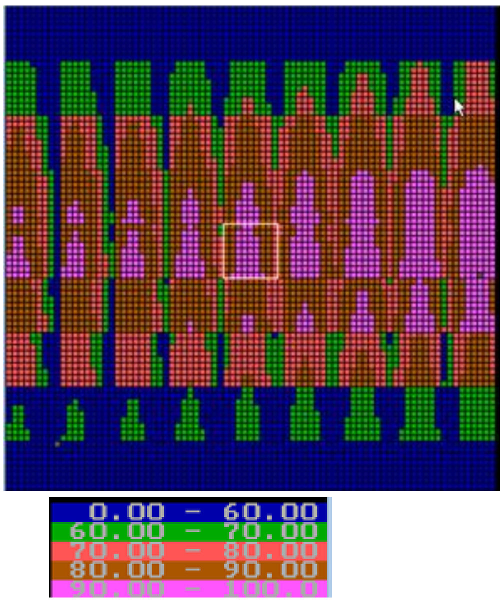


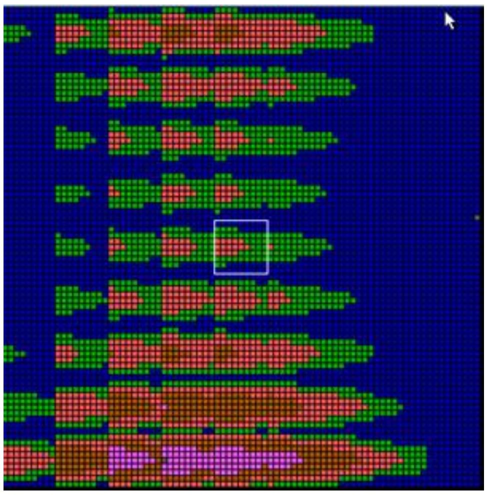
The peculiarity of it is that the local image in the small square on the right does not occur; the third parameter is treated as 9 striped rectangles instead.

They also have squares inserted because of the possible inclusion of the fourth parameter.

Here are two selected images with the fourth parameter included with the same color distribution of the color scales.

In the fixed position of the first and second parameters of the four-factor model (the white square), a contour diagram is constructed for the third and fourth parameters.





The software automatically changes the coloring in the percentage intervals and there can be observed/read the real and the normalized values of the explored quantities with two pair of scrolling tools (one for the global location and the other for the local one).

This task is a problem for analyzing the value of the explored quantity from the influence of the four technological parameters.

The optimization problem is solved in the space of the technological parameters and not as in the traditional approaches in the criteria plane.

The proposed variable algorithm in the variable space may also recommend a weak Pareto solution, but with a more substantial contribution to less energy-intensive and material-intensive solutions.

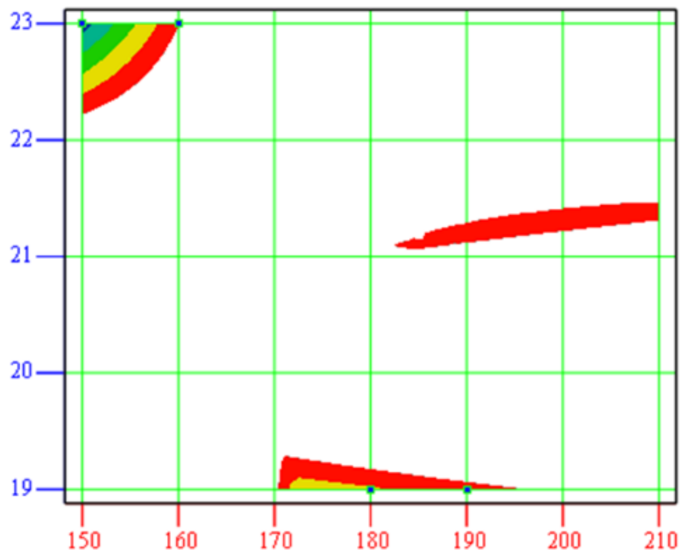
This is the reason for the user-friendliness of the analysis.

Three optimization solutions are presented in the figure, in which the ordering in the achieved requirements between the studied criteria is different.

The decision maker selects the corresponding control parameters depending on his/her own considerations.

The case is two - dimensional.

It is the same mechanism also for multi-parametric cases.

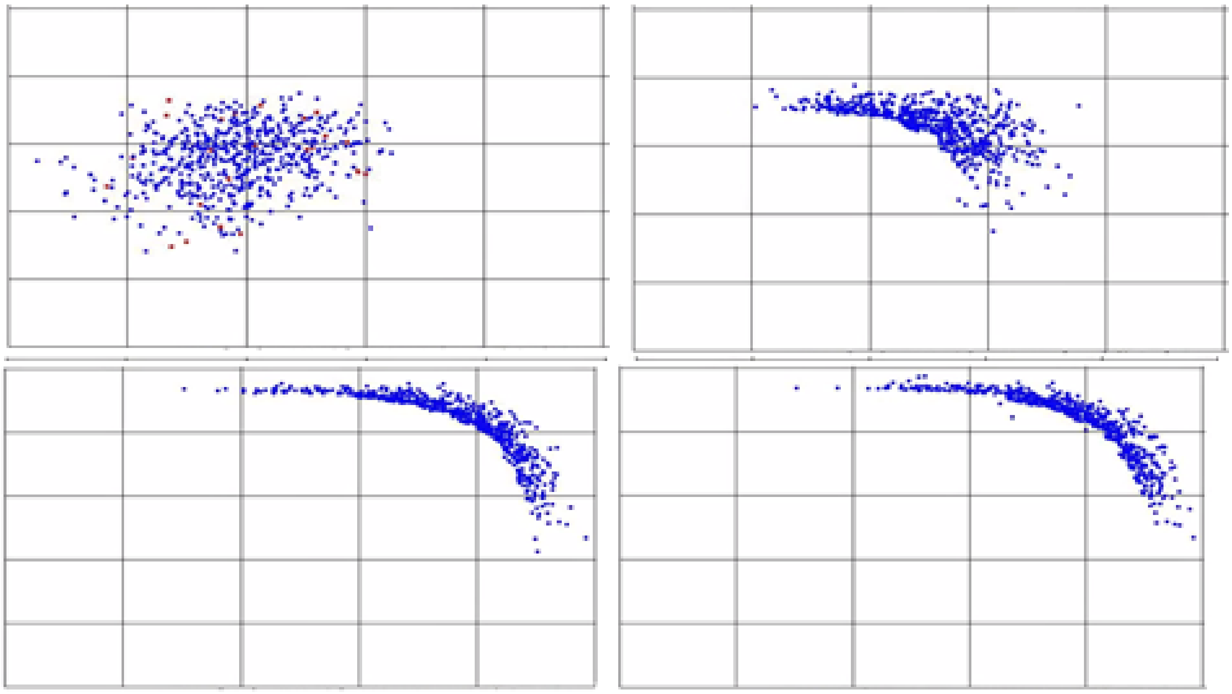


Initially, by refining /localizing at percentage intervals/, the decision is directed to fixing the global coordinates.

After the global coordinates have been fixed, the local situation of the others, which are arranged in color, is taken into account.

The choice of one or other global coordinates is again carried out by the decision maker (DM), for example by economic or environmental considerations.

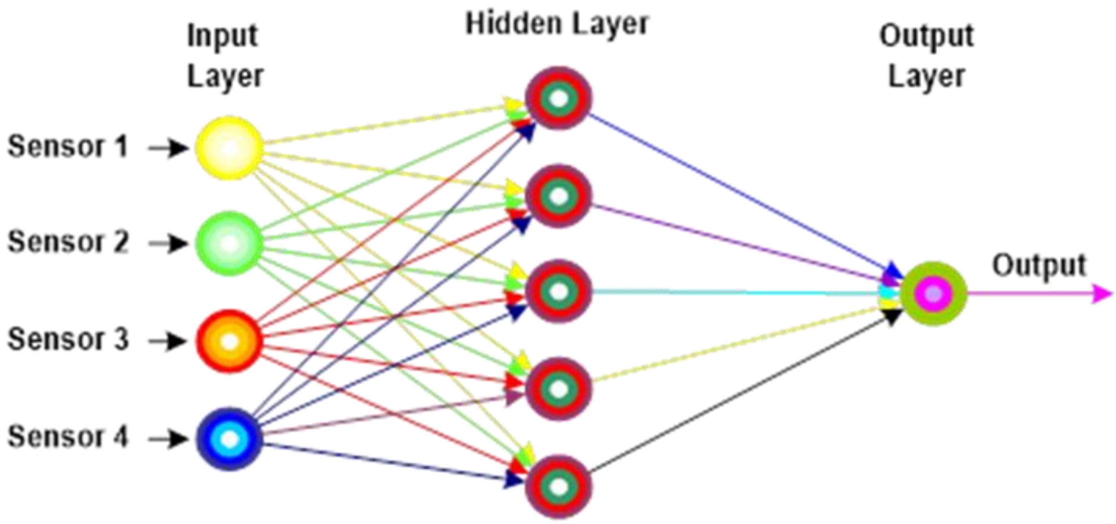
A graphical demonstration of the multicriteria optimization method to maximize two criteria/properties in the criteria space in several iterations is discussed below.



In the criteria space, Pareto's front is being built. The inconvenience of this approach is the ~~many~~ set of the decisions that are subsequently sought by an evaluation system on which the decision maker (DM) can recommend a solution.

For this reason, we have abandoned and do not use the criteria space.

Recently, the neural approximation is much more valued rather than the regression.



Our explanation for this is that in some cases there is a substantial difference between the predicted and the real value.

Although the presented approach is set for regression approximations, the idea can be applied to a neural approximation, having the know-how about it.

Besides, the software is constructed for up to four parameters.

But we have developed a paper that develops the idea of analysis and optimization with up to 10 technological control[ling] parameters.

By normalizing /aligning them to an even percentage scale/ of the predicted values of the models, all inaccuracies are ignored and only the tendency of the model can be worked out, and the predicted values are for reference.

The presented approach, which is being discussed, monitors the whole area of the explored property in the change of all control[ling] parameters with a certain step.

When a complex of properties must be explored, each property can be analyzed separately by the controlling technological factors and then the conditions f the complex forming properties are defined.

It is obligatory to set the identifier of each property that determines whether the researcher is interested in the minimal, maximal or values of the relevant criterion in the complex.

I.1. Applying the Method of Analysis and Multi-criteria Optimization of the Mechanical properties for Mg-Li-Al Alloys.

METHODOLOGY FOR CONDUCTING THE SURVEY

The methodology for conducting the study consists of the following steps:

- Preliminary statistical analysis of the study data with visualization of the dependencies between observed quantities. This includes the determination of the baseline (descriptive) statistical characteristics, the correlation of the parameters of the experimental studies and the construction of two-dimensional contour diagrams between the independent and dependent variables in the study.

- Simplification of dependencies between chemical compounds involved in the chemical alloy and its mechanical properties using neural models.

- Implementation of a Pareto front modeling software for tensile strengths - Rm and relative elongation - A. This is based on the results obtained from the previous steps of the study.

The number of experiments must be sufficient to obtain the models. The database used at the Dalian University of Technology was used for the analysis. To make the calculation more accurate and to keep the secret around it, encryption is applied.

Coding is performed for each factor based on its minimum and maximum values. Analysis and optimization results can be used only after decoding. Coding is done following the dependencies

$$bio := \frac{(bmin + bmax)}{2}$$

$$w := bmax - bio$$

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

Decoding is done using the formula:

$$bdekod := w \cdot bkod + bio$$

	Alloys	X_1 /Li/	X_2 /Al/	Rm [MPa]	A[%]
1.	**Mg-1Li-1Al**	-0.981	-0.872	160.31	11.98
2.	**Mg-1Li-3Al**	-1.00	-0.23	179.37	10.65
3.	**Mg-1Li-5Al**	-0.993	0.333	191.78	12.05
4.	**Mg-1Li-7Al**	-1.00	0.986	170.22	6.65
5.	**Mg-3Li-1Al**	-0.804	-1.00	138.31	10.63
6.	**Mg-3Li-3Al**	-0.84	-0.348	191.7	15.25
7.	**Mg-3Li-5Al**	-0.818	0.266	227.07	15.5
8.	**Mg-3Li-7Al**	-0.825	0.847	203.82	6.70
9.	**Mg-5Li-1Al**	-0.360	-0.914	147.53	21.8
10.	**Mg-5Li-3Al**	-0.364	-0.319	160.14	11.9
11.	**Mg-5Li-5Al**	-0.376	0.287	199.17	8.0
12.	**Mg-5Li-7Al**	-0.513	1.00	220.03	6.15
13.	**Mg-7Li-1Al**	-0.073	-0.943	171.18	24.7
14.	**Mg-7Li-3Al**	-0.107	-0.373	199.84	19.93
15.	**Mg-7Li-5Al**	-0.259	0.216	222.93	10.1
16.	**Mg-7Li-7Al**	-0.211	0.797	210.99	4.45
17.	**Mg-9Li-1Al**	0.211	-0.882	175.96	22.3
18.	**Mg-9Li-3Al**	0.121	0.348	182.33	21.2
19.	**Mg-9Li-5Al**	0.099	0.184	195.06	5.7
20.	**Mg-9Li-7Al**	0.055	0.847	225.32	9.56
21.	**Mg-11Li-1Al**	0.323	-0.954	189.49	13.45
22.	**Mg-11Li-3Al**	0.416	-0.422	201.43	14.55

23.	**Mg-11Li-5Al**	0.38	0.234	192.68	5.4
24.	**Mg-11Li-7Al**	0.397	0.811	180.33	4.05
25.	**Mg-13Li-1Al**	0.724	-0.986	177.02	11.5
26.	**Mg-13Li-3Al**	0.627	-0.387	217.09	8.57
27.	**Mg-13Li-5Al**	0.813	0.201	236.47	2.50
28.	**Mg-13Li-7Al**	0.773	0.761	224.13	1.00
29.	**Mg-15Li-1Al**	1.00	-0.936	123.81	26.10
30.	**Mg-15Li-7Al**	0.478	0.971	124.78	2.23

Table 1. Variation of control parameters.

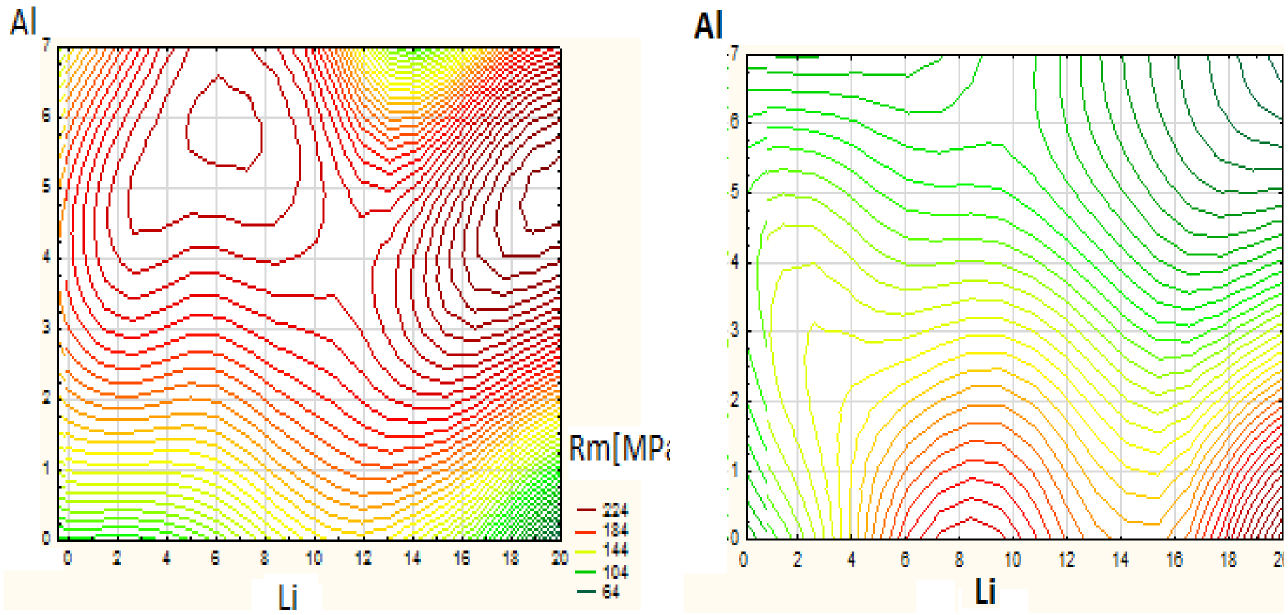
Factors	**Levels of variability for the control factors**		
	Код [-1]	**Код [0]**	**Код [1]**
X_1(Mg) ,[%]	77,93	88,03	98,14
X_2(Li) ,[%]	0,55	9,46	18,37
X_3(Al) ,[%]	0,78	3,58	6,39

ANALYSIS AND VISUALIZATION

The most important task at this stage is to find an opportunity to find a possible link between independent parameters and dependent characteristics in experimental research. The statistical analysis allows to determine the uncorrelated input parameters from the experiment that can be used to construct a regression model, the percentage of Li and Al elements in the alloy composition.

STATISTICAL DATA

The visualization of the presented primary experimental data illustrates the available information for altering the mechanical parameters of the alloy of its chemical composition. In Fig. 1a) shows the two-dimensional contour diagram of the Rm dependence on the percentage of Li and Al elements in the experiment.



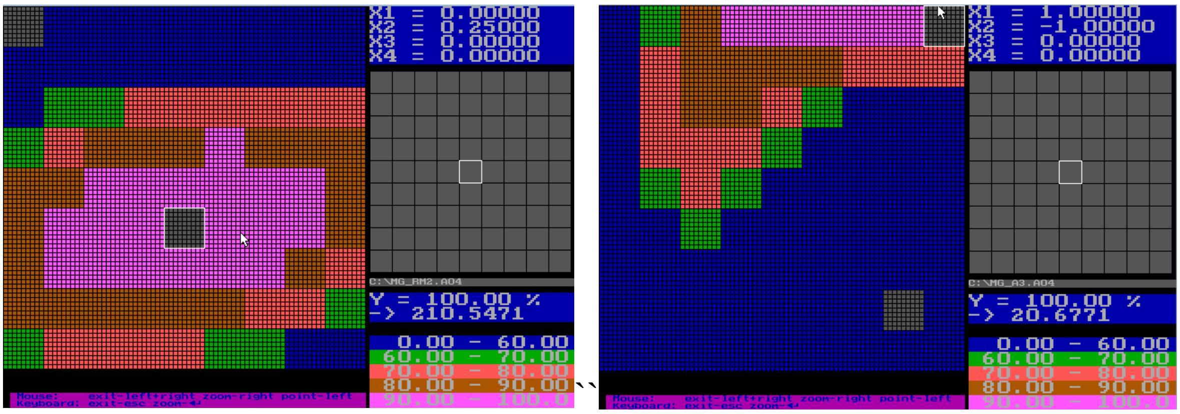
a) b)

Fig. 1. Two-dimensional diagrams of the tensile strength dependence - a) and the relative elongation - b) of the chemical composition of the percentage ratio between Li and Al.

The models obtained in coded values are as follows. The model output is accompanied by a dispersion analysis. The models listed in the table are adequate and they can be used for further analysis and optimization.

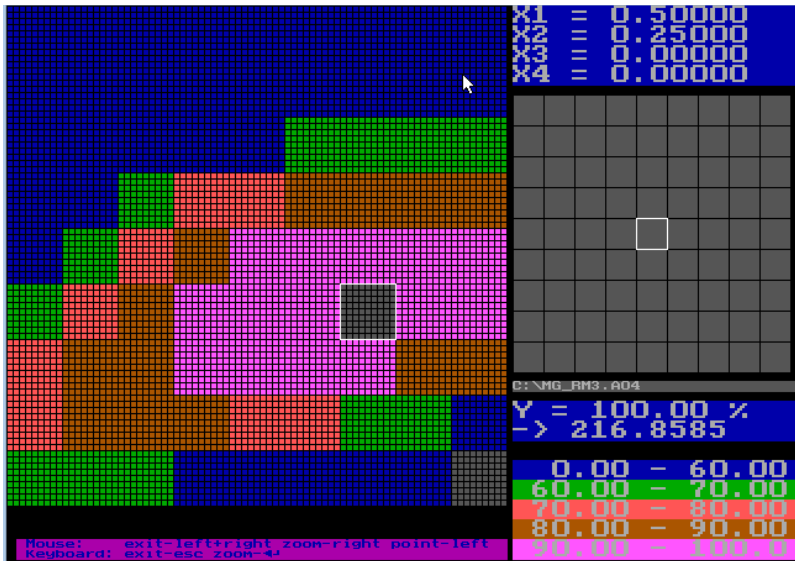
	Rm (X_1,X_2)	**Rm (X_1,X_2)**	**A (X_1,X_2)**
b(000)=	**208.890**	**210.154**	**12.2858**
b(100)=	**1.82142**	**13.9206**	**-8.86290**
b(200)=	**15.1890**	**28.8338**	**-8.25563**
b(110)=	**-11.1139**	**-9.36795**	**-3.35146**
b(120)=	**-10.6079**	**-13.0864**	**-3.31422**
b(220)=	**-34.2428**	**-38.7124**	**0.532559**
b(111)=	**-**	**-**	**5.93115**
b(112)=	**-**	**-**	**1.78261**
b(122)=	**-**	**-24.4375**	**5.38542**
b(222)=	**-**	**-19.4066**	**1.03071**
	R = 0 .6411	**R = 0.6740**	**R = 0 .7936**
	3.3504 > 2.6207	**2.6168 > 2.4638**	**3.7812>2.3928**

The figures below show in one color the distribution of the mechanical properties for the change of the two elements lithium and aluminum. The amount of lithium is changed in the horizontal direction of the domain area, and the amount of aluminum varies vertically. The different models of the table are consistently examined. Different criteria in a normalized form are generalized in a total criterion, which is maximized. Simultaneous maximal values of the criteria are arranged in color.

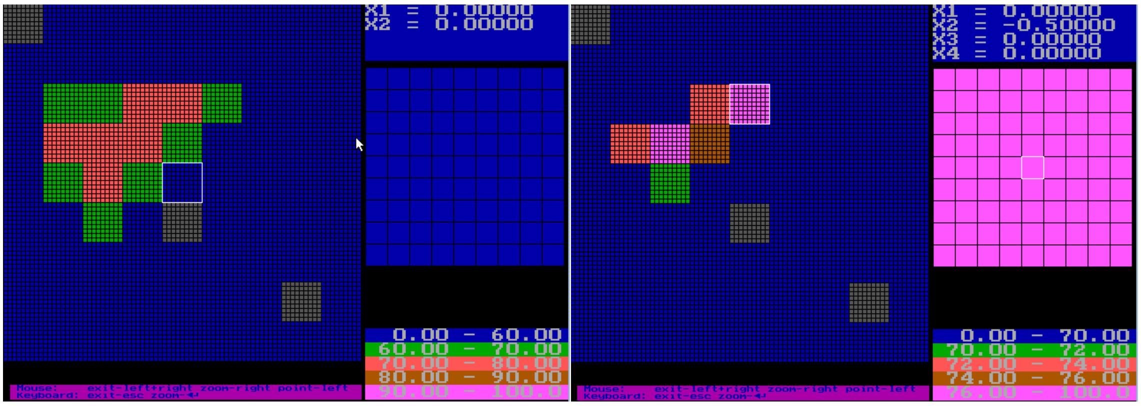


a) b)

Distribution of tensile strength a) and relative elongation b) depending on the percentage of aluminum and lithium in the alloy.



Distribution of tensile strength for the second adequate model depending on the percentage of aluminum and lithium in the alloy.



The last two iterations in determining the optimal solution for the maximal strength and the maximal elongation

A multi-criteria approach is applied to expertly assess the influence of alloy composition elements on pre-selected quality indicators to improve the mechanical properties of the products. Models describing the mechanical properties of aluminum and lithium, which are relevant to the performance properties of the product, have been produced. By the applied approach it is possible to define a composition providing relatively better meanings of the values of the selected mechanical indices. With new means, facts known to science and practice are confirmed.

The proposed approach facilitates the optimization of the magnesium alloy chemical composition improving the properties of the final product. These requirements generally are followed according to the standards but also may be associated with certain additional requirements claimed by users. All these pre-imposed conditions lead to a set of constraints that must be satisfied by acceptable solutions. Some restrictions can be defined as relations with true quantitative nature. This is especially important to restrictions on mechanical properties of the final product. Their proper formula is based on good mathematical models describing the effect of alloy composition and processing parameters on the final properties of casting magnesium alloy. The statistical analysis of industrial data is an important and supporting alternative in such cases. That is why we have limited the field of study only to the influence of the chemical composition of the heat-treated alloys on the set of properties.   The statistical analysis presented in this paper is based on of data collected during the real production process.

I.2. Analysis of Properties of Magnesium Alloys Using the Described Approach

The analysis is based on a specific database of the relationship between the composition and the properties. Based on this database, the interval in which each of the alloying elements varies is determined.

Table 1. Minimum and maximum values of alloying components

Input parameter	Chemical symbol	min [%]	max [%]
x_1	Al	0.0	10.0
x_2	Mn	0.0	1.5
x_3	Zn	0.0	6.5
x_4	Cu	0.0	2.7
x_5	Ni	0.0	0.3
x_6	Si	0.0	1.0

Regardless of that, the proposed optimization approach for modeling the final mechanical properties of alloys can be applied to any production process with steel manufacturing.

The analysis presented in this paper is related to the analysis of mechanical properties of magnesium specimens described by the following parameters: tensile strength - *Rm* [MPa] and relative elongation - A [%]). The limitations connected with these parameters are due to magnesium grade characteristics and customer's specifications.

However, the main problem is that these parameters cannot be under direct observation during the manufacturing process, so any limitations associated with them can not be clearly defined in the optimization model. That means that we must develop models linking the final mechanical properties of the specimen/sample of the steel chemical composition as all as the parameters of the production process.

The regression analysis allows describing the relation between the variables of input and output, without going into the phenomenon nature during the process.

The regression models presented below have been created based on the data collected during the industrial production process.

The statistical analysis described in this section is based on a data set of 53 records extracted from the whole database.

The Least Squares method, LS is used to estimate the regression parameters. The estimated models of parameters *Rm* and *A* obtained in the examinations are given below.

In respect to the problem under examination, nonlinear regression dependencies have been identified for each of the mechanical properties of magnesium alloys. The regression dependencies are of the following kind:

$$f_i(x) = b_0^i + \sum_{j=1}^{6} b_j^i x_j + \sum_{j=1}^{6} \sum_{l=j+1}^{6} b_{jl} x_j x_l + \sum_{j=1}^{6} b_{jj}^i x_j^2$$

Here b_{ij} are the regression model parameters. The coefficients in equations are defined in Table*. The models can be used for prediction if the check-up F > F (0.5, ν_1,ν_2) described in details has been made.

The analysis of these regression models is performed in a nominalized form in the range of 0-100%. In this dimensionless scale, all properties can be analyzed simultaneously and the conclusions about them are generalized and they are easy for perception.

To minimize the values, it is necessary to define the minimal and maximal meanings of each of the tested properties. The first step in this determination is to find values of the chemical composition that meet the minimal and maximal properties respectively. For the specific case this is defined as follows separately for each extremum of each property:

Table *. Coefficients of regression modelds of the examined target parameters.

No	Coefficient	Rm [MPa]	A [MPa]
1	Free member	114.255	16.33366
2	X_1	25.97015	0.6716988
3	X_2	9.704941	-18.22966
4	X_3	74.42215	-3.222518
5	X_4	66.06575	12.28882
6	X_5	3114.254	101.5687
7	X_6	140.6771	12.65238
8	X_1 X_2	-0.40418	-0.1963183

9	$X_1 X_3$	-1.084408	-0.0068298
10	$X_1 X_4$	-72.2078	-0.6545856
11	$X_1 X_5$	237.9817	9.555618
12	$X_1 X_6$	-0.778058	0.1666764
13	$X_2 X_3$	-44.53689	2.326275
14	$X_2 X_4$	101.9566	-15.04205
15	$X_2 X_5$	1768.658	336.508
16	$X_2 X_6$	-36.39456	21.76996
17	$X_3 X_4$	0.7895336	0.1440411
18	$X_3 X_5$	-414.173	18.49442
19	$X_3 X_6$	-99.81348	0.05190802
20	$X_4 X_5$	2369.462	150.6452
21	$X_4 X_6$	138.7343	-61.84769
22	$X_5 X_6$	-2435.761	-121.6928
23	X_1^2	-1.798813	-0.1700993
24	X_2^2	53.00094	7.873145
25	X_3^2	-5.917203	0.3912327
26	X_4^2	-43.78463	-2.977206
27	X_5^2	-74966.48	-4711.342
28	X_6^2	-105.1666	-24.45902
R		0.888	0.914
F		3.449	4.684

$$\mathbf{Minimize\,(UTS\,,\,Al\,,\,Mn\,,\,Zn\,,\,Cu\,,\,Ni\,,\,Si)} = \begin{pmatrix} \mathbf{10} \\ \mathbf{0.08} \\ \mathbf{0} \\ \mathbf{2.7} \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix}$$

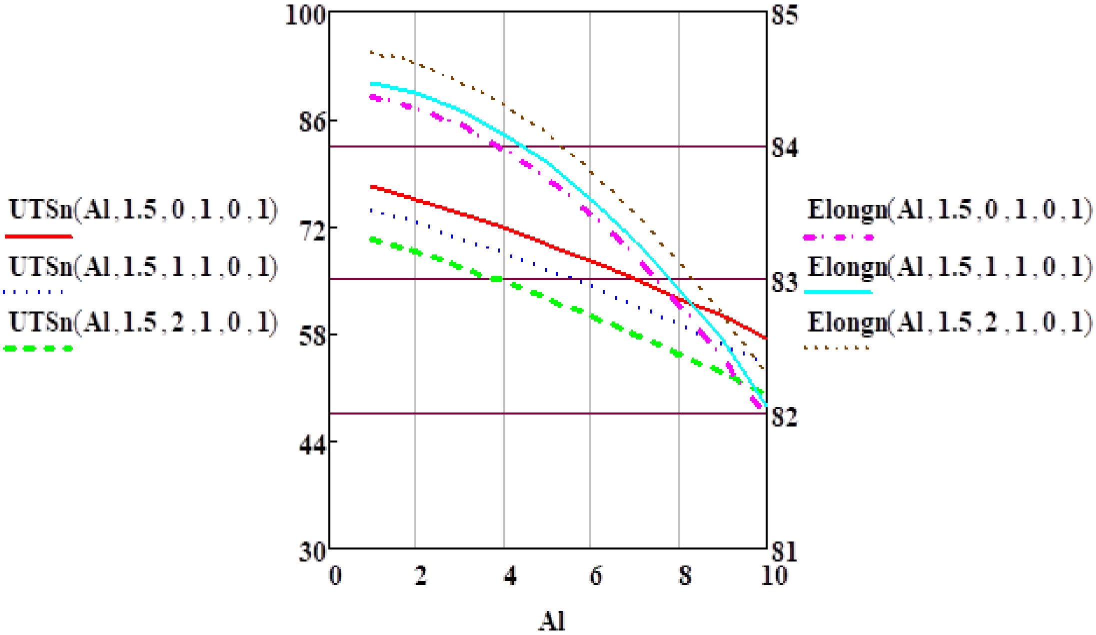
$$\textbf{Maximize}(\textbf{UTS}, \textbf{Al}, \textbf{Mn}, \textbf{Zn}, \textbf{Cu}, \textbf{Ni}, \textbf{Si}) = \begin{pmatrix} \mathbf{0} \\ \mathbf{1.5} \\ \mathbf{0} \\ \mathbf{2.7} \\ \mathbf{0.065} \\ \mathbf{1} \end{pmatrix}$$

$$\textbf{Minimize}(\textbf{Elon}, \textbf{Al}, \textbf{Mn}, \textbf{Zn}, \textbf{Cu}, \textbf{Ni}, \textbf{Si}) = \begin{pmatrix} \mathbf{10} \\ \mathbf{1.5} \\ \mathbf{0} \\ \mathbf{2.7} \\ \mathbf{0} \\ \mathbf{1} \end{pmatrix}$$

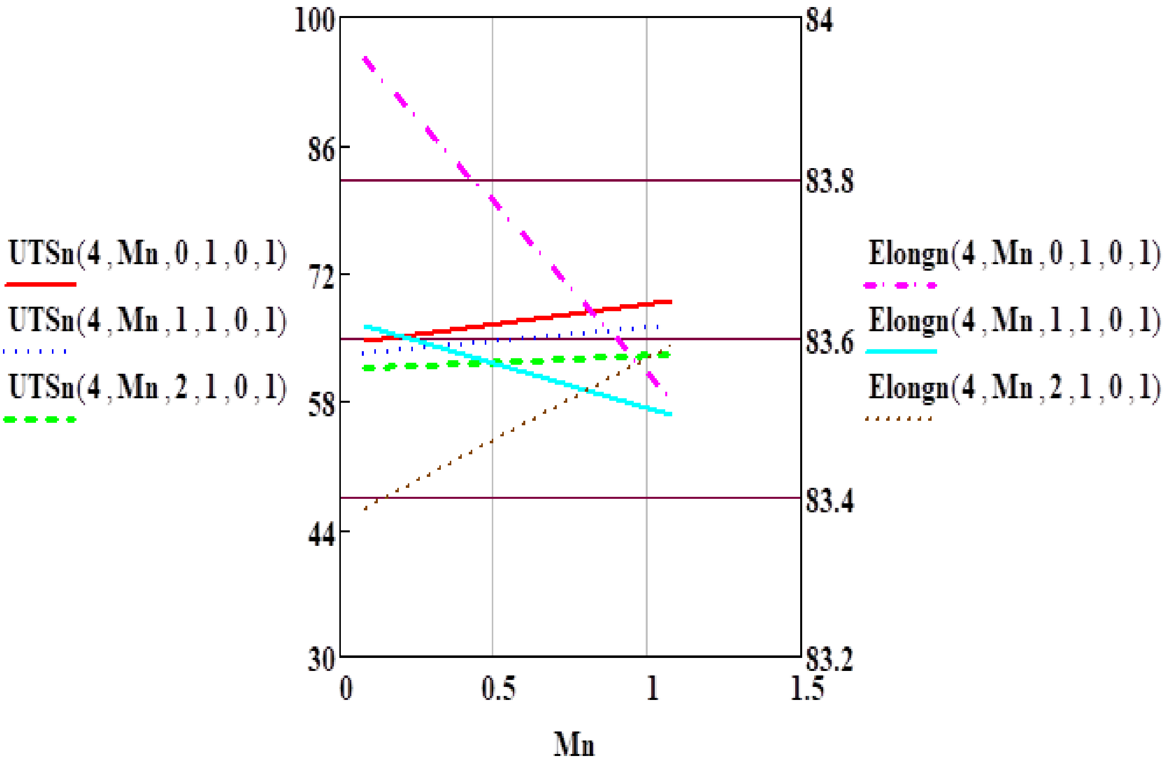
$$\textbf{Maximize}(\textbf{Elon}, \textbf{Al}, \textbf{Mn}, \textbf{Zn}, \textbf{Cu}, \textbf{Ni}, \textbf{Si}) = \begin{pmatrix} \mathbf{3.337} \\ \mathbf{1.5} \\ \mathbf{6.5} \\ \mathbf{0} \\ \mathbf{0.071} \\ \mathbf{0.769} \end{pmatrix}$$

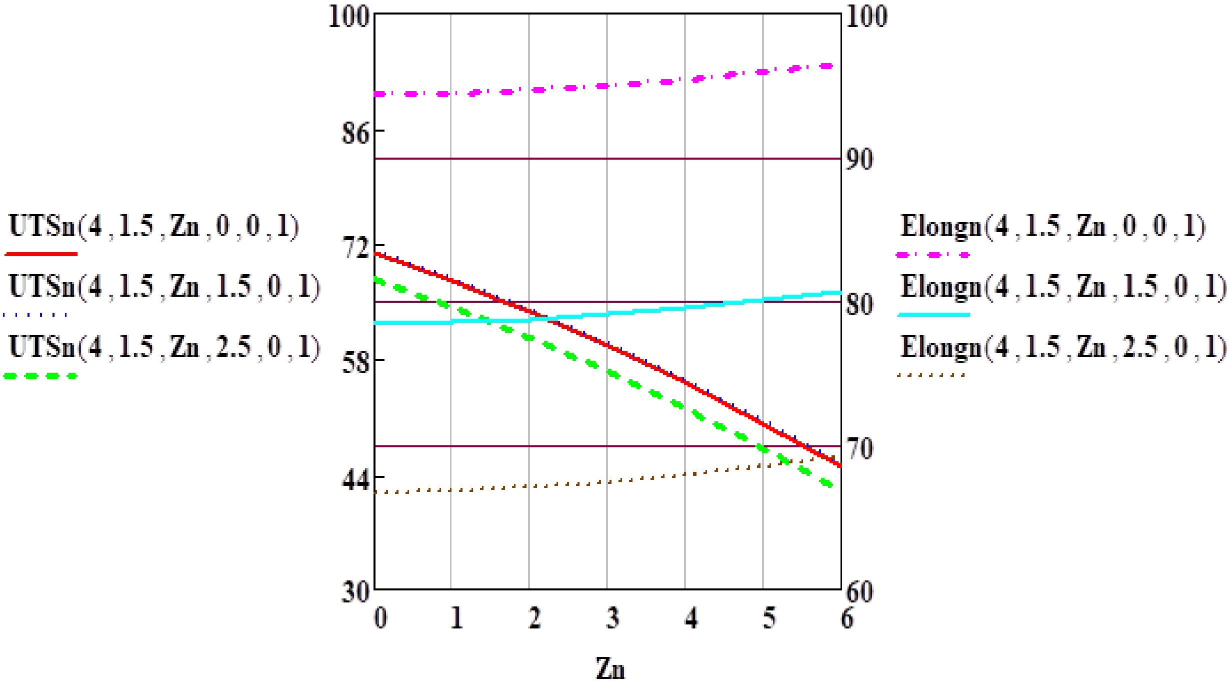
After determining the composition of each element in which the corresponding extremum is present, the assigned combination of this composition is replaced in the corresponding model to determine the value of the extremum necessary to determine the normalized values.

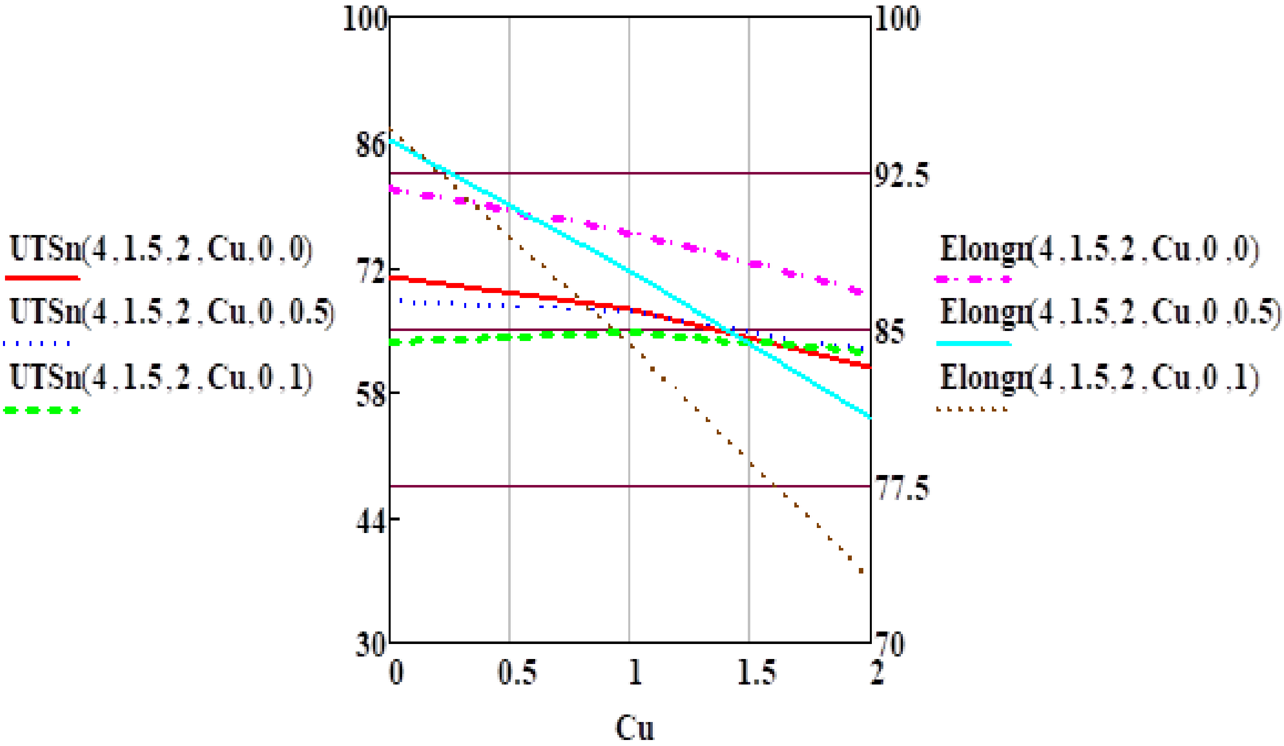
The figures show the possibility of comparing both analyzed properties when changing a pre-selected alloying element. Usually the other varying elements are fixed to the maximal values of one of the optional properties. In some cases, these levels overlap.

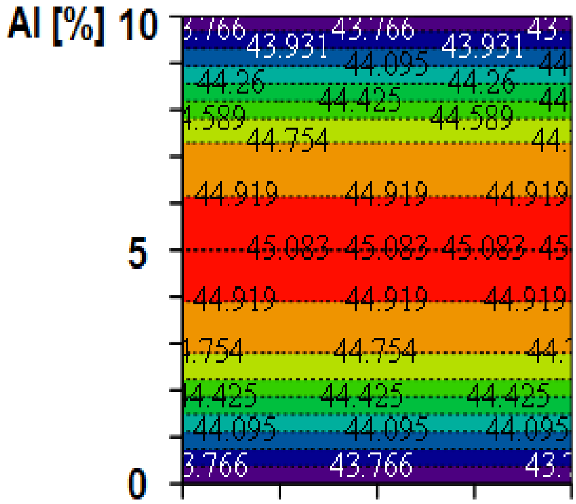


On the figure except aluminum in its entire range, zinc is also changed in three positions, at values of 0, 1, and 2%. According to the depicted scales, it can be determined that the tensile curves vary much more steeply than the relative elongation because the two vertical scales are scaled differently. Such an analysis can be carried out for each of the graphs below.

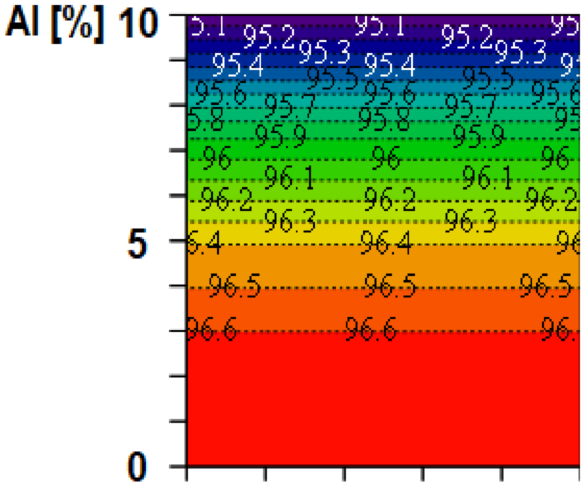



100
86
72
58
44
30
100
90
80
70
60
0
1
2
3
4
5
6
Zn
UTSn(4 , 1.5 , Zn , 0 , 0 , 1)
UTSn(4 , 1.5 , Zn , 1.5 , 0 , 1)
UTSn(4 , 1.5 , Zn , 2.5 , 0 , 1)
Elongn(4 , 1.5 , Zn , 0 , 0 , 1)
Elongn(4 , 1.5 , Zn , 1.5 , 0 , 1)
Elongn(4 , 1.5 , Zn , 2.5 , 0 , 1)

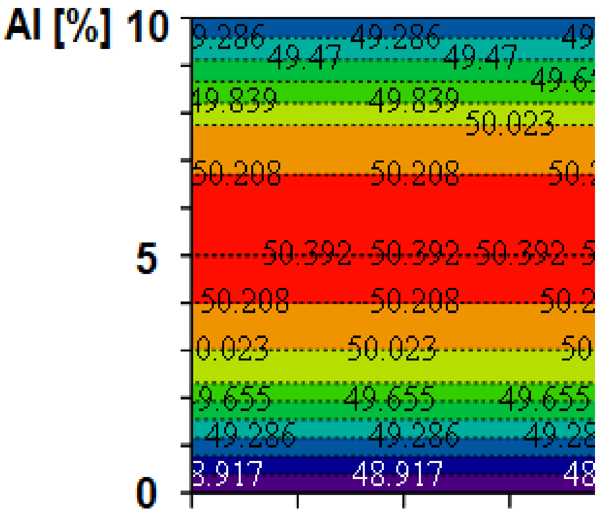

100
86
72
58
44
30
100
92.5
85
77.5
70
0
0.5
1
1.5
2
Cu
UTSn(4 , 1.5 , 2 , Cu , 0 , 0)
UTSn(4 , 1.5 , 2 , Cu , 0 , 0.5)
UTSn(4 , 1.5 , 2 , Cu , 0 , 1)
Elongn(4 , 1.5 , 2 , Cu , 0 , 0)
Elongn(4 , 1.5 , 2 , Cu , 0 , 0.5)
Elongn(4 , 1.5 , 2 , Cu , 0 , 1)



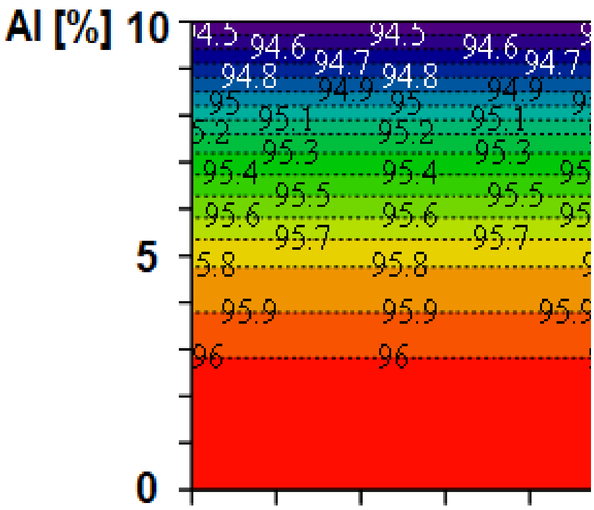
Zn = 6 % const



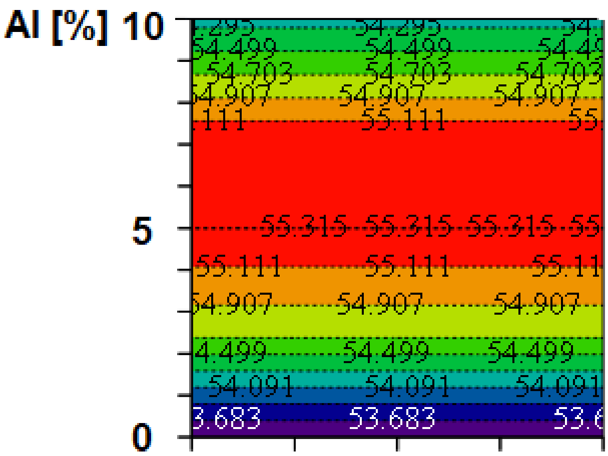
Zn = 6 % const



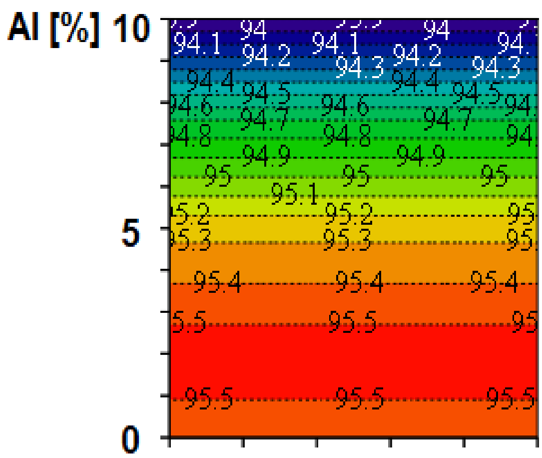
Zn = 5 % const



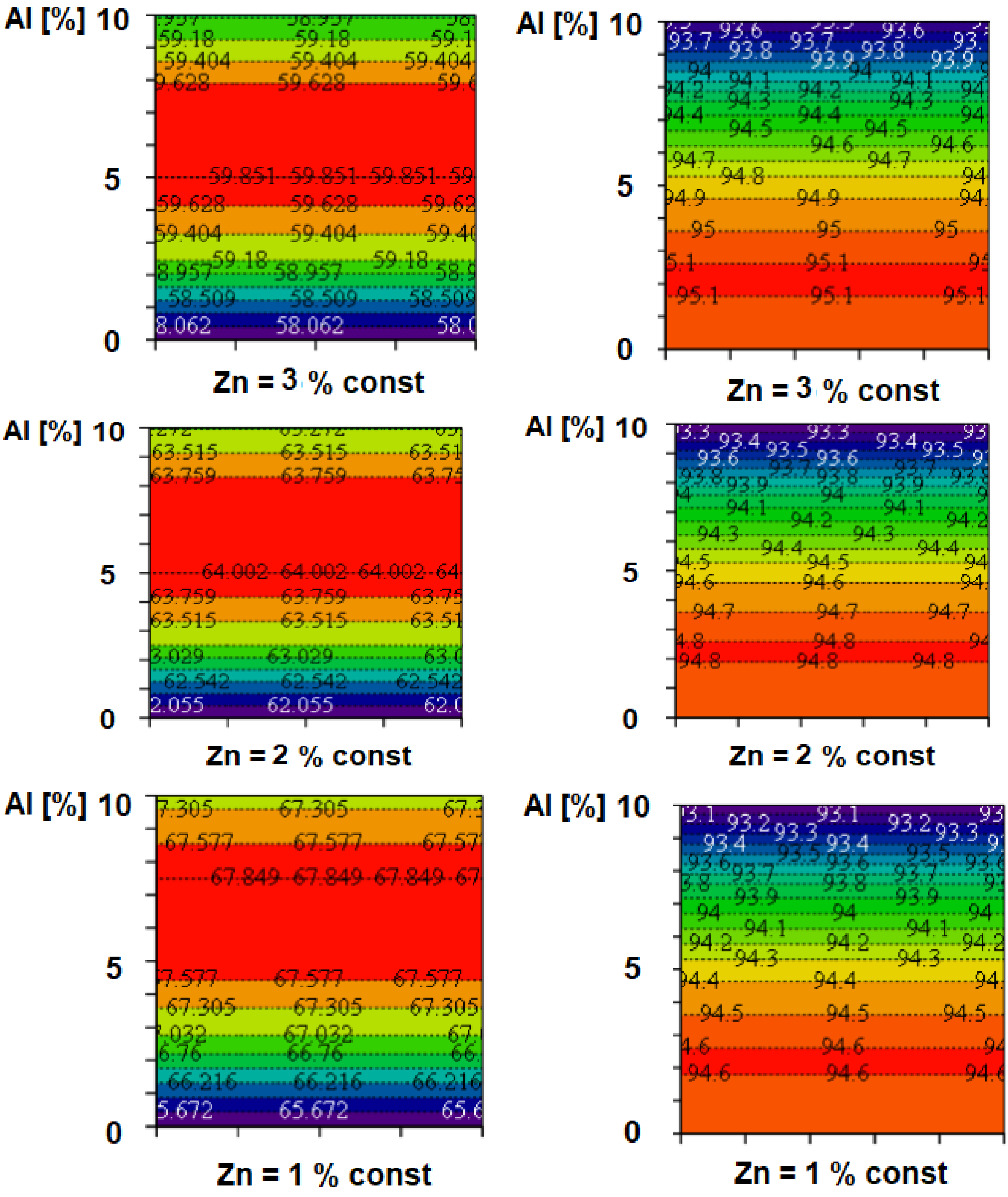
Zn = 5 % const



Zn = 4 % const



Zn = 4 % const

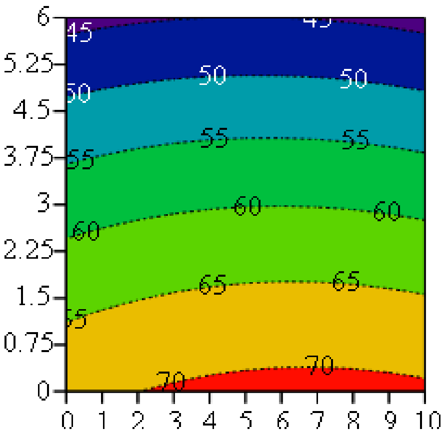


From the analysis of the graphical dependencies, the following conclusions can be made: Assuming that we have fixed most of the alloying elements at their optimal levels, then for the alumina variation we can note that the optimal aluminum content at the tensile strength is a little above 5%, and for the elongation, it is about 2%.. The optimal zone expands or narrows following the different zinc content of both properties. In terms of the strength it grows with the zinc reduction. In a much lesser ratio, the relative elongation value of the zinc change is changed.

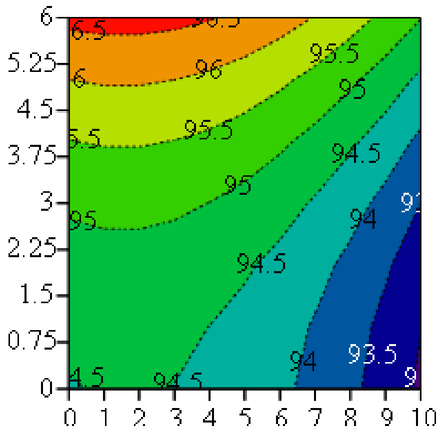
With these two types of less common graphic analyses we present analyses of regression models that can be useful as evidence of one or another trend.

$$\mathbf{UTS\%n_{Al,Zn} := UTSn(Al, 1.5, Zn, 0, 0, 1)}$$

$$\mathbf{Elong\%n_{Al,Zn} := Elongn(Al, 1.5, Zn, 0, 0, 1)}$$



UTS%n

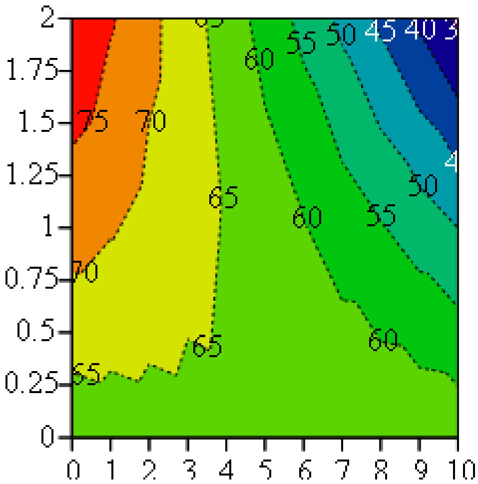


Elong%n

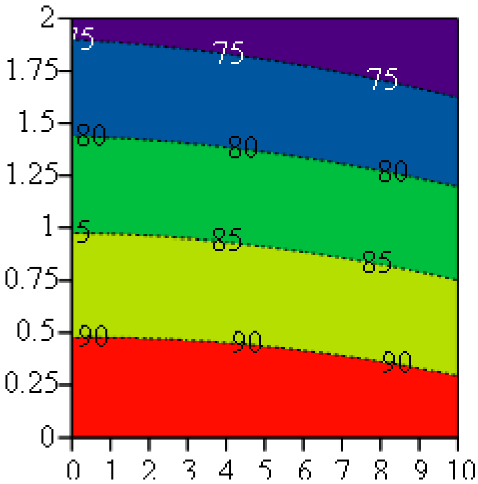
The contour diagrams with equilevel lines are very popular as three-dimensional diagrams of the response surface depending on the change of two parameters. Unlike the traditional three-dimensional diagrams, these graphs readily measure the value of the test parameter at fixed control parameters.. This way for presentations has made it a complete procedure of previous imagery with fewer images to provide more information.

$$\mathbf{UTSn_{Al,Cu} := UTSn(Al, 1.5, 2, Cu, 0, 1)}$$

$$\mathbf{Elongn_{Al,Cu} := Elongn(Al, 1.5, 2, Cu, 0, 1)}$$



UTSn



Elongn

I.3 Taguchi methodology applied to the magnesium alloys design

The second contribution in the development of methods for metallurgical design is associated with the Taguchi methodology for analysis of the selected quality parameters.

With respect to the objective problem, for each of the mechanical properties of the steels there are identified nonlinear regressions of the form:

$Relation$ (S/N)= $\frac{signal}{noise}$ The effects of the factors are determined for each row, using the formula to minimize performance characteristics:

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{j=1}^{n} y_{ij}^2\right)$$

,

for maximaze

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{j=1}^{n} \frac{1}{y_{ij}^2}\right)$$

-

The composition optimization is performed only in respect to yield strength Rm and respective elongation A.

Table. Orthogonal matrix I (27,13) developed by Taguchi with factors at three levels

Run	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

Following Taguchi methodology (Khosrow Dehnad, 1989) an experiment is made modeled on orthogonal matrices developed by him. The experiment can be performed in two ways by:

- a real experiment leading to obtaining results for processing;
- a numerical experiment with the presence of adequate regression models.

The availability of the described model coefficients, which can be used to predict, give a possibility to make a numerical experiment involving Taguchi method. The noise matrix is selected from orthogonal matrix I (27,13) with 27 rows and 13 columns developed by Taguchi. The matrix is worked out with factors at three levels – Table 3.

The methodology proposed is implemented for tensile strength Rm and relative elongation A. To take out the models of these two target functions, 53 experiments that form the data matrix A (53, 6 +1) have been used. Here the added column "1" is for the output target function Rm or A stored compactly in the matrix.

To optimize the computing process, the scheme, which having been processed for the particular case takes the following kind, is selected.

In numerical experiments that use models based on the chemical composition the noise can be expressed only in the change of the respective components. It is assumed to express noise Δ in the following way $\Delta_i = \frac{\bar{x}_i}{k}$ where further calculations are made for k equal to 100 and 70.

Here $\bar{x}_i$ is the mean value of relevant variable "i".

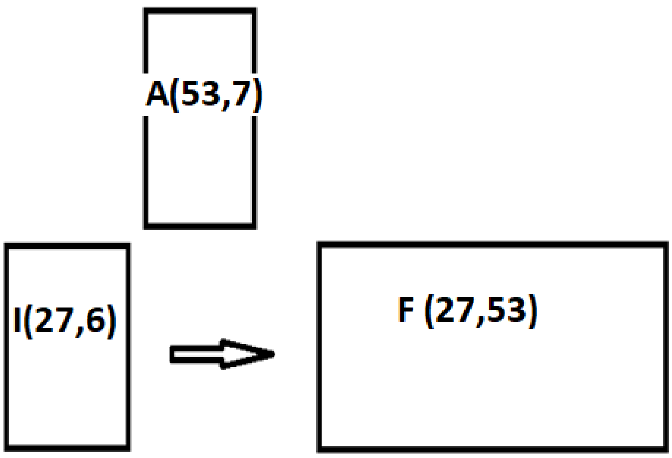


Fig.*. Organizing experiments with parametric planning with matrices I, A and F

For level "1" of I (27,6) noise is subtracted from relevant x_i taking the value of $x_i - \Delta_i$. With level "2" no correction is applied, the value of x_i is preserved. With level "3" noise is added to relevant x_i taking the value of $x_i + \Delta_i$. In numerical experiments where models based on chemical composition are used, noise can be expressed only in the change of the respective components. Noise Δ is assumed to be expressed as follows $\Delta_i = \frac{\bar{x}_i}{k}$, where the further calculations are made for k equal to 100 and 70. Here $\bar{x}_i$ is the average value of the respective variable "i". In level "1" I (27,6) noise is subtracted from respective x_i taking the value of $x_i - \Delta_i$. In level "2" no correction is applied, the value of x_i is preserved. In level "3" noise is added to respective x_i taking the value of $x_i + \Delta_i$.

Thus, noise is formulated in the change of chemical composition. The calculation process is organized as follows:

A row of matrix I (27,6) is taken (for example, row 1 - I (1,6)). In this row level "1" is assigned for each x_i, i.e. noise will be taken out from each value x_i.

Thus F (1,1) of the matrix F (27,53) is obtained from the first row of A (53,7). The same rule is applied to the rest of the series F (53,6) and it forms F (27,53).

It is continued with the next row of matrix I (27,6) performing the following sequence.

Each row of matrix I (27,6) forms a relevant row of matrix F (27,53).

Calculations are performed according to the following algorithm.

If we take the first column of matrix I (27,6) relevant to X_1, it is evident that the first nine rows correspond to level "1" of noise, the second nine lines correspond to level "2" and the third nine rows correspond to level "3" of noise. This makes possible to use the values of the first nine rows of matrix F (27,53) to calculate level "1", to use the second nine rows to calculate level of "2" and the third nine rows for calculation at level "3" for X_1. For other columns from 2 to 8 it is necessary to sort in ascending order Xi from I(27,6). After sorting the column obtains the kind of the first column.

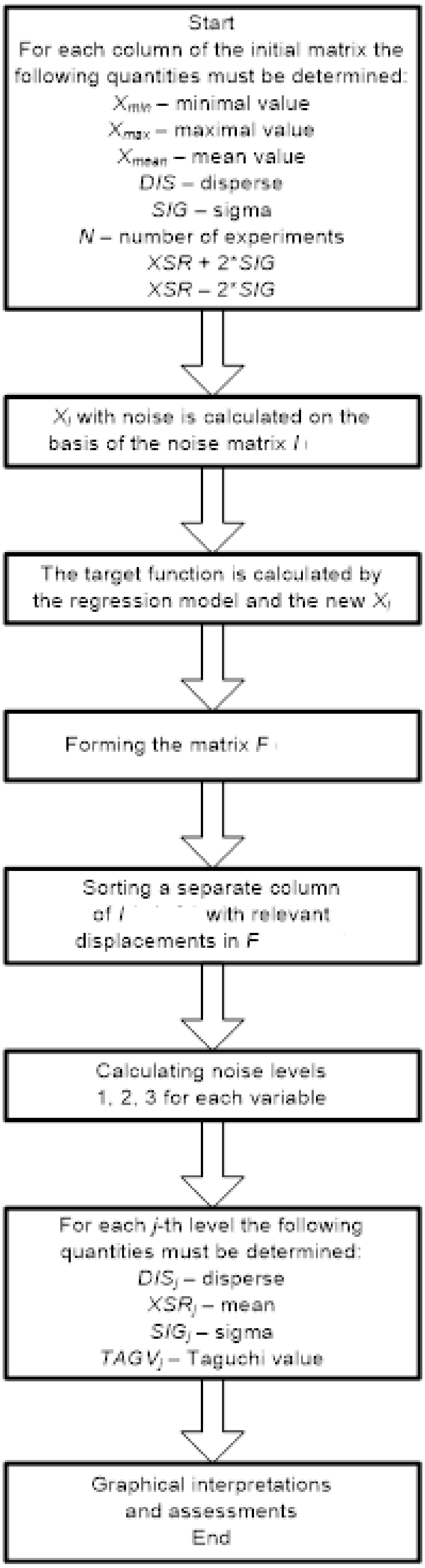


Fig. 2. Computational algorithm

After sorting of the respective variable, calculations for different levels can be made. It is continued with the next matrix row I (27,6) performing the following sequence. Each row of matrix I (27,6) forms a corresponding row of matrix F (27,53). If we take the first column of matrix I (27,6) corresponding to the X_1 , one can see that the first nine rows correspond to noise level "1" of noise, the second nine rows correspond to level "2" and the third nine rows correspond to noise level "3". That allows using the values of the first nine rows of matrix F (27,90) to calculate level "1", the second nine rows to calculate level "2" and the third nine rows to calculate level "3" for X_1. For the rest columns from 2 to 6 it is necessary to sort by ascending order of Xi of I(27,6). After sorting the column takes the kind of the first column. With sorting, if shifts are made, they are reflected in matrix F (27,53). After sorting the corresponding variable it is possible to make calculations for different levels.

In the numerical experiment noise was first determined with Ҡ=70. The analysis of the graphics shows low sensitivity for both Rm and A. In these calculations, as shown in the Table 4.

The conclusion that can be made for the tensile strength – Rm is that all the factors have a significant effect on aluminum, manganese, zinc and nickel and it is expected they to change in the direction of decreasing values, and copper and silicon to increasing values. About the results for the relative elongation – A, from all six variables two of the variables – nickel and silicon – should not be changed, and the rest of the variables – aluminum, manganese, zinc and copper – need to change in the direction of increasing their value. As the experiment is numerical, it is possible to perform numerical optimization with the mathematical models obtained as the values of X_i are remained to change within the limits defined by the output data (Table 1). The circumstance that some of the variables remain unchanged, i.e. they keep their initial values, imposes the necessity to separately carry out optimization for the chemical composition of each alloy. As a method of optimization, the method of Hook and Jives was chosen. This method is characterized as one of the best to solve problems with different parameters of the goal functions. Specifically, the tensile strength Rm is changed from X_1, X_2, X_3, X_4, X_5 and X_6, and the relative elongation is varied from X_1, X_2, X_3 and X_4.

Table 4. Levels of noise factors for the research parameters

Variable	Element of composition	Noise level	
		Rm	A
X_1	Al	1	3
X_2	Mn	1	3
X_3	Zn	1	3
X_4	Cu	3	3
X_5	Ni	1	2
X_6	Si	3	2

The fact that one of the variables does not change, i.e. they preserve their initial values requires optimization to be performed separately with chemical composition for each alloy. The ones mentioned, X_5 and X_6, are maintained at their level, but are held by changing the rest. In this way, 53 optimizations are performed, with each case obtaining a separate value of the extremum. Then all maxima are sorted in ascending order and the largest is selected. With the values of the variables of the relative elongation, the value of the tensile strength Rm is calculated. Thus, the two-criteria approach is implemented. The optimal composition is shown in the table.

Al	Mn	Zn	Cu	Ni	Si
10.0%	1.5%	6.5%	2,7%	0,3%	1%

Such an approach is justified because the task, if viewed from the point of view of technology, is that individual optimization is the refinement of a separate actual alloy.

Optimization in this way coincides with the approach of searching for a global extremum from a set of starting points.

This outcome indicates that the task is feasible and the approach applied can result in improvement of the alloy composition.

Conclusion

The numerical experiment has proved the ability to improve the quality of magnesium alloy of a certain class. Mathematical models suitable for forecasting and optimization have been derived. The approach of Taguchi applied has lead to a desired result, to separate variables Xi for the examined parameters that do not influence significantly on the final result. With this limit, the numerical optimization for maximum search has been conducted with each chemical composition. That allows improving it. Relative elongation A turned to be less variable index and tensile strength Re requires caution with extreme selecting. The decision of bi-criteria problem set has been defined thus proving that the Taguchi approach is applicable to a similar class of problems.

II. Activity Based on Experimental Results Obtained for the Relationship between Grain Size and Mechanical Properties

Data have been obtained from DUT University (大连理工大学) to establish the relationship between the grain size and the properties of manganese alloys.. The available data base is shown in Tabl.1.

Tabl.1. Experimental observations about the grain size from the properties

Grain Size (μm)	Tensile Strength （MPa）	Yield Strength (MPa)	Elongation(%)	Hardness （HB）	comment
142,9	173		1	56,5	
111,6	199,4		1,1	71,8	
92,5	210,5		1,2	74,9	
85,1	220,2		1,3	79,9	AZ91D
63,2	220,1		1,4	80,4	
86,1	221,9		1,3	78,2	
100	180	95	3,3	61	
48	208	107	3,5	69,5	
30	227	114	3,8	76,3	
23	243	125	4,95	83,1	AZ31
14	261	134	5,4	92,5	
26	229	117	4,1	85,6	
200	197,50	80,40	9,90		
160	207,30	81,30	12,40		AZ31
330	190,00	78,00	8,90		
420	185,00	75,00	12,90		
380	190,00	85,00	13,70		
300	195,60	83,10	14,30		AZ31
450	183,00	72,00	11,30		
86	158		1,2	570	
65	180		1,4	660	
50	212		1,6	790	AZ31
320	126		7,2		
178	142		8,7		
96	156		9,5		AZ63B
50	171		11,2		
212	160,07		3,83		
135	192,97		6,5		
108	195,46		6,5		
76	218,3		7,43		AZ91
98	206,76		7,33		
212	181,00		9,20		
140	210,00		18,30		
280	105		8,4		AZ91
118	138		12,3		
115	141		13,5		AZ91
110	156		13,6		
124	137		13,2		

The following relations have been formulated:

$$UTS(grain) := 253.2124234123008 - 0.950646578106493 \cdot grain + 0.003033869649217 \cdot grain^{2} - 0.0000027891247651007 \cdot grain^{3}$$

$$UTS1(grain) := 263.97911244 - 1.37491238 \cdot grain + 0.00740957334 \cdot grain^{2} - 0.0000183087 \cdot grain^{3} + 0.000000017437149 \cdot grain^{4}$$

$$A(grain) := 2.04561825424 + 0.059776211581257 \cdot grain - 0.00015323147316733 \cdot grain^{2} + 0.000000157565241133 8 \cdot grain^{3}$$

$$A1(grin) := 3.40900507916 + 0.00605139273899 \cdot grain + 0.0004008642895 \cdot grain^{2} - 0.000018076877 \cdot grain^{3} + 0.0000000220806786 8 \cdot grain^{4}$$

Fig. 1. Dependencies of tensile strength and relative elongation of grain size (third and fourth degree models)

With the help of specialized software, the aforementioned dependencies were obtained . In Fig. 1 and 2, polynomial approximations of the third and the fourth are presented, on the basis of which a generalized pattern of the grain size relationship was later constructed depending on the tensile strength and the relative elongation. As can be seen from the graph, the dispersion is too large, but the patterns are too high for determinations and can be useful as an initial approximation within the project.

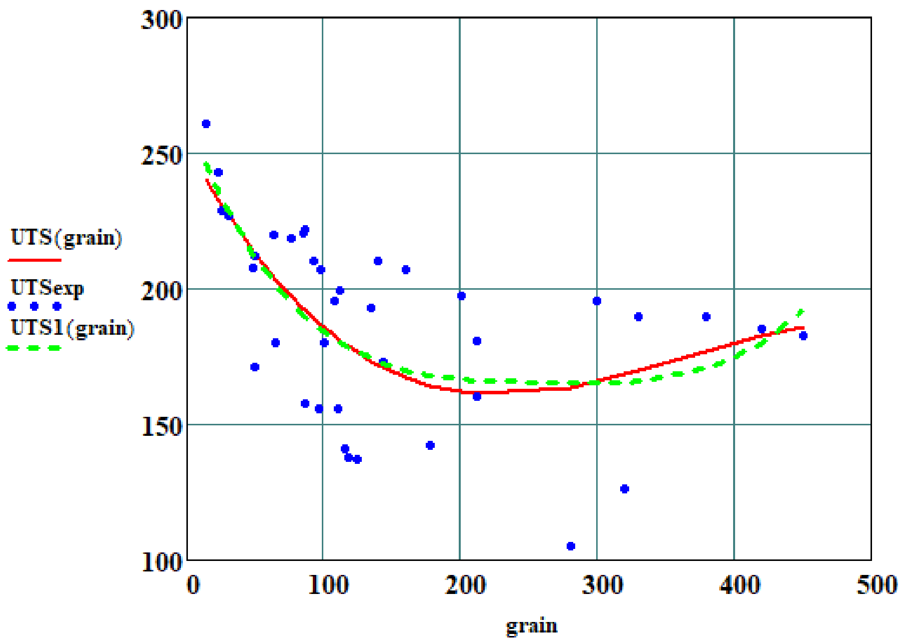


Fig. 2. Approximating dependencies of the tensile strength on the grain size

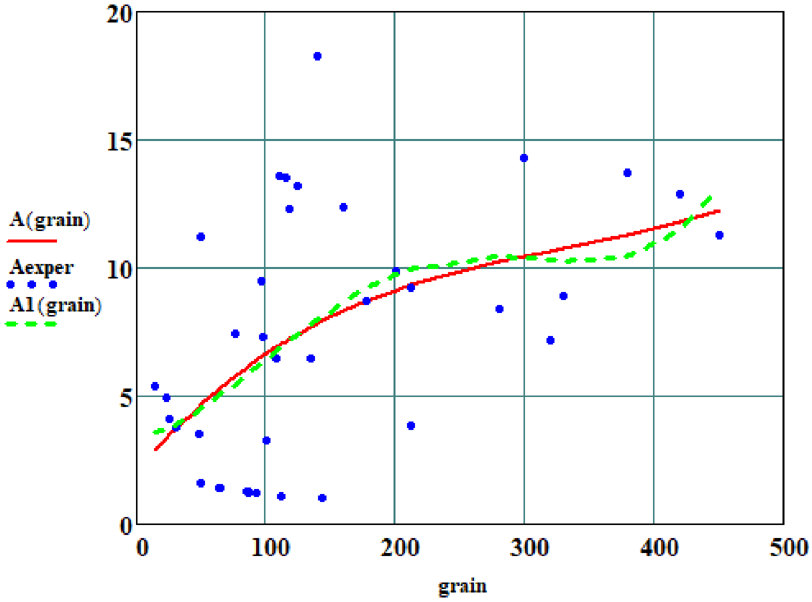


Fig. 3. Aproximating dependencies of the relative elongation on the grain size

grain =

	0
0	14
1	23
2	26
3	30
4	48
5	50
6	50
7	63.2
8	65
9	76
10	85.1
11	86
12	86.1
13	92.5
14	96
15	98
16	100
17	108
18	110
19	111.6
20	115
21	118
22	124
23	135
24	140

UTS(grain) =

	0
0	240.49
1	232.919
2	230.497
3	227.348
4	214.263
5	212.916
6	212.916
7	204.545
8	203.473
9	197.263
10	192.565
11	192.121
12	192.072
13	189.029
14	187.443
15	186.561
16	185.697
17	182.416
18	181.639
19	181.029
20	179.769
21	178.697
22	176.663
23	173.305
24	171.932

A(grain) =

	0
0	2.853
1	3.341
2	3.499
3	3.705
4	4.579
5	4.671
6	4.671
7	5.251
8	5.327
9	5.773
10	6.12
11	6.153
12	6.157
13	6.389
14	6.511
15	6.58
16	6.648
17	6.913
18	6.977
19	7.027
20	7.133
21	7.225
22	7.402
23	7.71
24	7.843

Fig. 4. Numeric values calculated by the models

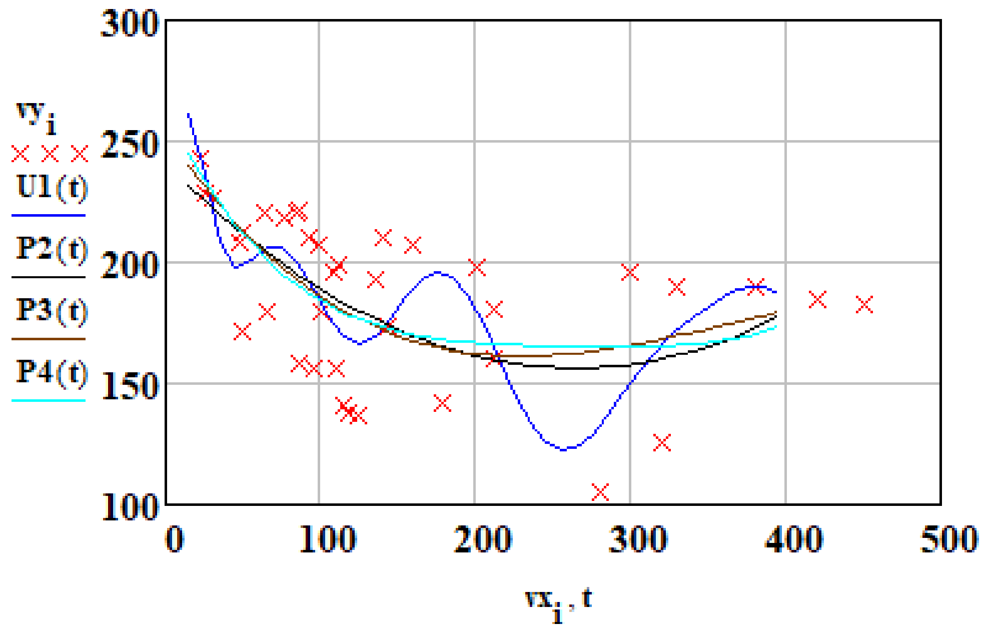


Fig. 5. Interpolation and approximation [dependencies] of the tensile strength on the grain size

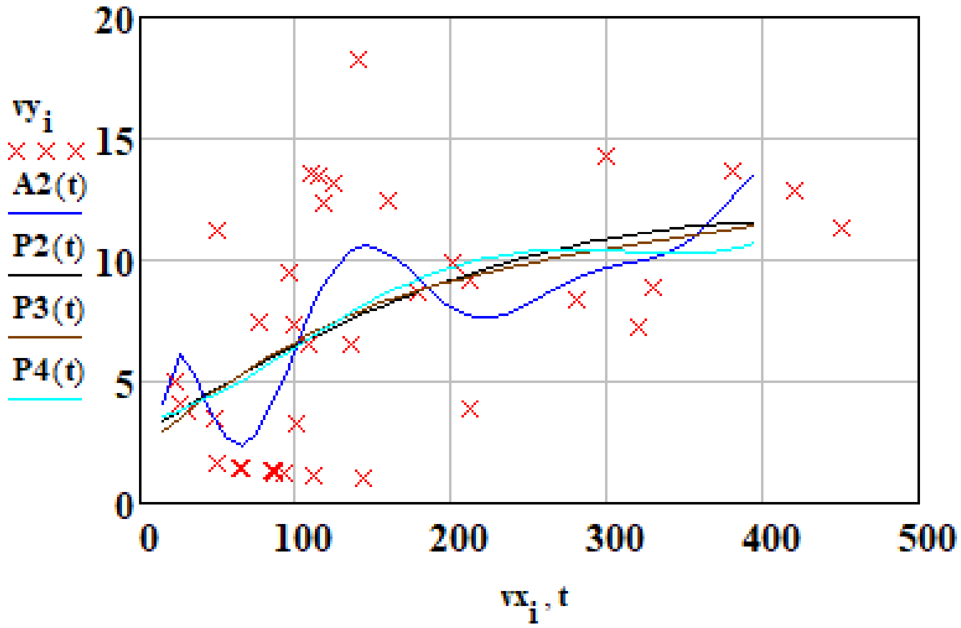


Fig. 6. Interpolation and approximation dependencies of the relative elongation on the grain size

The interpolation dependence of the tensile strength U1(t) on the relative elongation A2(t) shown on Fig.5 and 6 is a demo[nstration] possibility that can be used in the future. Exact values can be determined for these interpolations. They are presented in Fig.7.

t =	U1(t) =	A2(t) =
15	261.213	4.052
25	236.6	6.08
35	208.233	5.268
45	197.971	3.748
55	200.727	2.626
65	205.879	2.333
75	206.177	2.886
85	199.736	4.081
95	188.768	5.626
105	177.306	7.227
115	169.133	8.645
125	166.478	9.72
135	169.546	10.372
145	176.759	10.599
155	185.434	10.456
165	192.624	10.041
175	195.888	9.469
185	193.831	8.856
195	186.334	8.305
205	174.48	7.89
215	160.225	7.657
225	145.926	7.619
235	133.834	7.758
245	125.654	8.034
255	122.264	8.392

Fig. 7. Numeric values of presented interpolations.

According to an expert opinion for a further application, it is suggested to use the data from Fig. 4.

Another possibility is to solve an optimization problem with both tensile strength and relative elongation properties. For this purpose, regression relations were obtained/output in coded units of the grain size in the range [-1; +1].

Coding is done according to the dependencies

$$\mathrm{bio} := \frac{(\mathrm{bmin} + \mathrm{bmax})}{2} \quad w := \mathrm{bmax} - \mathrm{bio} \qquad \mathrm{bkod} := \frac{(b - \mathrm{bio})}{w}$$

Decoding is done using the formula.

$$\mathrm{bdekod} := w \cdot \mathrm{bkod} + \mathrm{bio}$$

The obtained /output models in coded values are as follows

$$\mathbf{d := -1 .. 1}$$

$$\mathbf{UTS(d) := 161.025 + 1.45003 \cdot d + 52.0744 \cdot d^2 - 28.9147 \cdot d^3}$$

$$\mathbf{A(d) := 9.63236 + 3.09638 \cdot d - 2.06551 \cdot d^2 + 1.60349 \cdot d^3}$$

In order to analyze the two properties, normalization is performed for their values. This operation brings them to the same percentage scale.

$$\mathbf{UTS\_n(d) := \frac{(UTS(d) - 161.025) \cdot 100}{(240.56 - 161.025)}}$$

$$\mathbf{A\_n(d) := \frac{(A(d) - 2.8669) \cdot 100}{(12.2667 - 2.8669)}}$$

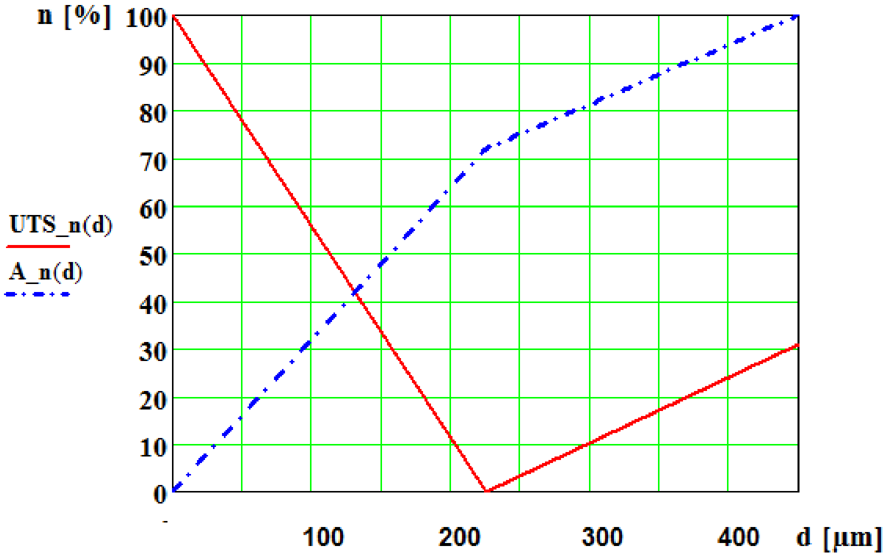


Fig. 8. Normalized values of the explored properties strength and elongation on the grain size

A polynomial model with a very high coefficient of multidimensional correlation is plotted for the yield trend depending on the grain size

$$Re(grain) := 136.8196898482 - 0.676636677879 \cdot grain + 0.0025694186047 \cdot grain^2 - 0.000003086765190765 \cdot grain^3$$

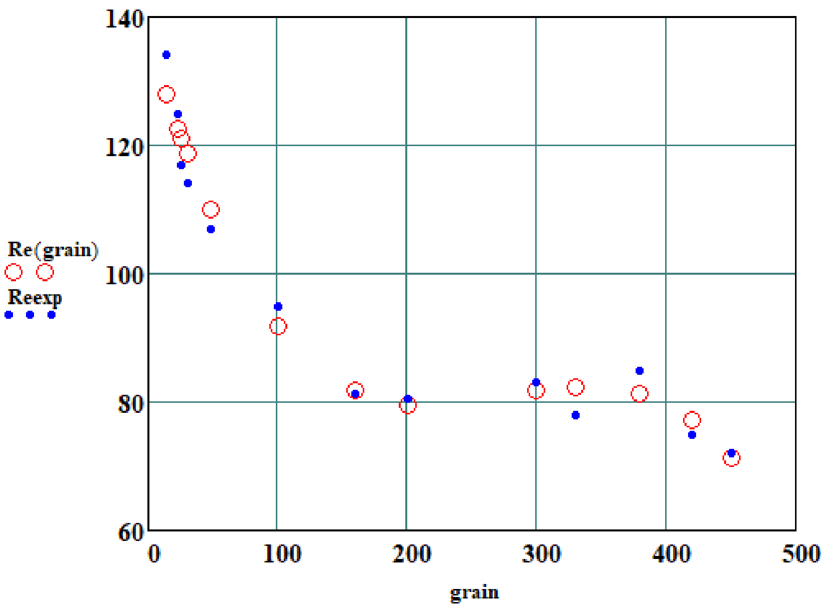


Fig. 9. Graphical interpretation of the relationship between the experimental and predicted values of the yield trend on the grain size

grain =

	0
0	14
1	23
2	26
3	30
4	48
5	100
6	380
7	300
8	160
9	200
10	330
11	420
12	450

Re(grain) =

	0
0	127.842
1	122.579
2	120.91
3	118.75
4	109.92
5	91.763
6	81.345
7	81.734
8	81.692
9	79.575
10	82.41
11	77.185
12	71.359

Reexp =

	0
0	134
1	125
2	117
3	114
4	107
5	95
6	85
7	83.1
8	81.3
9	80.4
10	78
11	75
12	72

Fig. 10. Numeric values calculated by the model and the experimentally determined values of the yield strenth

Fig.11 to Fig.22 show most of the possibilities for displaying the raw data in Table 1.

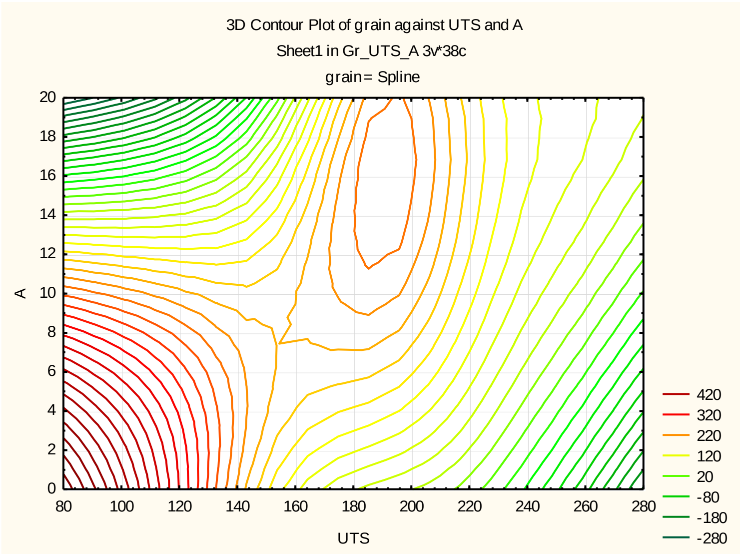


Fig. 11.

The grain size in the mold matrix is a consequence of the processing mode conditions. The corresponding structure determines the properties. Figures 11-13 show different capabilities of tool Statistica to display the independence of the mean grain value and the expected values for strength and relative plasticity. Fig. 11 is a contour image, and Fig. 12 and 13 are three-dimensional images. These graphs are entirely based on the experimental results provided. They do not express a particular pattern.

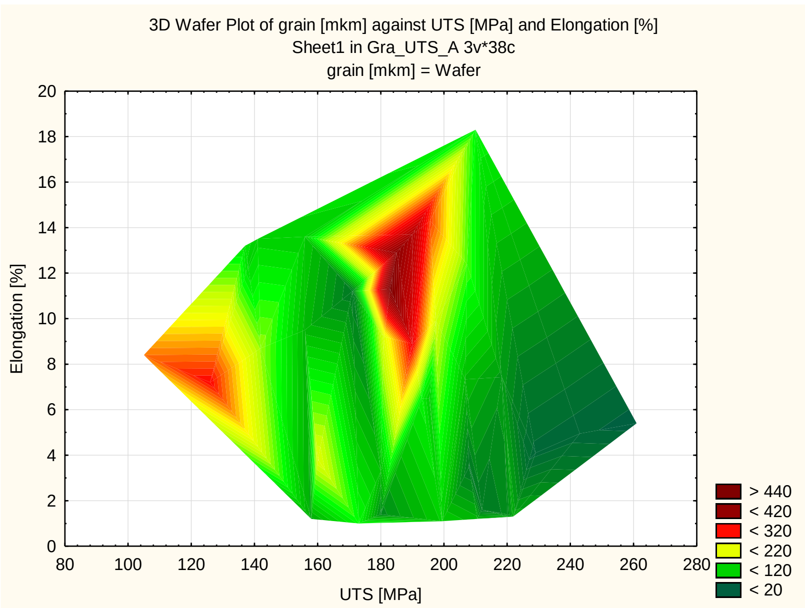


Fig. 12.

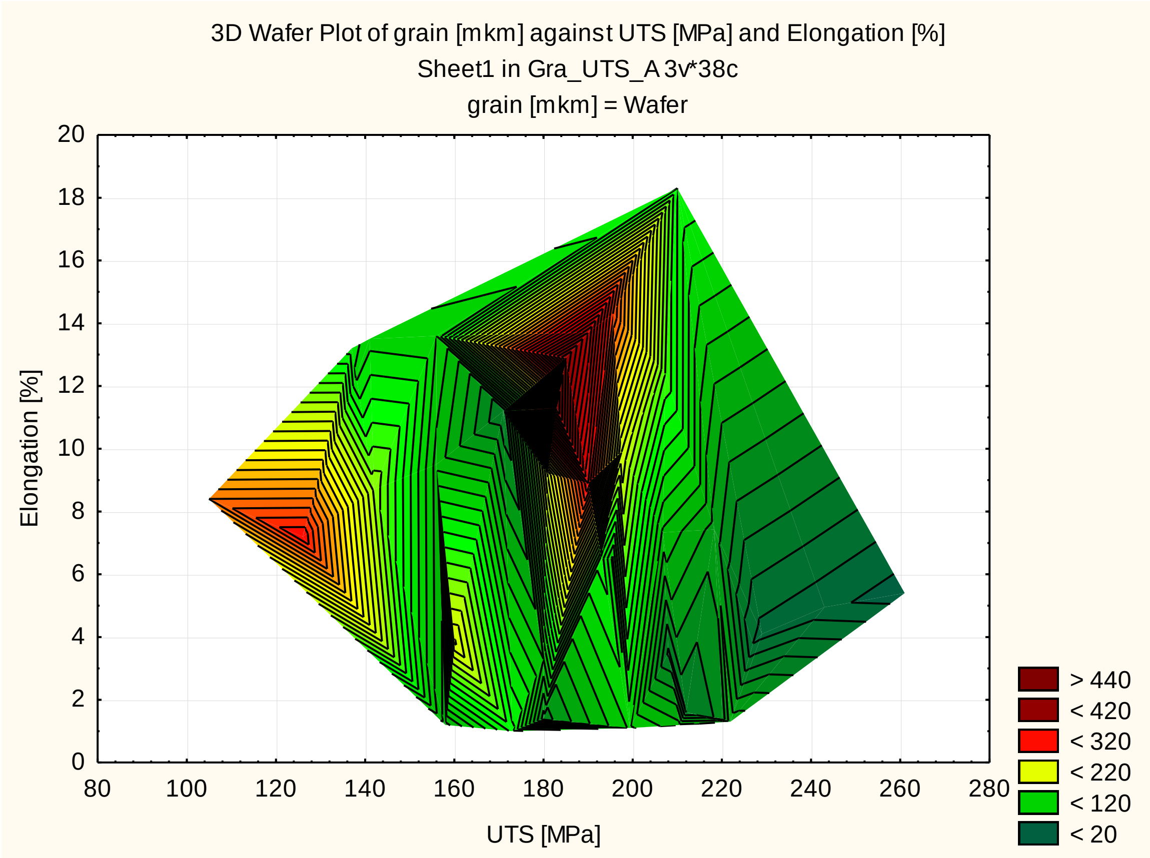

3D Wafer Plot of grain [mkm] against UTS [MPa] and Elongation [%]
Sheet1 in Gra_UTS_A 3v*38c
grain [mkm] = Wafer
Elongation [%]
20
18
16
14
12
10
8
6
4
2
0
80
100
120
140
160
180
200
220
240
260
280
UTS [MPa]
> 440
< 420
< 320
< 220
< 120
< 20

Fig. 13.

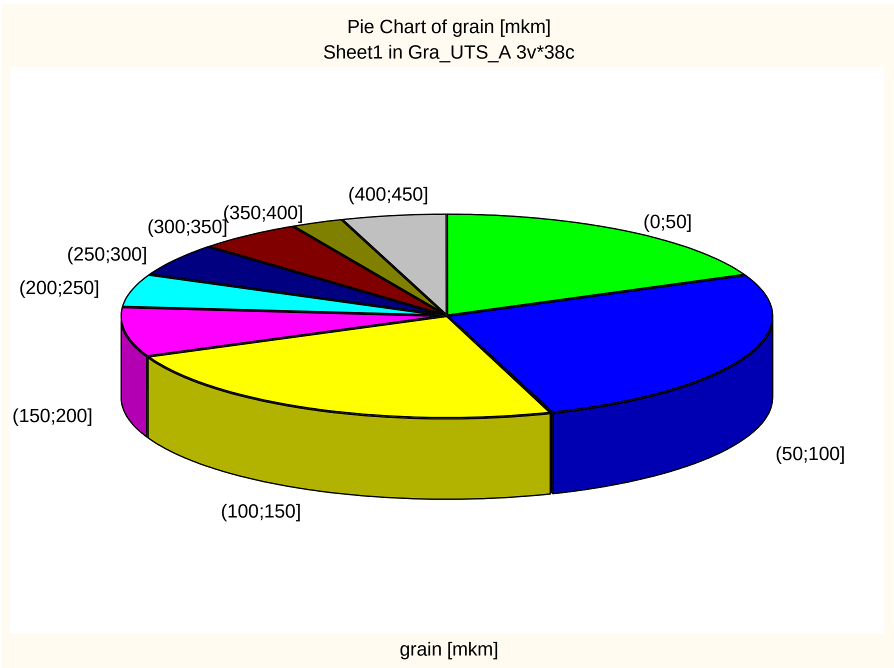

Pie Chart of grain [mkm]
Sheet1 in Gra_UTS_A 3v*38c
(400;450]
(350;400]
(300;350]
(250;300]
(200;250]
(150;200]
(100;150]
(50;100]
(0;50]
grain [mkm]

Fig. 14.

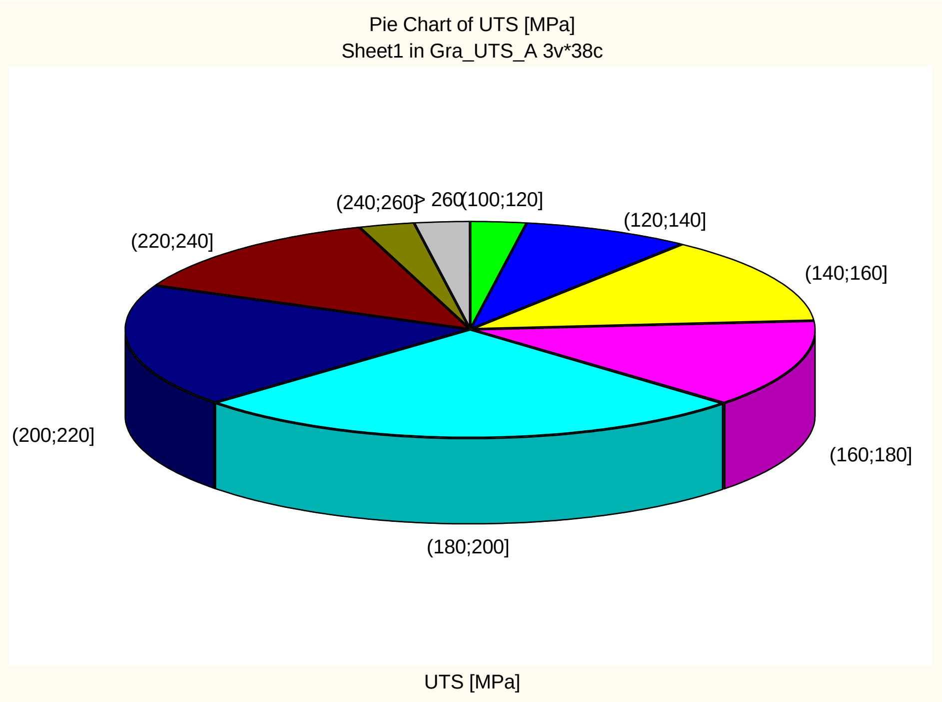


Fig. 15.

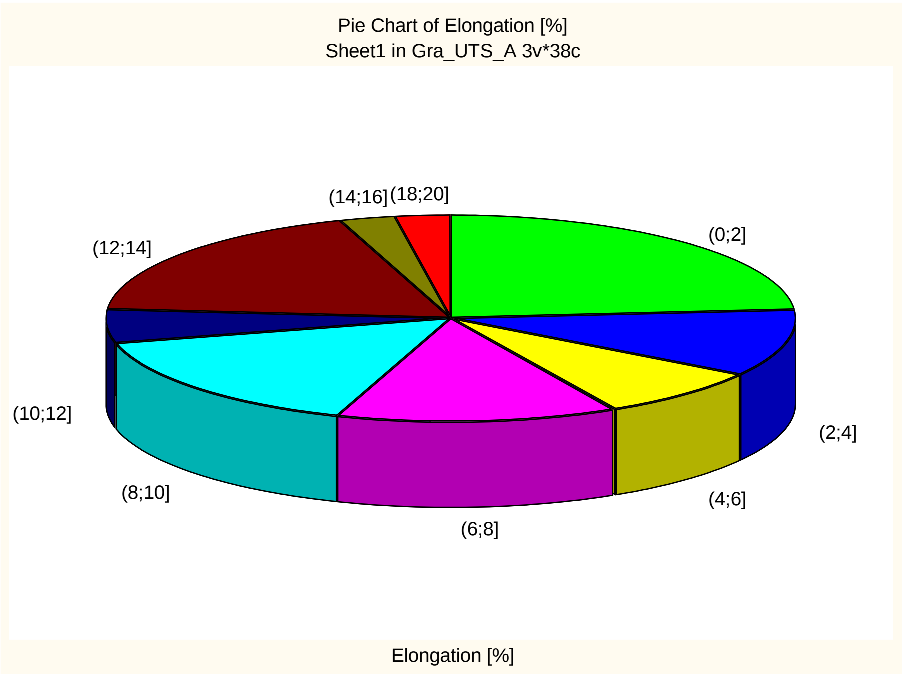


Fig. 14 - 16 show groups of values at specified intervals, respectively, for the grain size, the strength and the relative elongation. This is a direct representation of the table data for each type of the parameters. Fig. 17 shows the three groups of parameters in total, with the observation number on the abscissa axis, and on the ordinate axis the value of the parameter in a common scale of the different dimensions.

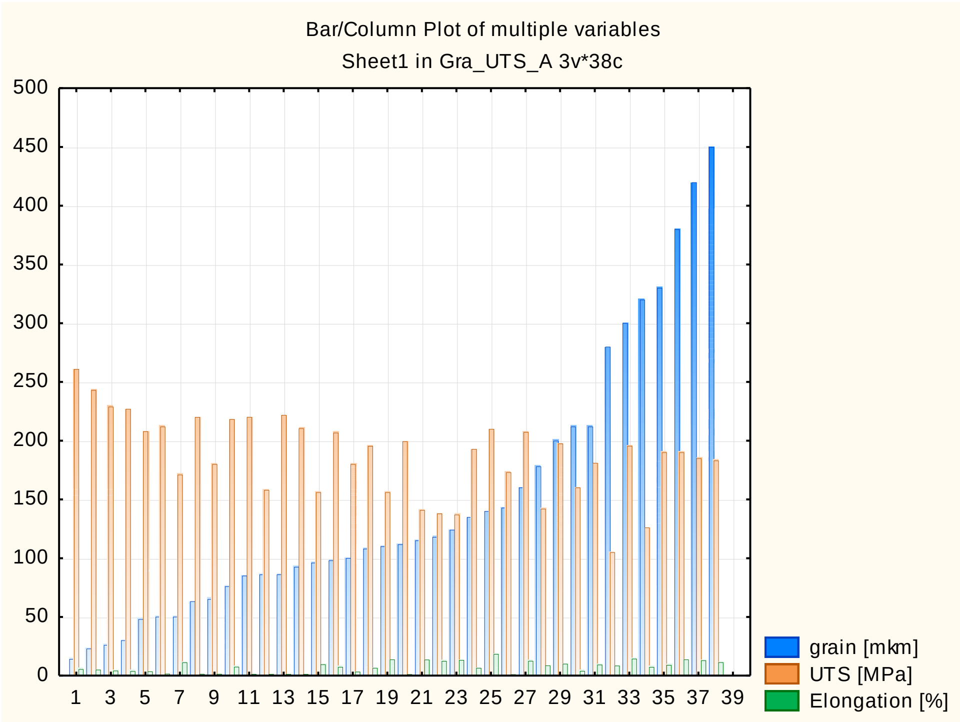


Fig. 17.

Fig. 18 and 19 present the tabulated data for the strength and the relative elongation as dependent on the grain size. Package Statistica can determine which values of the ones presented are of very large scattering. This can be accounted for by the represented figures respectively. These values can be excluded in the modeling process and thus the model's importance will be improved. Excluding the values is for those with the greatest deviation from the initial approximation, and this exclusion is done symmetrically to this approximation.

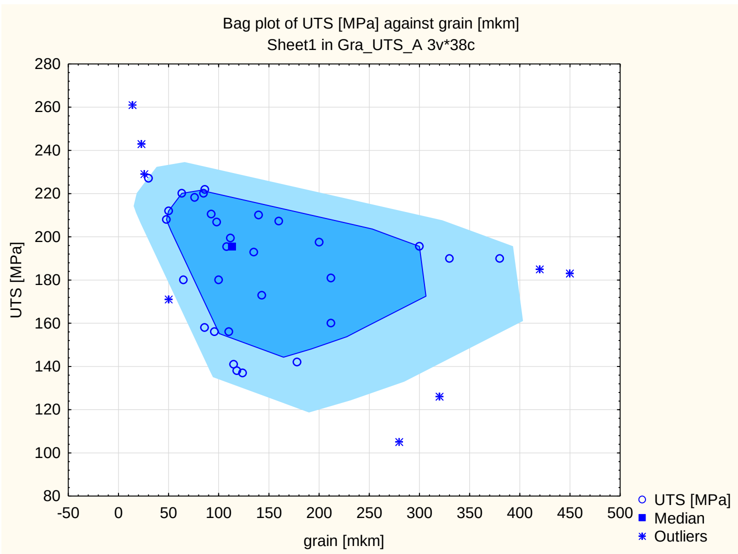


Fig. 18.

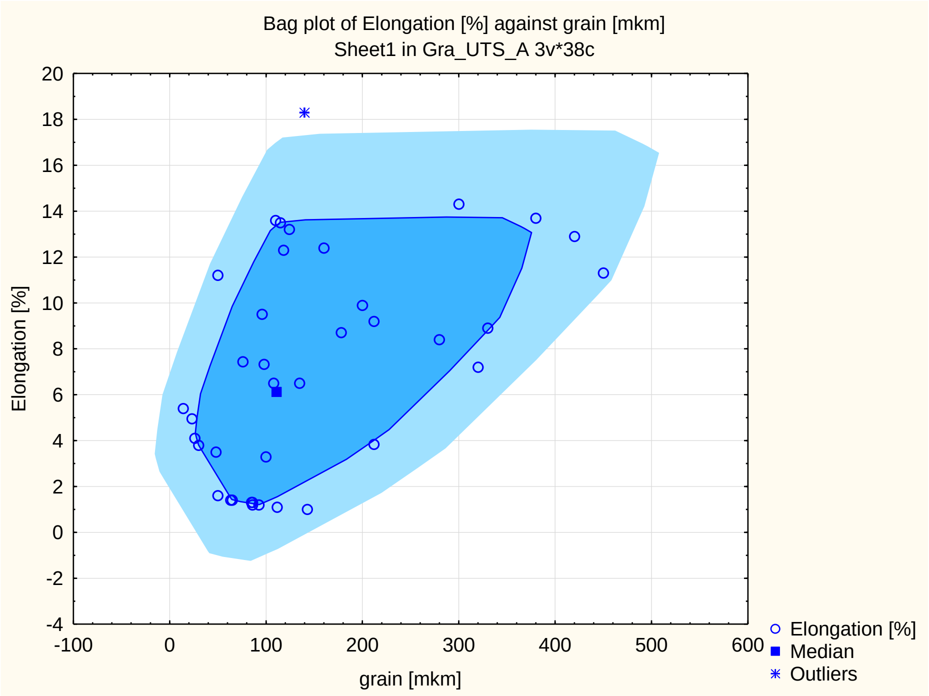


Fig. 19.

The table shows the characteristics of the best approximations obtained with neural models among 2000 analyzed networks. This is an opportunity for the Statistica package. In Fig. 20 shows the comparison of five networks between experimental and modeled values. The Statistica package allows for a selected approximation to create a code that can later be used for embedding into software.

Summary of active networks (Sheet1 in Gr_UTS)											
Index	Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 1-3-1	0,659207	0,499621	0,660885	351,9790	493,0205	261,2349	BFGS 29	SOS	Logistic	Logistic
2	MLP 1-2-1	0,652393	0,507376	0,689405	357,7484	486,2819	251,6479	BFGS 15	SOS	Tanh	Logistic
3	MLP 1-5-1	0,619192	0,553802	0,659930	394,2977	451,2450	308,4738	BFGS 4	SOS	Tanh	Logistic
4	MLP 1-2-1	0,659019	0,511414	0,679721	352,2023	487,7195	264,8800	BFGS 34	SOS	Logistic	Tanh
5	MLP 1-3-1	0,659045	0,515058	0,679060	352,0528	487,3959	267,2606	BFGS 31	SOS	Logistic	Logistic

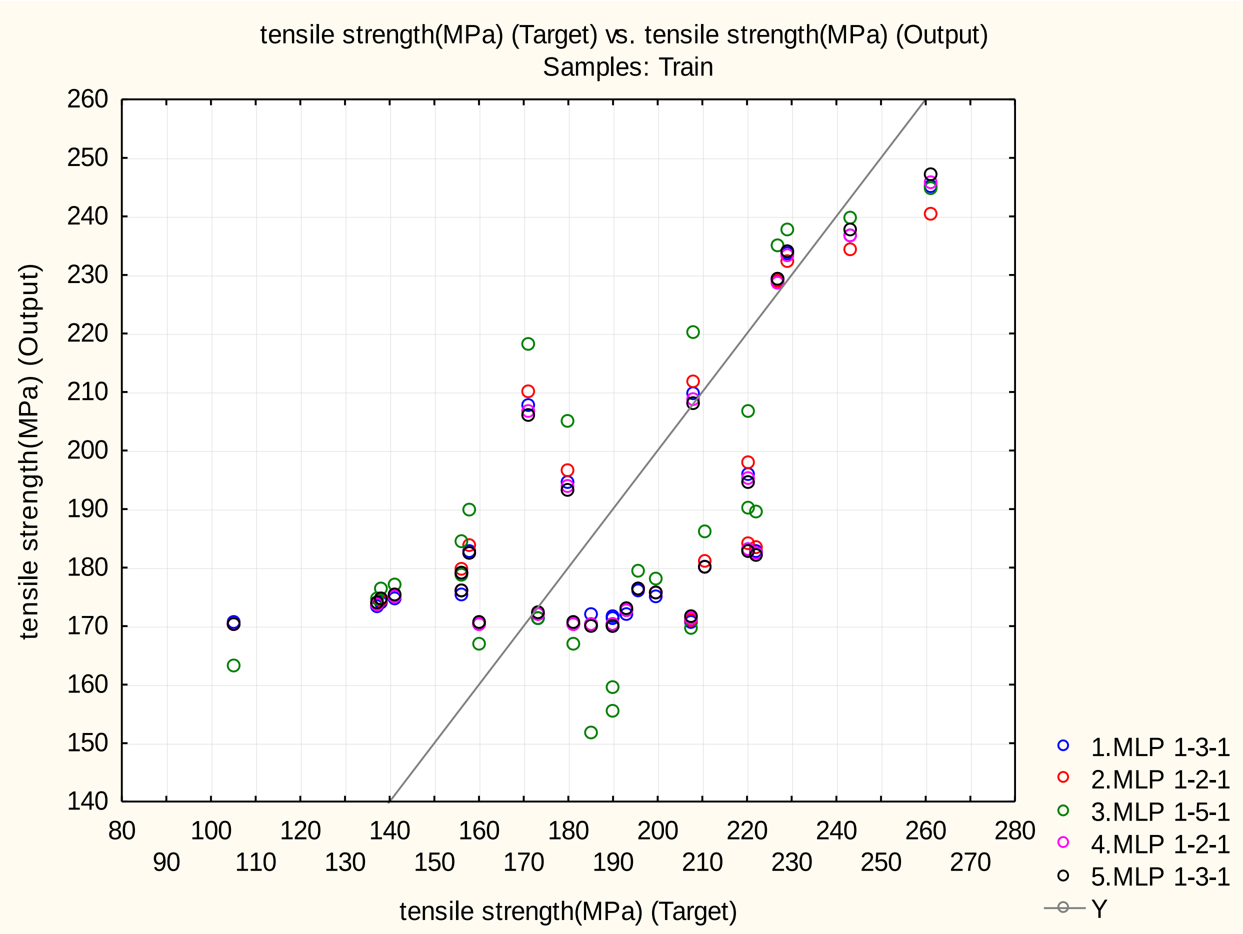


Fig. 20.

In the table, the experimental strength observations are compared to the five obtained models.

Case name	Predictions spreadsheet for tensile strength(MPa) (Sheet1 in Gr_UTS) Samples: Train					
	tensile strength(MPa) Target	tensile strength(MPa) - Output 1. MLP 1-3-1	tensile strength(MPa) - Output 2. MLP 1-2-1	tensile strength(MPa) - Output 3. MLP 1-5-1	tensile strength(MPa) - Output 4. MLP 1-2-1	tensile strength(MPa) - Output 5. MLP 1-3-1
2	261,0000	245,1128	240,4375	244,7512	245,9238	247,1279
3	243,0000	236,7967	234,5246	239,7705	236,7593	237,6811
4	229,0000	233,6752	232,2201	237,8340	233,3864	234,1214
5	227,0000	229,3370	228,9094	235,0430	228,7663	229,2117
6	208,0000	209,6608	211,9309	220,1630	208,6751	208,0039
8	171,0000	207,6507	209,9993	218,3705	206,6868	205,9548
9	220,1000	196,0144	198,1466	206,6555	195,3410	194,5358
10	180,0000	194,6618	196,7045	205,1262	194,0376	193,2564
12	220,2000	183,1086	184,1045	190,3486	183,0164	182,7077
13	158,0000	182,7258	183,6856	189,8011	182,6547	182,3690
14	221,9000	182,6839	183,6398	189,7409	182,6151	182,3319
15	210,5000	180,2424	180,9819	186,1471	180,3136	180,1850
16	156,0000	179,0918	179,7416	184,3923	179,2325	179,1804
19	195,4600	175,9673	176,4365	179,4093	176,3074	176,4663
20	156,0000	175,5517	176,0060	178,7200	175,9192	176,1054
21	199,4000	175,2379	175,6827	178,1947	175,6262	175,8327
22	141,0000	174,6224	175,0532	177,1521	175,0514	175,2966

23	138,0000	174,1331	174,5574	176,3102	174,5942	174,8689
24	137,0000	173,2886	173,7120	174,8257	173,8035	174,1249
25	192,9700	172,1234	172,5673	172,6860	172,7024	173,0741
27	173,0000	171,5255	171,9875	171,5182	172,1253	172,5113
28	207,3000	170,7094	171,1863	169,7244	171,2925	171,6687
31	160,0700	170,2007	170,4176	166,8979	170,4050	170,6322
32	181,0000	170,2007	170,4176	166,8979	170,4050	170,6322
33	105,0000	170,7509	170,3002	163,3073	170,2377	170,2902
36	190,0000	171,2235	170,2918	159,6458	170,2225	170,1930
37	190,0000	171,6389	170,2905	155,3821	170,2197	170,1358
38	185,0000	171,9239	170,2904	151,7703	170,2192	170,1054

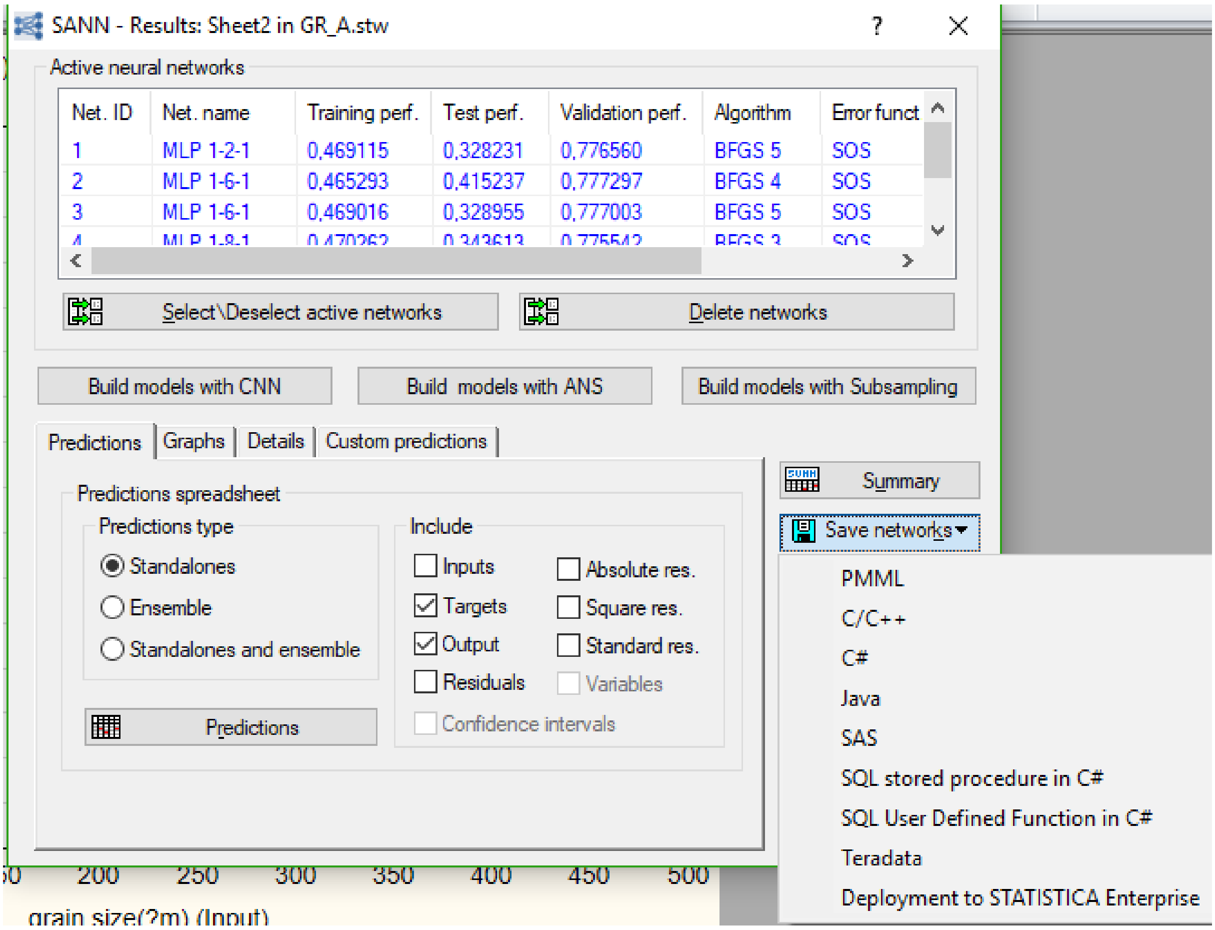
The product allows the network to be stored in a code for future use. Below is a sample code selected for a given network.

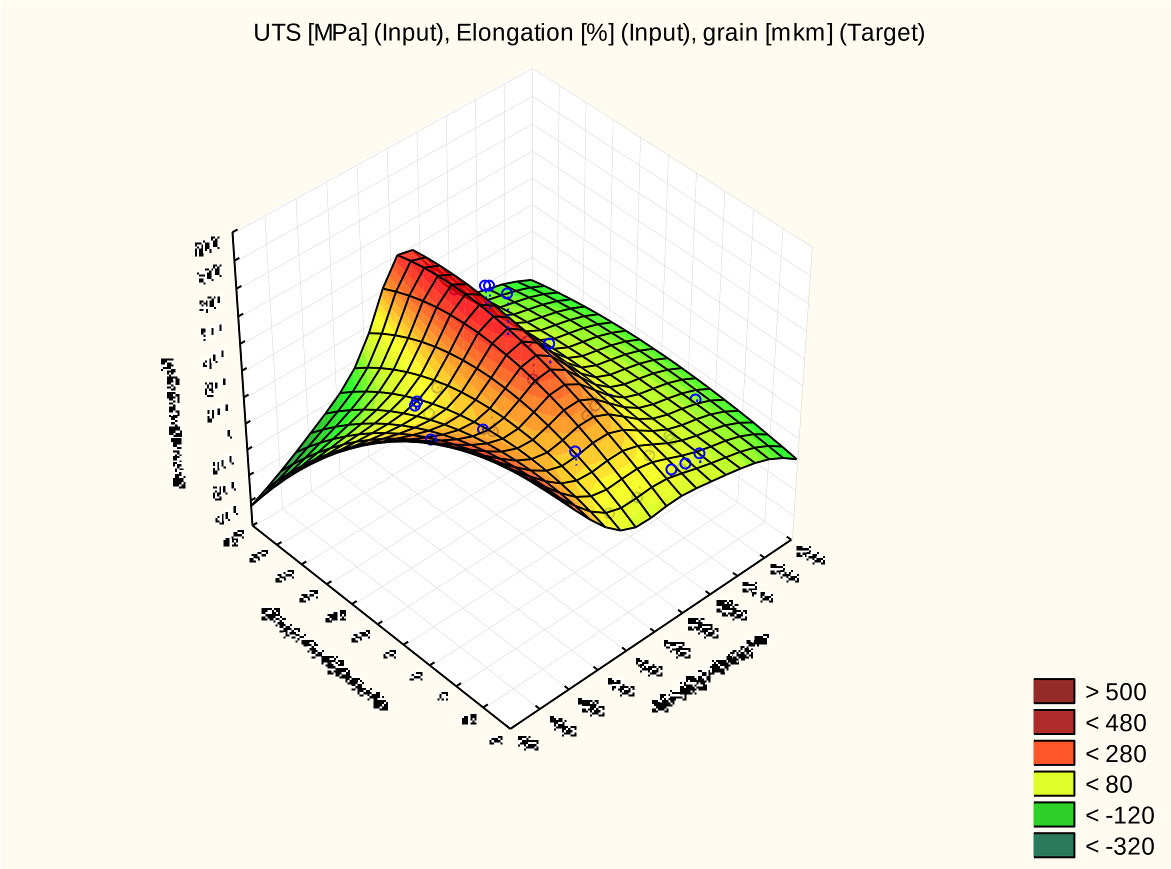
```
//Analysis Type - Regression
#include <stdio.h>
#include <conio.h>
#include <math.h>
#include <stdlib.h>

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_input_hidden_weights[3][1]=
{
 {-1.22080769298642e+001 },
 {1.79676014160609e-001 },
 {-1.46264349811217e+000 }
};

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_hidden_bias[3]={ -1.02738121460061e+000, -4.35761042008986e-001, -3.63720686592803e+000 };

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_hidden_output_wts[1][3]=
{
 {9.95764555530247e+000, -8.93541475553883e-002, -8.46173922682036e+000 }
};

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_output_bias[1]={ -1.95680571951655e-001 };

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_max_input[1]={ 4.20000000000000e+002 };

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_min_input[1]={ 1.40000000000000e+001 };

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_max_target[1]={ 2.61000000000000e+002 };

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_min_target[1]={ 1.05000000000000e+002 };

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_input[1];
double Sheet1_in_Gr_UTS_1_MLP_1_3_1_hidden[3];
double Sheet1_in_Gr_UTS_1_MLP_1_3_1_output[1];

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_MeanInputs[1]={ 1.32978571428571e+002 };

void Sheet1_in_Gr_UTS_1_MLP_1_3_1_ScaleInputs(double* input, double minimum, double maximum, int size)
{
 double delta;
 long i;
```

```
 for(i=0; i<size; i++)
 {
            delta = (maximum-minimum)/(Sheet1_in_Gr_UTS_1_MLP_1_3_1_max_input[i]-
Sheet1_in_Gr_UTS_1_MLP_1_3_1_min_input[i]);
            input[i] = minimum - delta*Sheet1_in_Gr_UTS_1_MLP_1_3_1_min_input[i]+ delta*input[i];
 }
}

void Sheet1_in_Gr_UTS_1_MLP_1_3_1_UnscaleTargets(double* output, double minimum, double maximum,
int size)
{
  double delta;
  long i;
  for(i=0; i<size; i++)
  {
    delta = (maximum-minimum)/(Sheet1_in_Gr_UTS_1_MLP_1_3_1_max_target[i]-
Sheet1_in_Gr_UTS_1_MLP_1_3_1_min_target[i]);
    output[i] = (output[i] - minimum + delta*Sheet1_in_Gr_UTS_1_MLP_1_3_1_min_target[i])/delta;
   }
}

double Sheet1_in_Gr_UTS_1_MLP_1_3_1_logistic(double x)
{
  if(x > 100.0) x = 1.0;
  else if (x < -100.0) x = 0.0;
  else x = 1.0/(1.0+exp(-x));
  return x;
}

void Sheet1_in_Gr_UTS_1_MLP_1_3_1_ComputeFeedForwardSignals(double* MAT_INOUT,double*
V_IN,double* V_OUT, double* V_BIAS,int size1,int size2,int layer)
{
  int row,col;
  for(row=0;row < size2; row++)
    {
      V_OUT[row]=0.0;
      for(col=0;col<size1;col++)V_OUT[row]+=(*(MAT_INOUT+(row*size1)+col)*V_IN[col]);
      V_OUT[row]+=V_BIAS[row];
      if(layer==0) V_OUT[row] = Sheet1_in_Gr_UTS_1_MLP_1_3_1_logistic(V_OUT[row]);
      if(layer==1) V_OUT[row] = Sheet1_in_Gr_UTS_1_MLP_1_3_1_logistic(V_OUT[row]);
   }
}

void Sheet1_in_Gr_UTS_1_MLP_1_3_1_RunNeuralNet_Regression ()
{

Sheet1_in_Gr_UTS_1_MLP_1_3_1_ComputeFeedForwardSignals((double*)Sheet1_in_Gr_UTS_1_MLP_1_3_
1_input_hidden_weights,Sheet1_in_Gr_UTS_1_MLP_1_3_1_input,Sheet1_in_Gr_UTS_1_MLP_1_3_1_hidden
,Sheet1_in_Gr_UTS_1_MLP_1_3_1_hidden_bias,1, 3,0);

Sheet1_in_Gr_UTS_1_MLP_1_3_1_ComputeFeedForwardSignals((double*)Sheet1_in_Gr_UTS_1_MLP_1_3_
1_hidden_output_wts,Sheet1_in_Gr_UTS_1_MLP_1_3_1_hidden,Sheet1_in_Gr_UTS_1_MLP_1_3_1_output,S
heet1_in_Gr_UTS_1_MLP_1_3_1_output_bias,3, 1,1);
}

int main()
{
  int cont_inps;
  int i=0;
  int keyin=1;
```

```
 while(1)
 {
          printf("\n%s\n","Enter values for Continuous inputs (To skip a continuous input please enter -9999)");
          printf("%s","Cont. Input-0(grain size(?m)): ");
          scanf("%lg",&Sheet1_in_Gr_UTS_1_MLP_1_3_1_input[0]);
          for(cont_inps=0;cont_inps<1;cont_inps++)
          {
   //Substitution of missing continuous variables
   if(Sheet1_in_Gr_UTS_1_MLP_1_3_1_input[cont_inps] == -9999)

Sheet1_in_Gr_UTS_1_MLP_1_3_1_input[cont_inps]=Sheet1_in_Gr_UTS_1_MLP_1_3_1_MeanInputs[cont_in
ps];
          }
   Sheet1_in_Gr_UTS_1_MLP_1_3_1_ScaleInputs(Sheet1_in_Gr_UTS_1_MLP_1_3_1_input,0,1,1);
          Sheet1_in_Gr_UTS_1_MLP_1_3_1_RunNeuralNet_Regression();
          Sheet1_in_Gr_UTS_1_MLP_1_3_1_UnscaleTargets(Sheet1_in_Gr_UTS_1_MLP_1_3_1_output,0,1,1)
;
          printf("\n%s%.14e","Predicted Output of tensile strength(MPa) =
",Sheet1_in_Gr_UTS_1_MLP_1_3_1_output[0]);
          printf("\n\n%s\n","Press any key to make another prediction or enter 0 to quit the program.");
          keyin=getch();
          if(keyin==48)break;
 }
          return 0;
}
```

The figure shows the program codes in which the program can record the neural model. What needs to be done is the user to indicate an approximation that suits him / her.





The selected model can be visualized. The visualization can track the difference between model values and experimental values. Below are various analyzes that the Statistica package performs. Analyses can provide the expert with an assessment of the selected model.

Statistics	Predictions statistics (Sheet1 in Gra_UTS_A) Target: grain [mkm]
	3.MLP 2-6-1
Minimum prediction (Train)	26,702
Maximum prediction (Train)	445,367
Minimum prediction (Test)	30,925
Maximum prediction (Test)	270,279
Minimum prediction (Validation)	68,451
Maximum prediction (Validation)	450,000
Minimum prediction (Missing)	
Maximum prediction (Missing)	
Minimum residual (Train)	-65,367
Maximum residual (Train)	49,660
Minimum residual (Test)	-7,925

Maximum residual (Test)	49,721
Minimum residual (Validation)	-150,000
Maximum residual (Validation)	16,649
Minimum standard residual (Train)	-3,923
Maximum standard residual (Train)	2,980
Minimum standard residual (Test)	-0,354
Maximum standard residual (Test)	2,223
Minimum standard residual (Validation)	-2,762
Maximum standard residual (Validation)	0,307

	Data statistics (Sheet1 in Gra_UTS_A)		
Samples	UTS [MPa] Input	Elongation [%] Input	grain [mkm] Target
Minimum (Train)	105,0000	1,10000	14,0000
Maximum (Train)	261,0000	18,30000	450,0000
Mean (Train)	185,9357	7,69964	151,5429
Standard deviation (Train)	35,2359	4,91550	118,3861
Minimum (Test)	126,0000	1,00000	23,0000
Maximum (Test)	243,0000	7,20000	320,0000
Mean (Test)	188,4200	3,57000	129,8200
Standard deviation (Test)	45,2425	2,57235	115,1928
Minimum (Validation)	171,0000	1,30000	50,0000
Maximum (Validation)	220,2000	14,30000	300,0000
Mean (Validation)	195,9520	8,64000	148,6200
Standard deviation (Validation)	46,4921	4,86237	135,2162
Minimum (Missing)			
Maximum (Missing)			
Mean (Missing)			
Std (Missing)			
Minimum (Overall)	105,0000	1,00000	14,0000
Maximum (Overall)	261,0000	18,30000	450,0000
Mean (Overall)	187,5805	7,28000	148,3000
Standard deviation (Overall)	34,2301	4,82246	113,2396

	Correlation coefficients (Sheet1 in Gra_UTS_A)		
	grain [mkm] Train	grain [mkm] Test	grain [mkm] Validation
3.MLP 2-6-1	0,979926	0,989246	0,964357

Effect	Parameter Estimates (Sheet1 in Gra_UTS_A) Sigma-restricted parameterization									
	grain [mkm] Param.	grain [mkm] Std.Err	grain [mkm] t	grain [mkm] p	-95,00% Cnf. Lmt	+95,00% Cnf.Lmt	grain [mkm] Beta (?)	grain [mkm] St.Err.?	-95,00% Cnf. Lmt	+95,00% Cnf.Lmt
Intercept	311,856	500,463	0,62314	0,53761	707,55	1331,				
UTS [MPa]	0,2080	4,7425	0,04386	0,96528	-9,452	9,868	0,06288	1,43355	-2,85	2,982
UTS [MPa]^2	-0,0078	0,0116	-0,6733	0,50559	-0,031	0,016	-0,8672	1,28800	-3,49	1,756
Elongation [%]	-25,659	28,1819	-0,9104	0,36937	83,064	31,74	-1,0927	1,20016	-3,53	1,351
Elongation [%]^2	-0,8080	0,7354	-1,0987	0,28009	-2,306	0,690	-0,5654	0,51462	-1,61	0,482
UTS [MPa]*Elongation [%]	0,2510	0,1390	1,80545	0,08042	-0,032	0,534	1,93887	1,07389	-0,24	4,126

CONCLUSION

This generalized research is devoted to numerical approaches to identify effective solutions in the field of magnesium alloys. Approaches to obtain the optimal combination of chemical composition and heat treatment to achieve certain properties are of fundamental importance for the realization of an effective project. They are at the basis to design or improve new alloys and the associated with them costs.

The research of the genome of the material in this generalization of publications, relies entirely on statistical processing and it is aimed at creating opportunities for predicting the mechanical parameters as a function of the chemical composition and the heat treatment parameters taking into account the relevant boundary conditions.

To determine how to deal with the issue of improving the properties of the chemical composition and processing through the methods of modeling and optimization, in [1] there were considered methods for preparation of alloys. Multiparametric regression analysis is one of the most popular methods for data processing. It has been applied successfully in the research of a set of relations in the metallurgical industry. Due to the nature of each statistical analysis, the coefficients of the restrictions caused by the regression analysis are known only approximately.

In this respect, competing metallurgical companies develop software tools and approaches, supporting their work in finding rational solutions on the final properties of the products. It is impressive in the analysis of the bibliography about the simultaneous improvement of the strength and the ductility that alloying or processing parameters do not guarantee much data. This fact in the subsequent studies should be considered for the creation of mathematical models to analyze the objects for the observed metallurgical process. This is an important motive in the implementation of future targets for research relevant to a new generation of steels.

Automated design of the composition and the procedures of processing ferritic steels of all generations is possible to realize with modern computing resources. The innovation of these technologies for the production of new generations of steel and also the widespread use of modern materials, are important for the economic development and for the ways to increase security, too.

The approbated approach is realized at the methodical level.

The Creation of nonlinear analytical models for control of the properties, depending on the chemical composition in the heat-treated condition. For this purpose there has been developed a procedure and software for analysis of the research parameters;

Multicriteria optimization realizes the possibility to achieve a compromise between characteristics of contradictory trends.

Analysis and optimization of selected quality indicators

The first contribution to the 'MGI' is adaptation of the method of shifting constraints for the purpose of multicriteria optimization.

Fig. presents a sample surface of the response for changing the quality indicator due to depending on the values of the technological inputs .

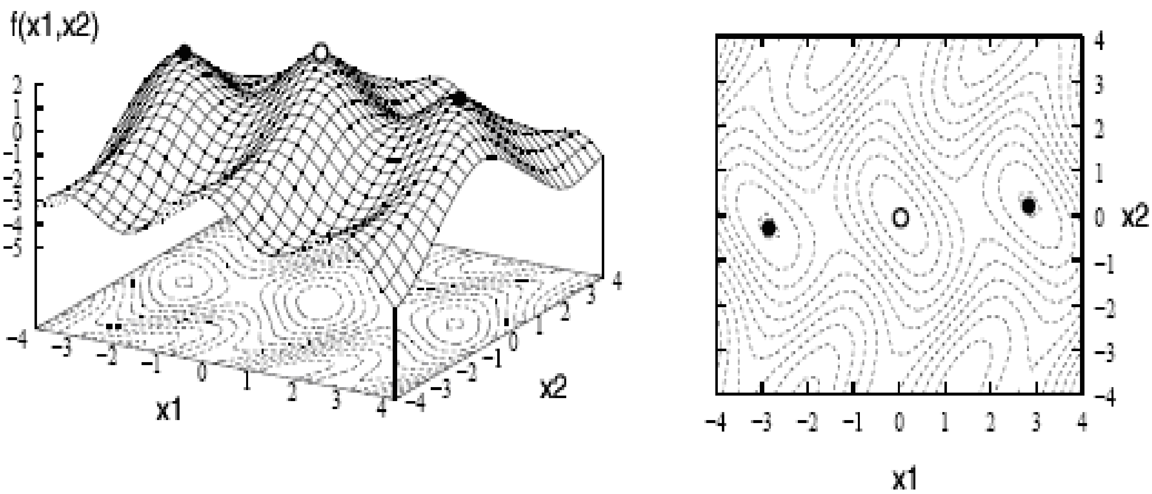


Fig.Graphical interpretation of single-criteria optimization problem with two factors of change.

The usual practice analyses such surfaces graphically via contour diagrams determined by equilevel lines. Thus it is possible to determine graphically coordinates of values for technological parameters with local or global maxima or minima of the goal parameter.

The scalarization of the problem for MKVR passes through two stages:

- Making criteria dimensionless values (thus making them comparable);
- Constructing a generalizing function /filter/.

The general scheme of the approach and the algorithm of this a priori approach is presented in Material Science area.

A single- criteria problem is solved unifying criteria according to a determined dependency on the basis of which a non-dominated solution is obtained.

APPLICATION

Essence and Mathematical Formalism to Manage Quality of Casting Processes of Magnesium Alloys

Part 1 / Defining the Problem /

The technological processes and combinations of their parameters, causing defects depending on the number of the explored quantities, are subdivided into single-criterion and multi-criteria.

The single-criterion influences of technological factors on the goal function examines one quality parameter associated with one defect. By examining a complex of properties from the same input parameters, it is possible to determine that combination of input parameters that provide exactly defined output parameter requirements.

From the set of defined optimally effective solutions it is possible to determine just one (most advantageous) associated with lower energy or materials consumption.

In this presentation, the essence, ideas, and mathematical background of problems of production quality management are developed. These principles are universal in all processes, but the problems in the present material are oriented to magnesium alloys treated by foundry processes.

The object of the study is magnesium alloys chosen because of their valuable properties, which is why they find specific applications. The table lists the applications of specific alloys.

Table 1. 2 - List of common Mg alloys and their applications

Name	Composition (Balance Mg, wt%)	Example Uses	Ref
AZ31	3% Al-1% Zn-0.20%Mn	Aircraft fuselage, cell phones, laptops	[7], [20]
AZ91	9% Al- 0.7 % Zn, 0.13 % Mn	Door mirror brackets, valve and cam covers, die casting	[9], [20]
AM50	5% Al- 0.13 % Mn trace Si	Steering wheel arm, seats	[9]
AM60	6% Al- 0.13 % Mn	Car seat frames, steering wheel, inlet manifolds	[9][20]
ZE41	4% Zn – 1 % Nd	Ballistics, aircraft parts	[9]
QE22	2% Ag – 2% Nd	Aerospace	[21]
ZK 60	6% Zn - <1 % Zr	Military components, tent poles, sports equipment	[9]
WE 43	4.3 % Y – 3 % RE – 0.4 % Zr	Helicopter transmission, race car	[22], [23], [24]

Valuable properties arise when compared to similar widespread materials. This is done on the graph when comparing magnesium with aluminum and iron.

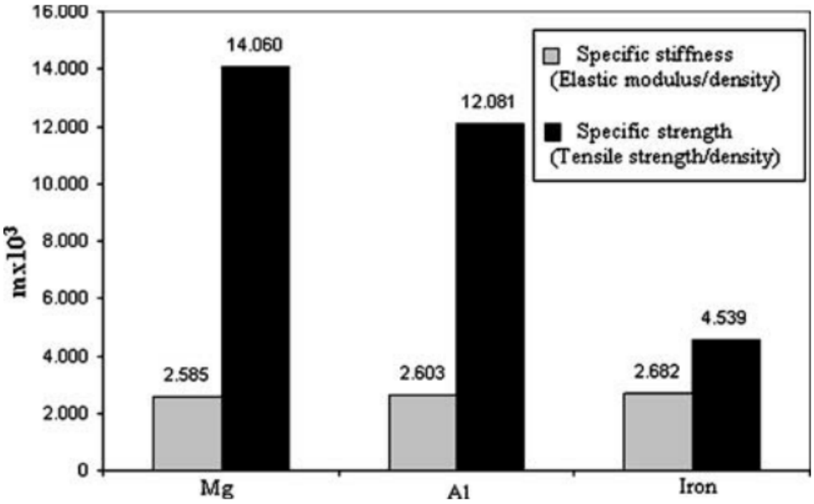


Figure 2- 1. Comparison of basic structural properties of magnesium with aluminum and iron [6].

[6] M. K. Kulekci, Magnesium and its alloys applications in automotive industry, The International Journal of Advanced Manufacturing Technology, vol. 39, no. 9-10 (2008) 851-865

Applications of magnesium alloys are performed by two types of blanks: cast by different methods and plastic deformed by different methods.

The figure shows the dependence of the properties on these two separate types of blanks. In cast alloys there is a more pronounced contradiction between strength and plasticity, which necessitates solving multi-criteria optimization problems.

With this optimization, it is possible to solve a compromise between both criteria in terms of chemical composition, casting process and heat treatment

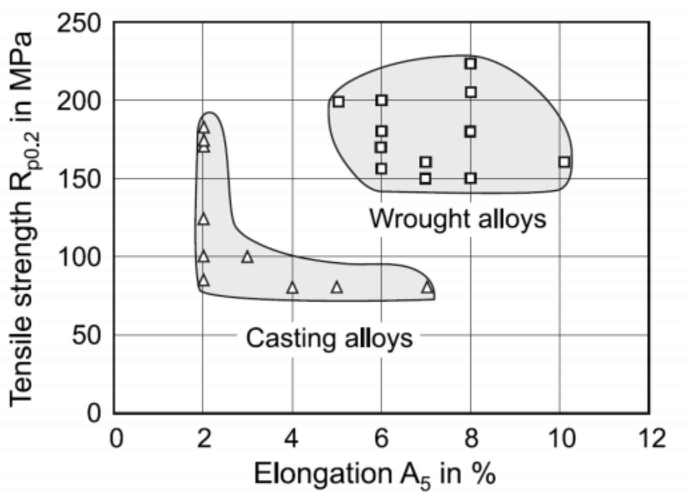
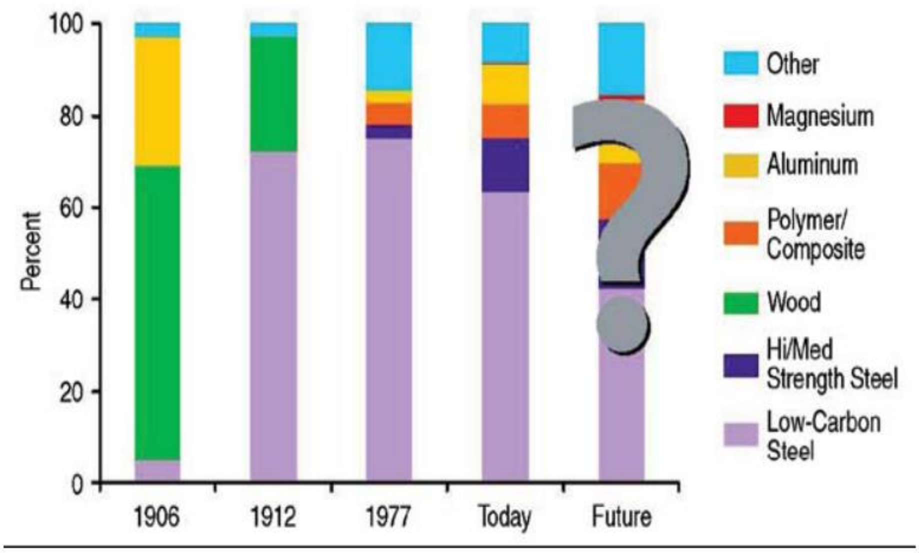


Figure 9. Comparison of cast and wrought alloys [77]

According to a research, magnesium alloys will continue to be important in the future, both in the automotive and aerospace industries. Specific examples of applications in the automotive industry are listed in the table.



'igure 1.2: The materials used in construction of a typical automobile over the past century (Taub, Krajewski, Luo, & Owens, 2007).

Table 2.3. Potential applications for magnesium alloys in the automotive industry.

Application	Product	Application	Product
Interior	Airbag housing	Body	Door frame (Inner)
	Window regulator housing		Hatchback frame
	Glove box		Spare tyre jack
Chassis	Wheel	Powertrain	Automatic transmission case
	Control arm		Engine block, engine mount
	Rack and pinion housing		Crankcase
	Bracket for rail frames		Oil pan, oil pump housing
	Spare tyre rim		Starter housing

Each product or quality process is characterized by one or several qualitative indicators. For each product to be qualitative, each of these indicators must have a specified value set to the standard.

Often it is called a target value. For a number of reasons, but not every product has the exact target value of the quality indicator. Non-compliance with the technology and for other reasons, deviations from the quality indicator from the target value appear. If these deviations are within a defined range called tolerance limits, the product is considered fit, otherwise it is defective.

Table 1. Typical Mechanical Properties of Magnesium at Room Temperature

Property	Unit	AZ91	AM60	AM50	AM20	AS41	AS21	AE42
Ultimate Tensile Strength	MPa	240 (250)	225 (240)	210 (230)	190 (210)	215 (240)	175 (220)	230 (230)
Tensile Yield Strength (0.2% offset)	MPa	160 (160)	130 (130)	125 (125)	90 (90)	140 (140)	110 (120)	145 (145)
Compressive Yield Strength	MPa	160	130	125	90	140	110	145
Fracture Elongation	%	3 (7)	8 (13)	10 (15)	12 (20)	6 (15)	9 (13)	10 (11)
Elastic Modulus, tension	GPa	45	45	45	45	45	45	45
Elastic Modulus, shear	GPa	17	17	17	17	17	17	17
Brinell Hardness		70	65	60	45	60	55	60
Impact Strength Charpy un-notched test bars	J	6 (9)	17 (18)	18 (18)	18 (18)	4 (16)	5 (12)	5 (12)

Note: Values in parentheses show mean property values obtained from separately diecast test bars.

Table 2. Typical Physical Properties of Magnesium

Property	Unit	Temp (F)	AZ91	AM60	AM50	AM20	AS41	AS21	AE42
Density	g/cu cm	68	1.81	1.8	1.77	1.75	1.77	1.76	1.79
Liquidus Temperature	F		1,110	1,139	1,148	1,182	1,144	1,169	1,157
Incipient Melting Temperature	F		788-815	788-815	788-815	788-815	788-815	788-815	1094
Linear Thermal Expansion Coefficient	µm/m	68-212	26	26	26	26	26.1	26.1	26.1
Specific Heat of Fusion	kJ/kg		370	370	370	370	370	370	370
Specific Heat	kJ/kg*K	68	1.02	1.02	1.02	1.02	1.02	1.02	1.02
Thermal Conductivity	W/K*m	68	51	61	65	94	68	84	84
Electrical Conductivity	MS/m	68	6.6	nm	9.1	13.1	nm	10.8	11.7

The tables set out certain mean values of magnesium alloys that are most widely used in practice. These data, coupled with other physical constants are staked in the specialized software, for specific casting calculations.

Like any other material, magnesium alloys, in addition to advantages and limitations, also exhibit disadvantages.

The idea is part of these deficiencies with alloying with different elements and different treatments to be overcome.

In this case, the application options will be expanded.

The disadvantages of magnesium alloys:

- Low elastic modulus
- Limited cold workability and toughness (hcp structure)
- Limited creep resistance at elevated temperatures (Tm = 650°C)
- High degree of shrinkage on solidification (high thermal expansion)
- High chemical reactivity (free $3s^2$ valence electron structure)
- In some applications limited corrosion resistance (electrode potential v = -2.31 V)

Focus:

- To improve high temperature performance
- To improve corrosion resistance

However, any other effect appreciated by the manufacturer or the user of the alloy within certain limits and measured according to a specified methodology of a relevant dimension may be subject to investigation as necessary

Table 1. 1 - List of common alloy elements and their effect in Mg alloy systems

Element	Alloy Designation	Properties	Ref
Ag	Q	Improve elevated temperature properties and creep when present with rare earths	[11]
Al	A	Improve castability, precipitation hardeners produced, corrosion protection	[11], [12]
Ca	X	Grain refinement, improves creep resistance, improve high temperature properties	[11], [13], [14]
Rare Earths (Ce, La, Nd)	E	Improve creep resistance, castability, grain refining, age hardening	[13], [15]
Si	S	Improves creep resistance	[13]
Sr	J	Improve creep resistance	[14]
Mn	M	Purification	[12]
Y	W	Improve tensile properties, grain refining	[13]
Zn	Z	Ductility and castability	[13]
Zr	K	Grain refiner, purification	[11], [12]

Two major factors in alloys affect the value of the effect, property, criterion. It is the combination of one or several alloying elements and the combination of the values of the casting mode or heat treatment applied after the casting of the workpiece.

These two large sets of parameters are subject to formalization for a mathematical description for forecasting and optimization. The table shows the impact of one of the parameters on a Quality Score.

Different alloying elements have different effects on alloys on different bases.

The table shows the characteristic influences of individual alloying elements in certain ratios in alloys of aluminum and magnesium.

Table 1. Effects of elements in the A356 and the AM60B alloys.

	[wt%]	A356* (AlSi7Mg0.35)	[wt%]	AM60B (MgAl6Mn0.5)
Si	6.5-7.5	Increased fluidity	< 0.1	Improved creep strength, fluidity
Al	Balance	Primary element	5.5-6.5	Increased strength, hardness, fluidity
Mg	0.25-0.45	Increased strength	Balance	Primary element
Fe**	< 0.2	Brittle Al_5FeSi particles	< 0.005	Impurity, reduced corrosion resistance
Mn***	0.3	$Al_{15}(Mn,Fe)_3Si_2$ particles [10]	0.25-0.6	Removes iron: Increased ductility, corrosion resistance
Ti, B	Ti < 0.2	Grain refinement	-	-
Sr	0.01	Modified Al-Si eutectic	-	-
Zn	< 0.1	Affects corrosion type	< 0.22	Increased strength, fluidity
Be	-	-	0.0005-0.0015	Minimize oxidation
Cu	< 0.03	Impurity	< 0.01	Reduced corrosion resist.

*The A356 alloy composition depends on the batch; **Fe content is typically higher in HPDC to reduce die soldering. It is necessary to keep the sludge factor (SF) low, i.e. SF = wt%Fe + 2wt%Mn + 3wt%Cr < 1.75 [11]), to avoid large intermetallic inclusions; ***Mn is added to improve the ductility.

The combination of one or several elements in different percentages determines areas of certain qualities (properties). As an example, the properties of magnesium alloys doped with zinc and aluminum are indicated.

They are explored according to certain methodologie, and each ratio of the determined chemical composition corresponds to a precisely defined property value.

The value of the property may vary within a range depending on the conditions in which the test sample was obtained.

In this sense, the chemical composition in terms of counts, the amount of doped elements and process mode parameters are input parameters, varied as combinations, and the property being tested is an output parameter.

Different states of input parameters give a different set of indicators.

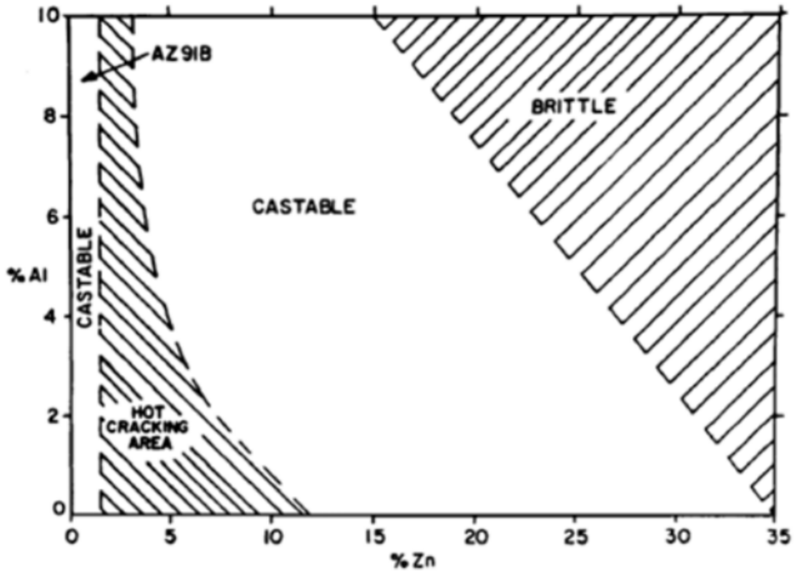
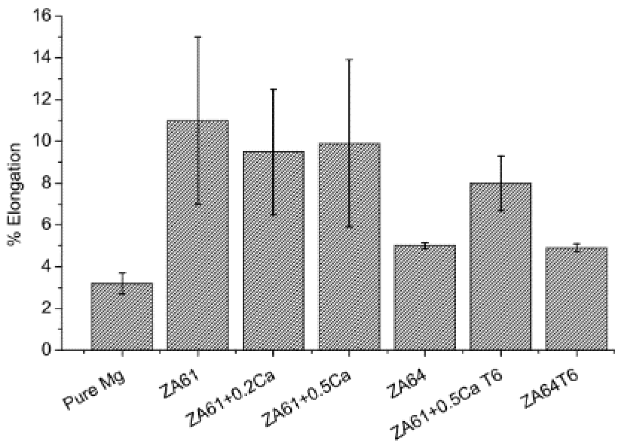
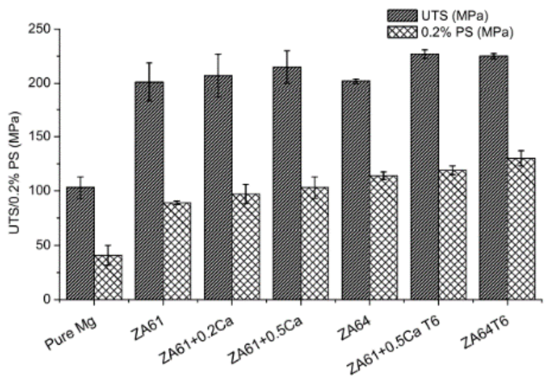
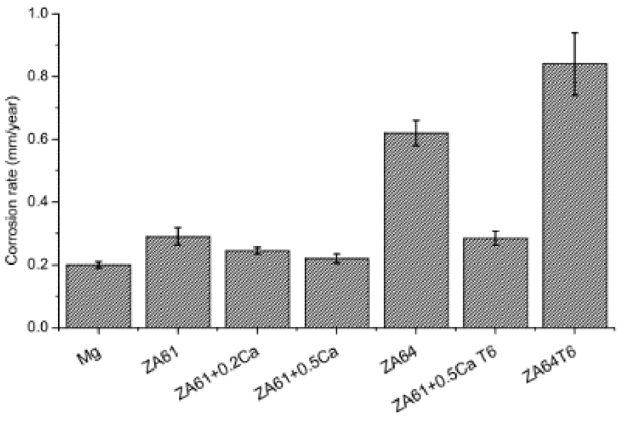


Figure 2.6: Die castability of ZA alloys

An example of the change of three target indicators / criteria and the scattering of the research value around the mean and the importance of this value depending on the change of zinc and alumina in magnesium alloys are presented as follows.





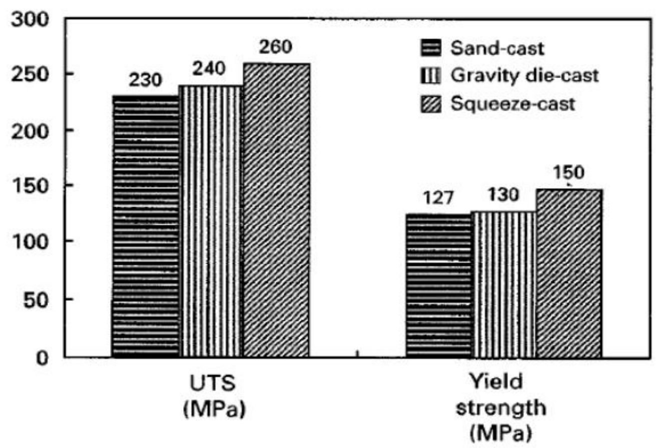


The main criteria with which metal production can be qualified are the values of certain strength characteristics.

The figure shows the values of two strength endpoints derived from three technological methods.

The technological methods are applied to the same control values of the manufacturing process.

The difference in values is explained by the presence or absence of foundry defects, such as a porosity that varies between different methods.



[27] G. A. Chadwick and T. M. Yue, Squeeze casting of light alloys and their composites, Journal of Materials processing technology, vol. 5, no. 1 (1991) 6.

Both the type of the method and the type of the alloy is influenced by the value of the criterion.

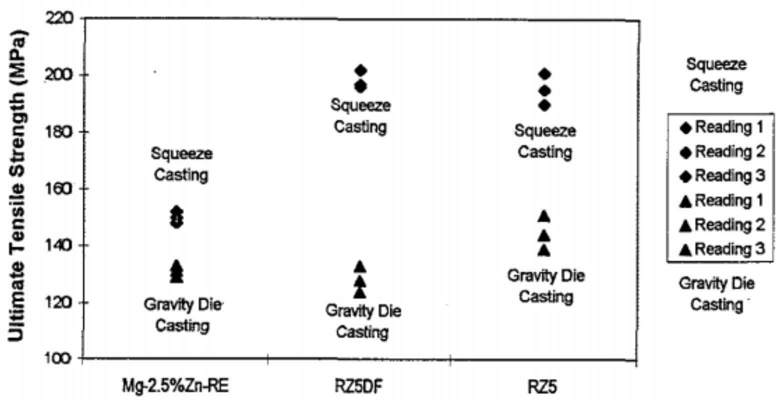


Figure 8-1 The plot of as-cast UTS for squeeze cast (diamonds) and gravity die cast specimens (triangles) cast with constant process parameters (other than applied pressure).

There is no generalized approximation rule at once set parameters for an alloy or method that can be automatically transferred to other alloys or similar methods.

Figure 2- 8. Porosity levels of squeeze cast and die cast AM50 alloy [28].

[28] M. Zhou H. Hu, N. Li, and J. Lo, Microstructure and tensile properties of squeeze cast magnesium alloy AM50, Journal of materials engineering and performance, vol. 14, no. 4 (2005) 539-545.

A proof of the influence of the method on the percentage defect is shown in the figure.

The defect is dependent on the conditions of crystallization and other technological indicators. Not all of them are subject to formalization.

The porosity weakens the cross section and therefore reduces the strength. Pore control can also be an output parameter.

The conditions under which the experiments are conducted have a significant effect on the studied magnitude.

The results of the bibliographic research should be considered as average. For specific production conditions, the normalization of the explored qualitative indicators according to the applied practice is made.

Dissipation around the average is directly related to the quality of the process. Greater distraction is a sign of a lower quality process.

Table 5.5 Tensile strength and elongation of AM series Mg-alloy scrap recycled with the MC-HPDC process and properties of fresh AM50A and AM60B alloy castings reported in the literature, compared to the recycled AM-series alloy scrap recycled in this study.

Alloy	Processing	UTS (MPa)	Elongation (%)	Reference
AM50A	HPDC	210	8.5	[Aune and Westengen 1992]
		210	10	[Avedasian and Baker 1999]
		225.5±33.5	6.9±2.1	[Song et al. 2008]
		241±7	12.9±2.1	[Ji et al. 2005]
AM60B	HPDC	225	8	[Avedasian and Baker 1999]
		214±43.3	7.5±4.2	[Lee 2007(a)]
		205.8±40.4	9.2±5.5	[Lee 2007(c)]
AM series scrap	HPDC	230.9±17.2	12.4±3.4	Current study
	MC-HPDC	231.5±11.1	14.1±1.9	Current study

There are certain differences between experimental and calculated data due to the imperfection of the computation process.

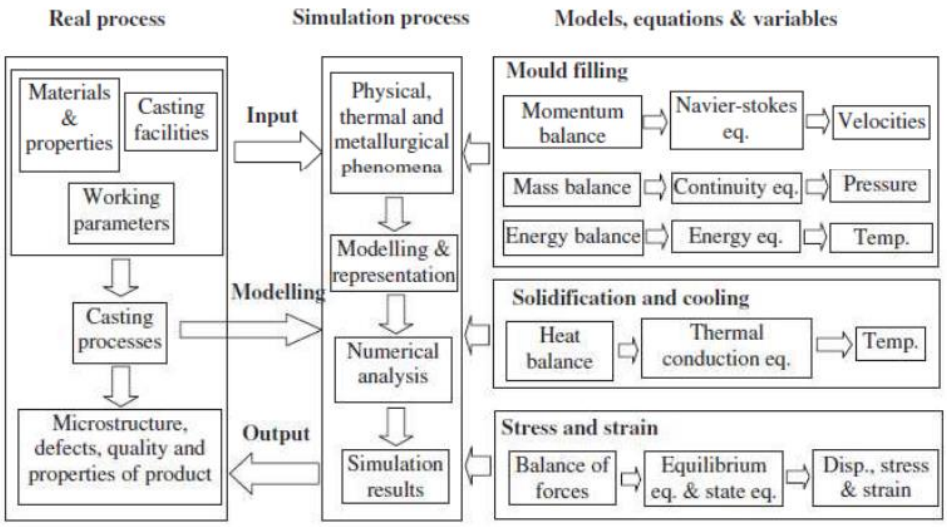


Figure 2. Association among the process, modelling, simulation and output variables.

The specialized software can be used as a tool for obtaining statistics for the process quality analysis.

The result of applied specialized statistical processing from simulations must be confirmed in practice.

For the analysis of the process a qualitative indicator or **a** system of indicators to be controlled is selected.

Table 1. Casting simulation programs

Software Program	**Company and Location**
AutoCAST	Advanced Reasoning Technologies P. Ltd., Mumbai
CAP/WRAFTS	EKK, Inc., Walled Lake, Michigan, USA
CastCAE	CT-Castech Inc. Oy, Espoo, Finland
Castflow, Castherm	Walkington Engineering, Inc., Australia
JSCast	Komatsu Soft Ltd., Osaka, Japan
MAGMASoft	MAGMA GmbH, Aachen, Germany
MAVIS	Alphacast Software, Swansea, UK
Nova-Solid/Flow	Novacast AB, Ronneby, Sweden
PAM-CAST/ProCAST	ESI Group, Paris, France
RAPID/CAST	Concurrent Technologies Corp., USA
SIMTEC	RWP GmbH, Roetgen, Germany
SOLIDCast	Finite Solutions, Inc., Illinois, USA

For a specific case, with a precisely defined filling and cooling scheme, simulations can be made to model a given casting process.

These simulations are made with specialized software for foundry purposes. A list of specialized software is shown in table and the diagram shows the interaction of the basic modules in the research of various simulations of foundry processes.

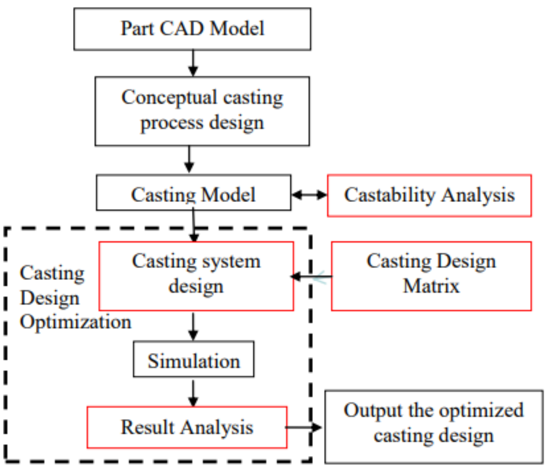


Figure 3.1 Computer aided system workflow

Another major influence on the strength of the alloy is expressed by the grain size of the microstructure of the obtained casting. The fine-grained structure is characterized by better properties.

The crystallization conditions and the additives added to this process are mainly influenced by the grain size. The figure shows the mean value of the grain size when deposited in the process of crystallization of certain additives.

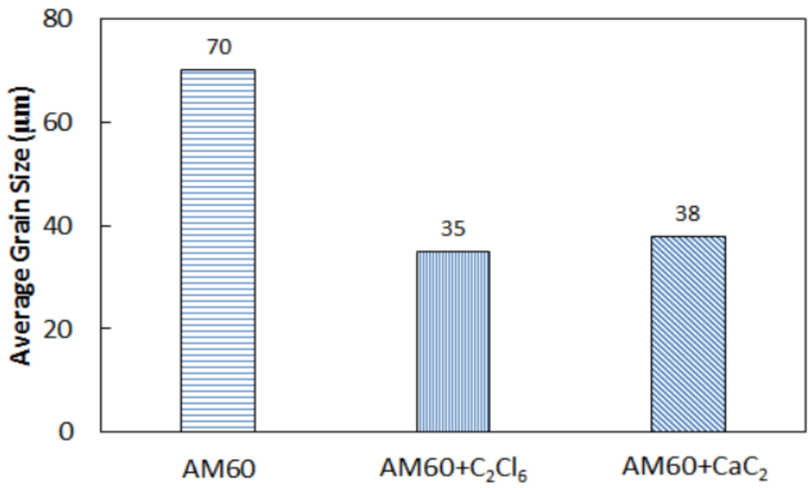


Figure 4- 22. Grain size measurement of grain refined AM60 and untreated AM60.

2014

Effect of grain refiners on squeeze casting of magnesium alloy AM60

Yanda Zou

University of Windsor

Data on the impact of additives in a given percentage for two types of specimens on the grain size is presented in the table.

The optimization that can be recommended in this case will depend on the **additive** amount and the casting volume in which it is placed.

It is clear from the attached table that for two different casting volumes the optimal percentage of the additive is different.

In addition to strength, grain scale assays may be performed with respect to other mechanical performance as shown by the micro hardness.

The pursuit of sufficient observations **is** to make generalizations and forecasts. Different alloys obtained under different conditions can be arranged / classified according to different qualitative indices.

Table 8.4. Mean grain size of AZ91 sand cast samples[3]

C_2Cl_6-addition, weight-%.	50 mm sample diameter				16 mm sample diameter			
	Min, µm	Max, µm	Mean Grain Size, µm	Std. Deviation	Min, µm	Max, µm	Mean Grain Size, µm	Std. Deviation, µm
0% C_2Cl_6	8,34	891,95	283,36	158,58	3,26	626,69	152,84	103,86
0,3% C_2Cl_6	3,28	347,8	120,21	54,6	4,37	272,33	82,45	34,63
0,6% C_2Cl_6	3,28	340,14	128,75	63,68	10,94	197,96	71,26	28,56
0,9% C_2Cl_6	20,78	290,92	113,53	45,21	2,19	202,34	78,31	31,34

The specific relationship between the additive type, the used percentage content and the volume of the sample on the mechanical performance is presented in the table.

For a specific application of an alloy, optimization of the amount of incorporated additive and its evaluation on the mechanical properties can be performed.

With a given set of properties, it may be advisable to optimize the additive as an amount added to the melt.

Table 8.3. Results of the grain refinement tests with TiC- and C_2Cl_6-additions[2].

Grain refiner, Weight- %	Sample diameter, mm	Tensile Strength, MPa	Yield Strength, MPa	Elongation at Fracture, %
Non grain refined	50 mm	97	83	0,7
	16 mm	171	98	3,4
0,3% TiC	16 mm	160	115	2,3
0,6% TiC	16 mm	149	116	1,9
0,9% TiC	16 mm	150	119	1,6
0,3% C_2Cl_6	50 mm	122	96	0,8
	16 mm	188	106	3,6
0,6% C_2Cl_6	50 mm	127	98	0,9
	16 mm	192	110	3,8
0,9% C_2Cl_6	50 mm	139	98	1,1
	16 mm	178	108	2,8
1,2% C_2Cl_6	50 mm	118	90	1,3
	16 mm	169	121	2,5
2% C_2Cl_6	50 mm	139	107	1,7
	16 mm	165	118	2,6

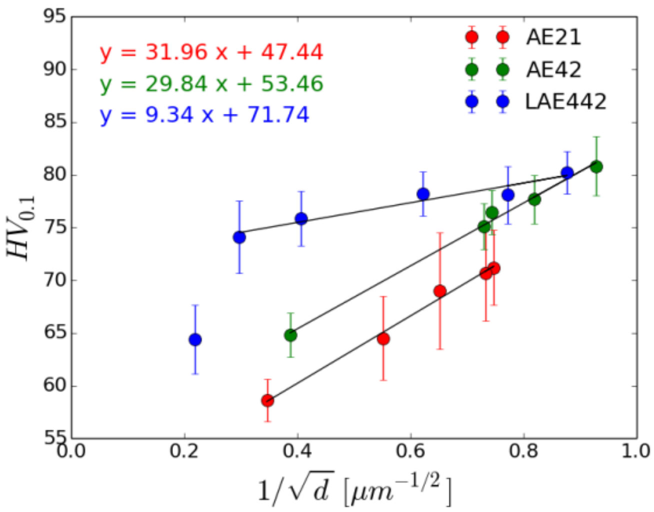


Fig. 46: Microhardness vs. (grain size)$^{-1/2}$ plot of the AE21, AE42 and LAE442 alloys

This will provide a scientifically grounded proposal in which conditions an alloy of them with a certain set of properties is better used than another.

The main material presented in the above paper contains the results of experiments conducted. Each process of data acquisition is called an experiment.

Each process for Data Mining (DM) is called an experiment

An important prerequisite for successful selection of a model is the correct selection of the factors included in it.

If the factors are quantitative, they are required not only to be measurable and manageable but also to have a significant effect on the output quantity.

Incorporating insignificant factors into the model increases the cost of experimental research without leading to a higher-quality model.

To estimate the influence of the factor on the output parameter it varies with a number of pre-selected values, called factor levels.

Since the measured output parameter also is affected by random interference, for each level of the factor there is realized a number of *n* observations.

In the statistical dependencies, only the trends of variation of the variables are persistent, but not their values in the individual measurements

Other applicatins from different articles

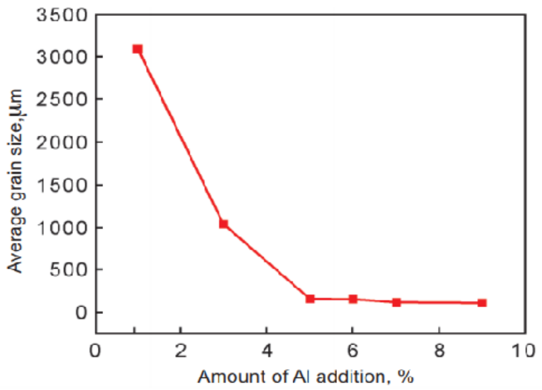


Fig. 2 Relation between average grain size and different amounts of added Al for Mg-Al binary alloys

Microstructure and properties of Mg-Al binary alloys

***ZHENG Wei-chao[1,2], LI Shuang-shou[1], TANG Bin[3], ZENG Da-ben[2]**

(1. Fundamental Industry Training Center; 2. Department of Mechanical Engineering; 3. Department of Engineering Mechanics, Tsinghua University, Beijing 100084, China)

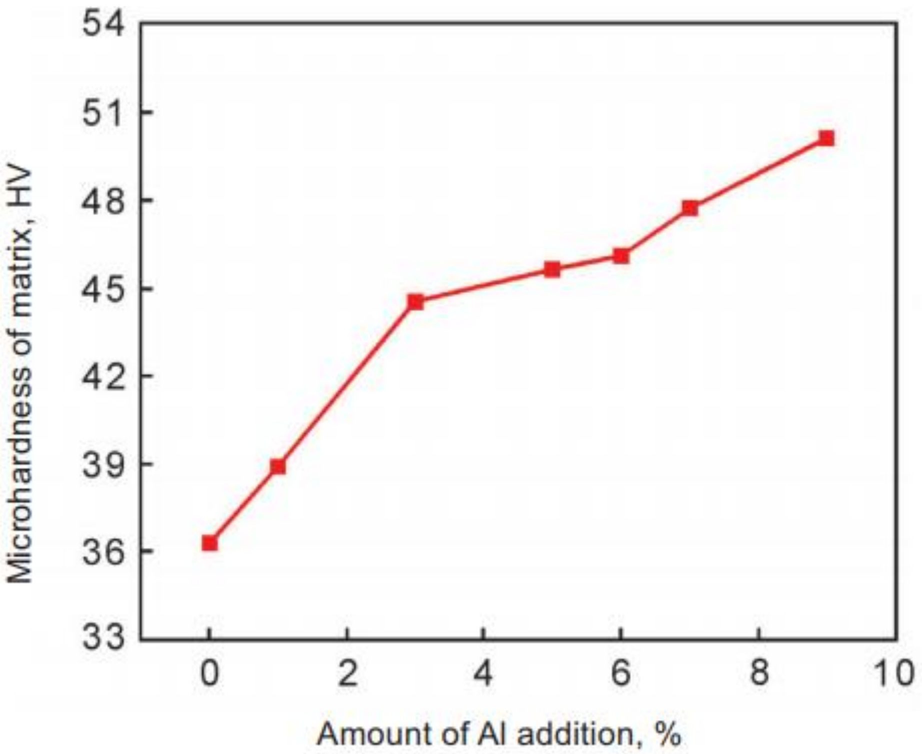


Fig. 7 Micro-hardness of the α-Mg matrix of Mg-Al binary alloys

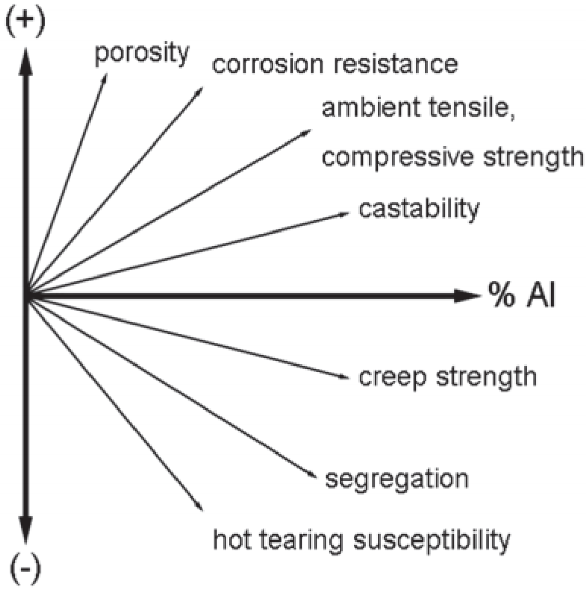
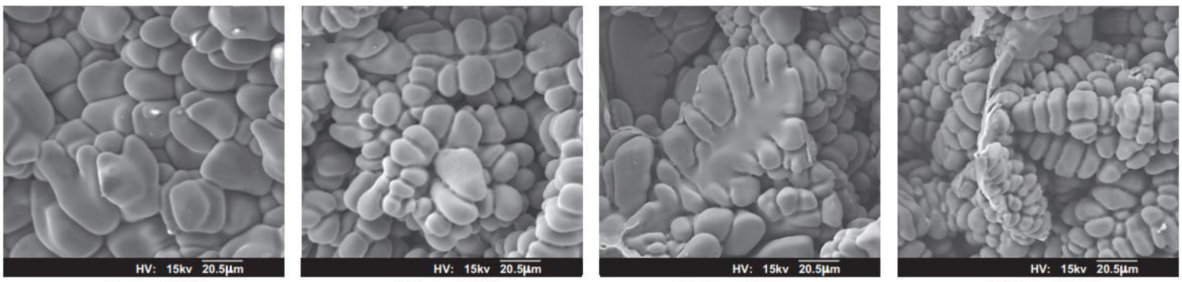
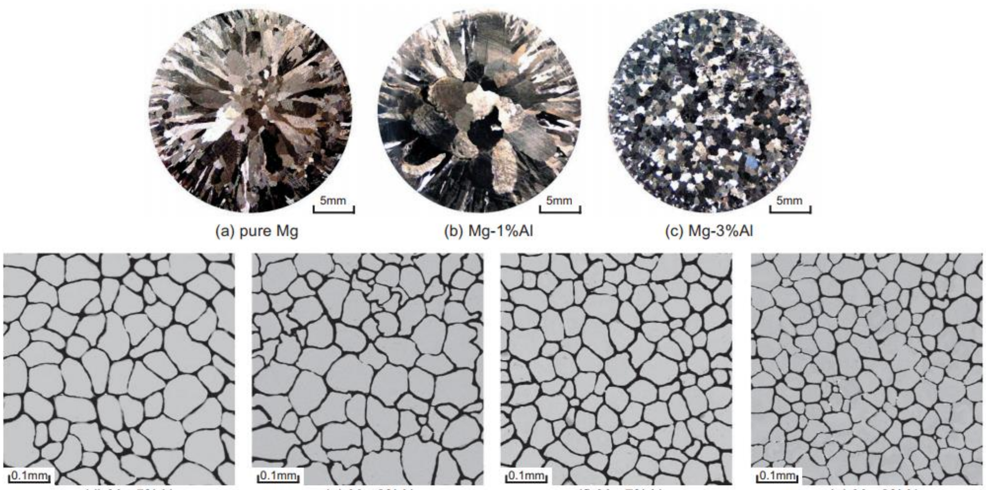


Fig.8 Influence of different amounts of Al addition on the properties of Mg-Al alloys



(a) Mg-1%Al (b) Mg-5%Al (c) Mg-6%Al (d) Mg-9%Al

Fig. 4 Size and morphology of α-Mg dendrites of Mg-Al binary alloys



(a) pure Mg (b) Mg-1%Al (c) Mg-3%Al

(d) Mg-5%Al (e) Mg-6%Al (f) Mg-7%Al (g) Mg-9%Al

Fig. 3 Photographs showing grain structures of Mg-Al binary alloys

Table 1. Tensile properties of various Mg-alloys

Alloy Designation	Tensile Strength (MPa)	0.2% Proof Stress (MPa)	Elong. to Failure (%)	Magnesium Elektron Datasheet*
AZ31B-H24	235	125	7	482
ZK60A-T5	290	180	6	486
AZ91E-T6	270	170	4.5	456
Electron 21	280	170	5	455
WE54-T5	300	200	10	480
WE43-T5	280	195	10	478
Elektron 675	410	310	9	102

* http://www.magnesium-elektron.com/.

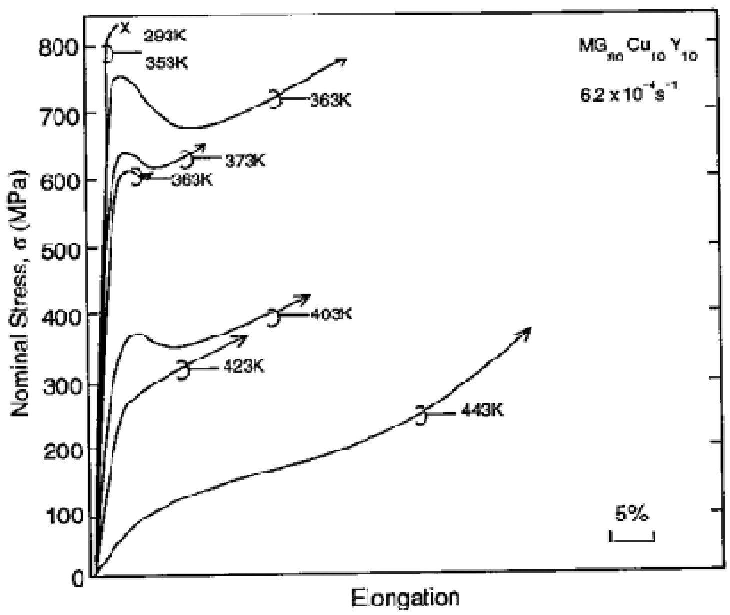
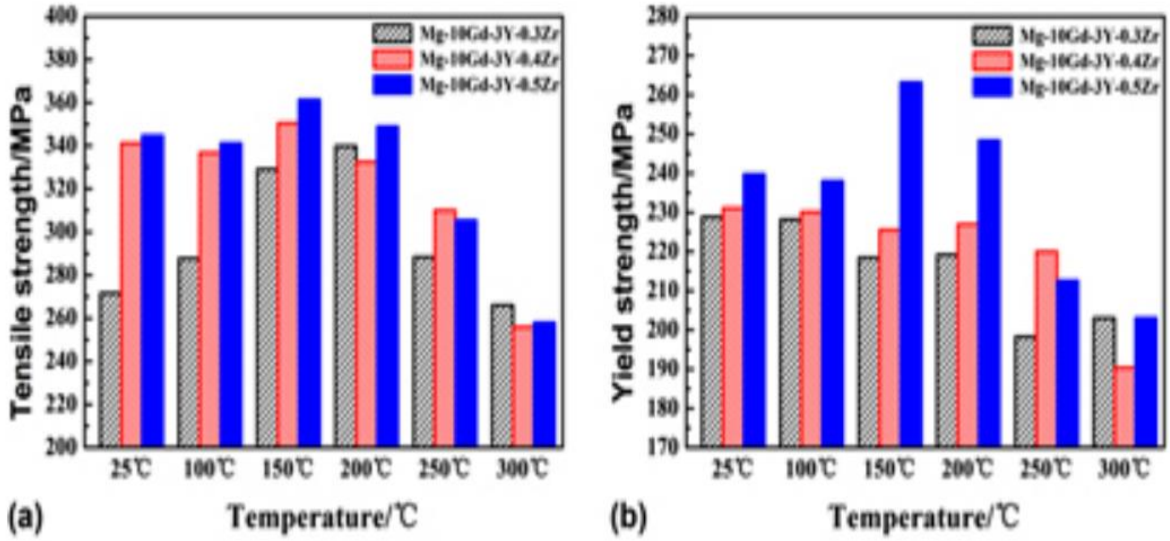
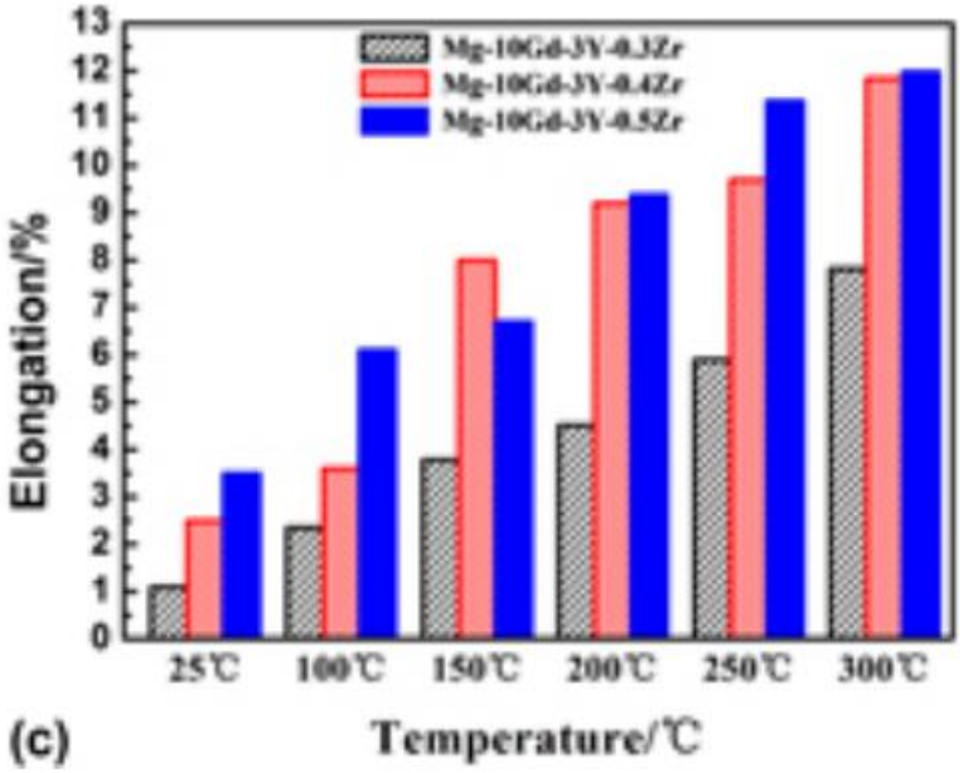
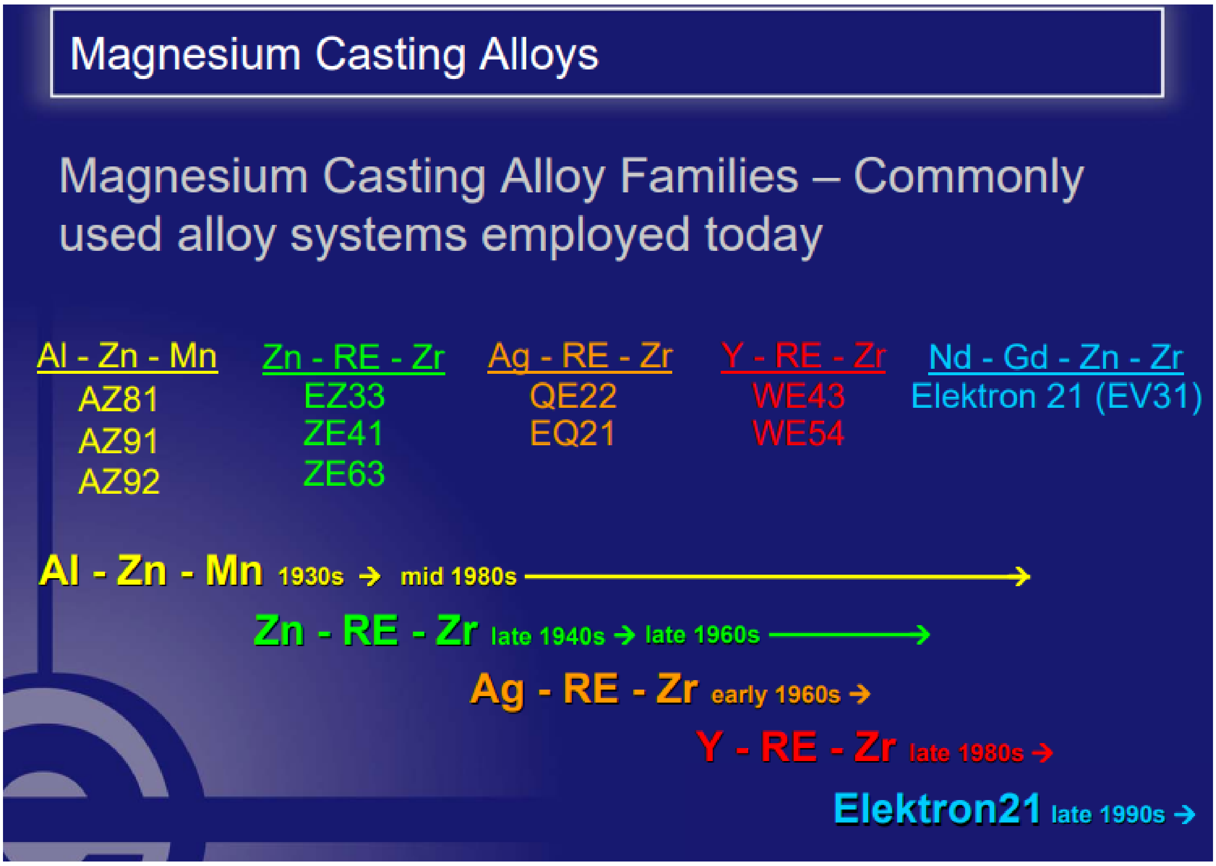


Figure 19. Nominal stress-strain curves at various temperatures. Amorphous Mg(80 at%)-Cu(10 at%)-Y(10 at %) (22).

22. Inoue, A., et. al., Materials Transactions JIM, vol. 32, no. 7, 1991, 609


Mg-10Gd-3Y-0.3Zr
Mg-10Gd-3Y-0.4Zr
Mg-10Gd-3Y-0.5Zr
Tensile strength/MPa
Yield strength/MPa
25℃
100℃
150℃
200℃
250℃
300℃
(a)
(b)
Temperature/℃


Mg-10Gd-3Y-0.3Zr
Mg-10Gd-3Y-0.4Zr
Mg-10Gd-3Y-0.5Zr
Elongation/%
25℃
100℃
150℃
200℃
250℃
300℃
(c)
Temperature/℃


Magnesium Casting Alloys
Magnesium Casting Alloy Families – Commonly used alloy systems employed today
Al - Zn - Mn
AZ81
AZ91
AZ92
Zn - RE - Zr
EZ33
ZE41
ZE63
Ag - RE - Zr
QE22
EQ21
Y - RE - Zr
WE43
WE54
Nd - Gd - Zn - Zr
Elektron 21 (EV31)
Al - Zn - Mn 1930s → mid 1980s
Zn - RE - Zr late 1940s → late 1960s
Ag - RE - Zr early 1960s →
Y - RE - Zr late 1980s →
Elektron21 late 1990s →

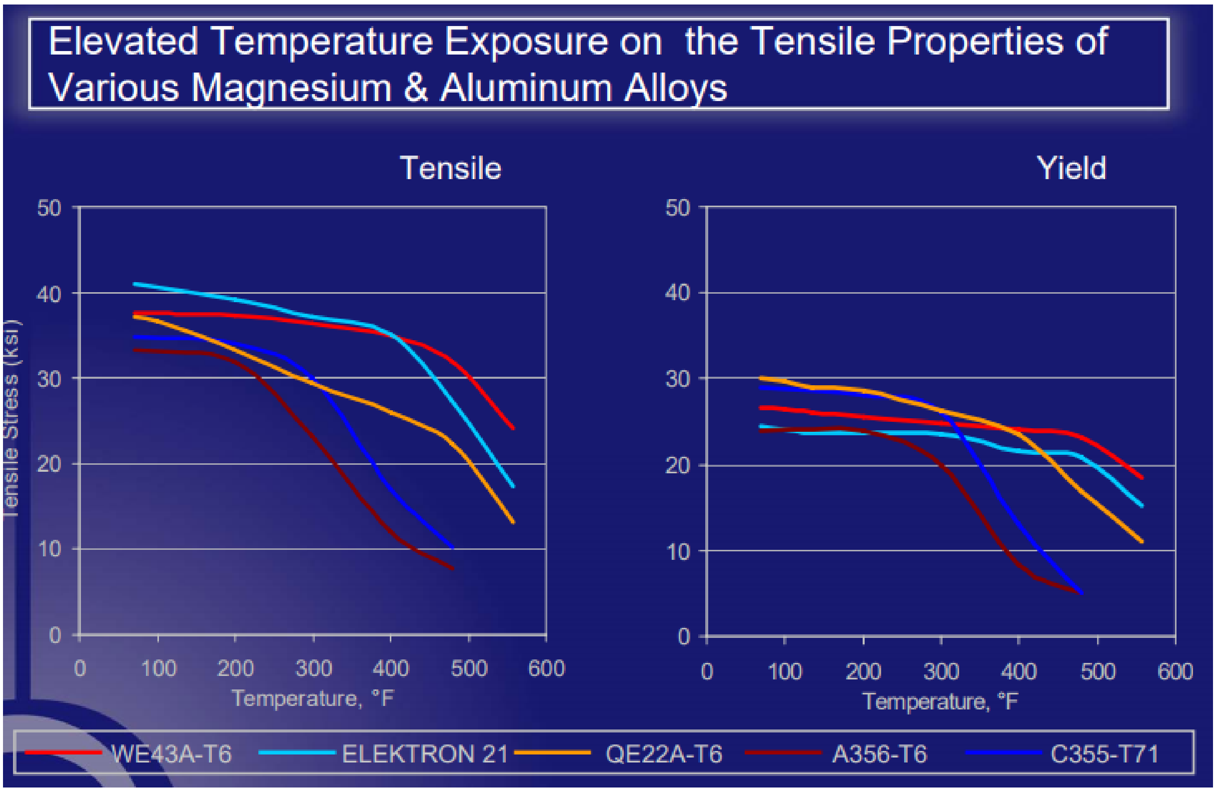

Elevated Temperature Exposure on the Tensile Properties of Various Magnesium & Aluminum Alloys
Tensile
Yield
Tensile Stress (ksi)
50
40
30
20
10
0
0
100
200
300
400
500
600
Temperature, °F
WE43A-T6
ELEKTRON 21
QE22A-T6
A356-T6
C355-T71

Table I. Mg-based casting alloys. Nominal chemical composition (wt%).

Designation	Al	Zn	Mn*	Si	Zr	Y	Ag	Others
AM20	2.0	<0.1	0.4	<0.1				
AM50	5.0	<0.1	0.2	<0.1				
AM60	6.0	<0.2	0.25	<0.1				
AS21	2.2	<0.1	0.2	1.0				
AS41	4.5	<0.1	0.2	1.0				
AE42	4.0	<0.2	0.25	<0.1				2.0-3.0 RE (Ce-rich)
AZ63	6.0	3.0	0.15	<0.3				
AZ91	9.0	0.7	0.15	<0.1				
EZ33		2.7			0.6			3.3 RE (Ce-rich)
ZE41		4.2			0.7			1.2 RE (Ce-rich)
EK31					0.7			3.7 RE (Nd-rich)
EQ21					0.5		1.5	2.1 RE (Nd-rich)
QE22					0.7		2.5	2.1 RE (Nd-rich)
WE54					0.5	5.3		3.5 RE (Nd-rich)
WE43					0.5	4.0		3.0 RE (Nd-rich)

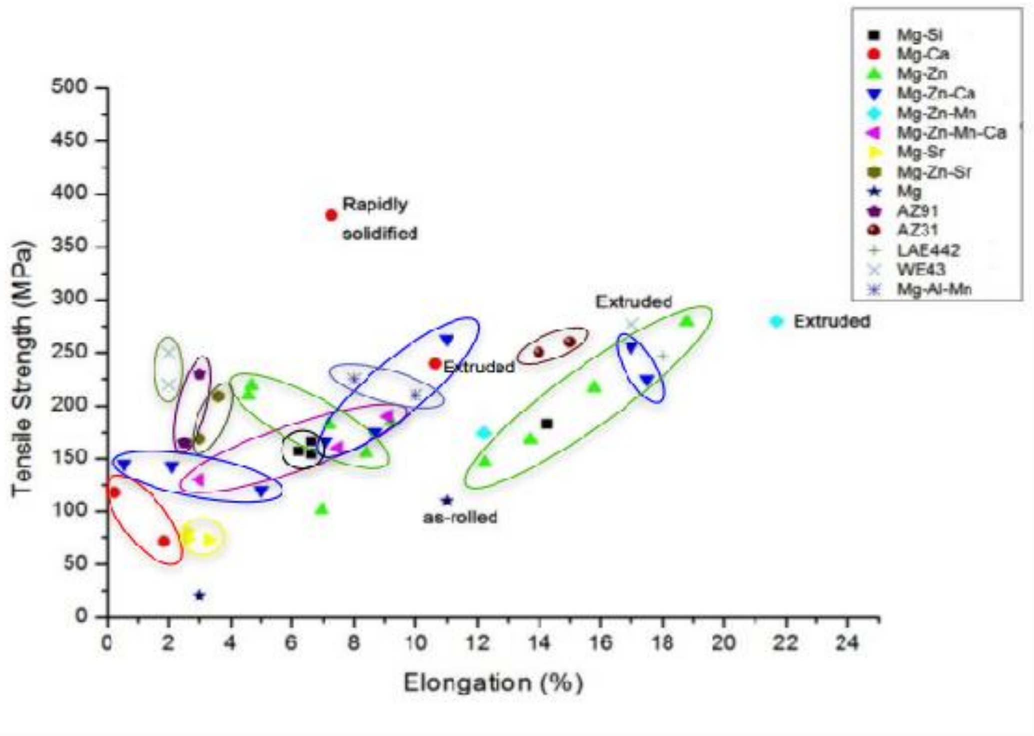


Fig. 2.5 Published tensile strength and elongation data for various magnesium alloys [10, 13, 36, 42, 58, 104-109].

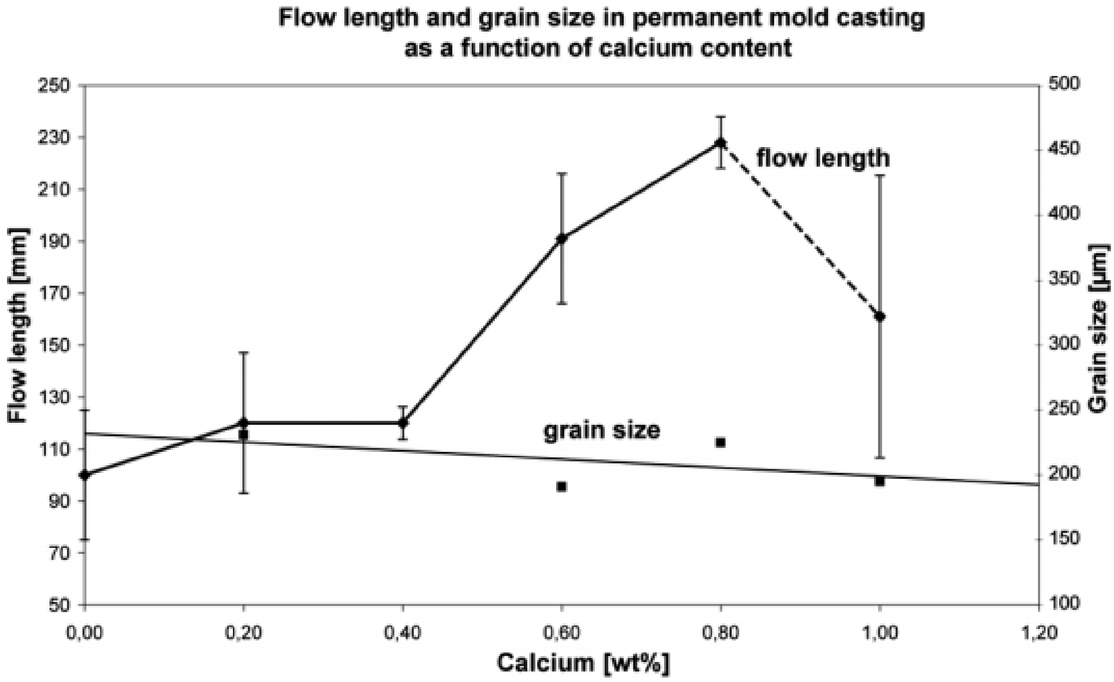


Fig. 9. Flow length of AZ 31 in permanent mold as a function of calcium content.

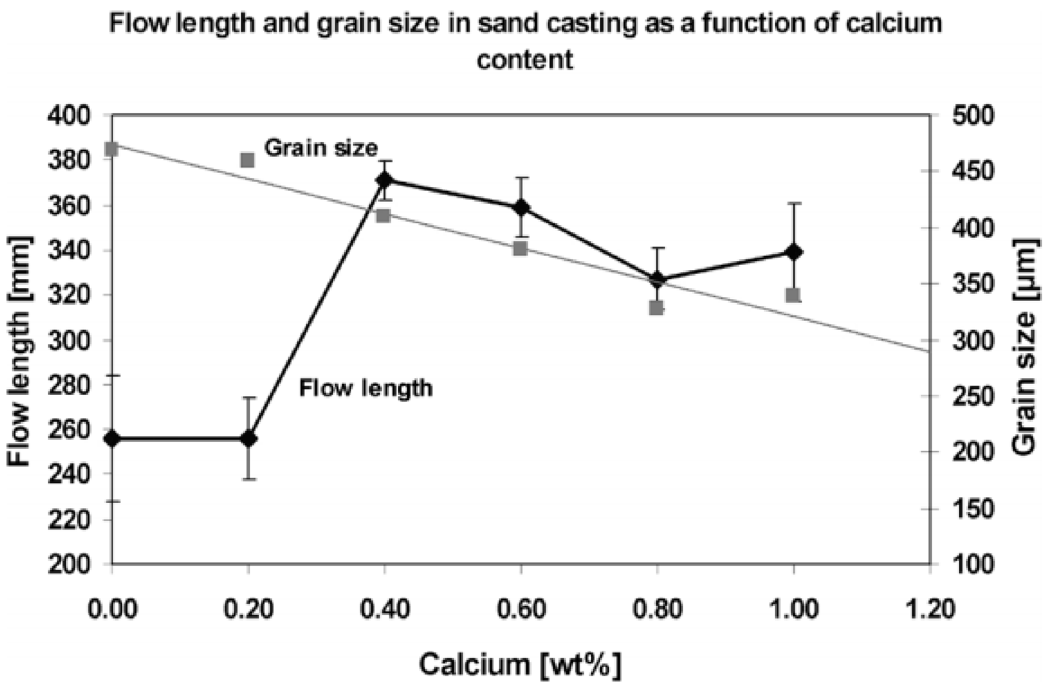


Fig. 10. Flow length of AZ 31 in sand mold as a function of calcium content.

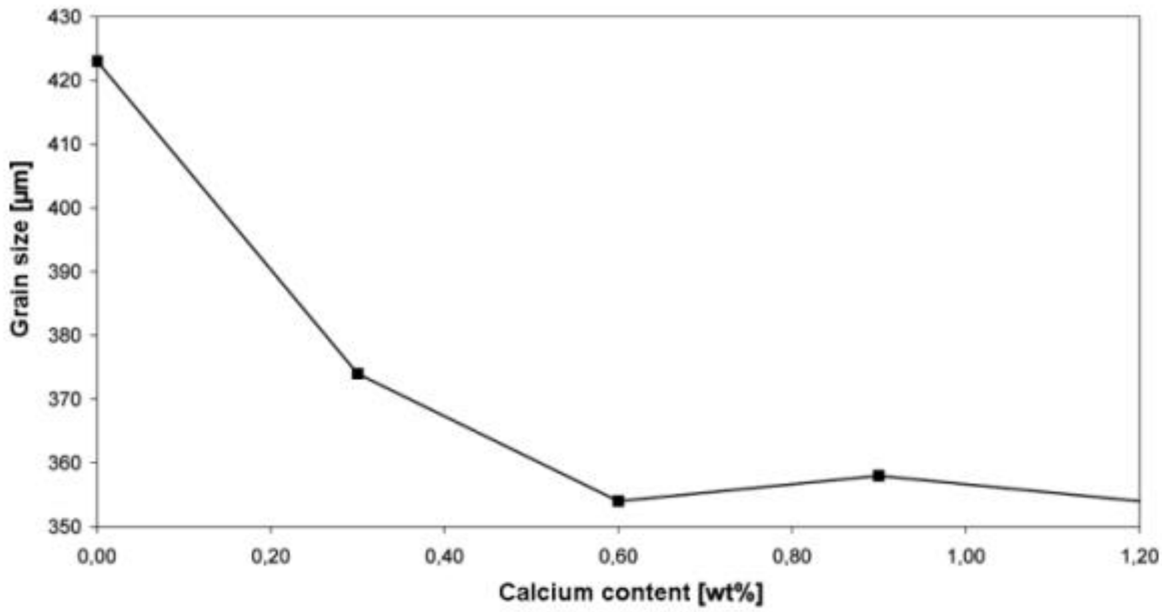


Fig. 5. Grain size as a function of calcium content.

DOI: 10.1002/adem.200500241

Controlling Microstructure in Magnesium Alloys: A Combined Thermodynamic, Experimental and Simulation Approach

By *Bernd Böttger, Janin Eiken, Munekazu Ohno, Gerald Klaus, Martin Fehlbier, Rainer Schmid-Fetzer, Ingo Steinbach*, and *Andreas Bührig-Polaczek*

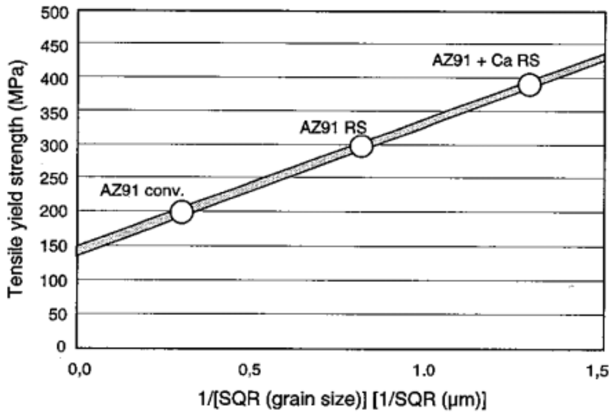


Figure 17. Hall Petch relation describing the influence of grain size on tensile yield strength (20).

20. Gjestland, H., et. al. Proc. Conf. 'Rapidly Quenched Materials', RQ7, Stockholm 1990, Elsevier, 1197

Table 1. 1 - List of common alloy elements and their effect in Mg alloy systems

Element	Alloy Designation	Properties	Ref
Ag	Q	Improve elevated temperature properties and creep when present with rare earths	[11]
Al	A	Improve castability, precipitation hardeners produced, corrosion protection	[11], [12]
Ca	X	Grain refinement, improves creep resistance, improve high temperature properties	[11], [13], [14]
Rare Earths (Ce, La, Nd)	E	Improve creep resistance, castability, grain refining, age hardening	[13], [15]
Si	S	Improves creep resistance	[13]
Sr	J	Improve creep resistance	[14]
Mn	M	Purification	[12]
Y	W	Improve tensile properties, grain refining	[13]
Zn	Z	Ductility and castability	[13]
Zr	K	Grain refiner, purification	[11], [12]

Table 2.4. Typical room-temperature mechanical properties of cast AZ91 (F: As-cast condition; T4: Solution treated Condition; T6: Solution treated and aged condition.) [16].

Properties	**Die Castings**	**Sand Castings**		
	F	**F**	**T4**	**T6**
Tensile strength	230 MPa	165 MPa	275 MPa	275 MPa
Tensile yield strength	150 MPa	97 MPa	90 MPa	145 MPa
Elongation of 50 mm	3%	2.5%	15%	6%
Compressive yield strength	165 MPa	97 MPa	90 MPa	130 MPa
Shear strength	140 MPa	---	---	---
Hardness	75 HRE	66 HRE	62 HRE	77 HRE
Tension elastic modulus	45 GPa			
Shear elastic modulus	17 GPa			
Principal fracture mode	Cleavage usually along {0001}			

[16] M.M. Avedesian, H. Baker, Magnesium and Magnesium Alloys – ASM Specialty Handbook, ASM International, Materials Park, OH 1999.

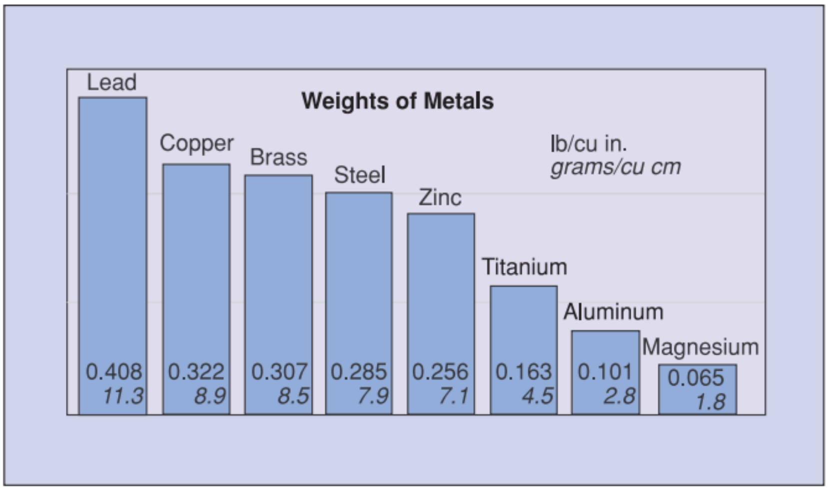


Fig. 1. Magnesium's light weight has allowed it to become the alloy of choice for a number of new markets and applications, such as the automotive, power tool, computer and electronics industries.

Tab. 5.4: Density of the magnesium alloy AZ31

Temperature (in K)	Density ZENG [29] (in kg/m^3)	Temperature (in K)	Density PROCAST [76] (in kg/m^3)
293	1 780	480	1 750
373	1 760	610	1 723
473	1 750	671	1 710
573	1 740	715	1 701
673	1 730	763	1 690
773	1 720	839	1 671
848	1 710	875	1 658
903	1 690	899	1 638
923	1 660	907	1 627
973	1 640	1 023	1 592

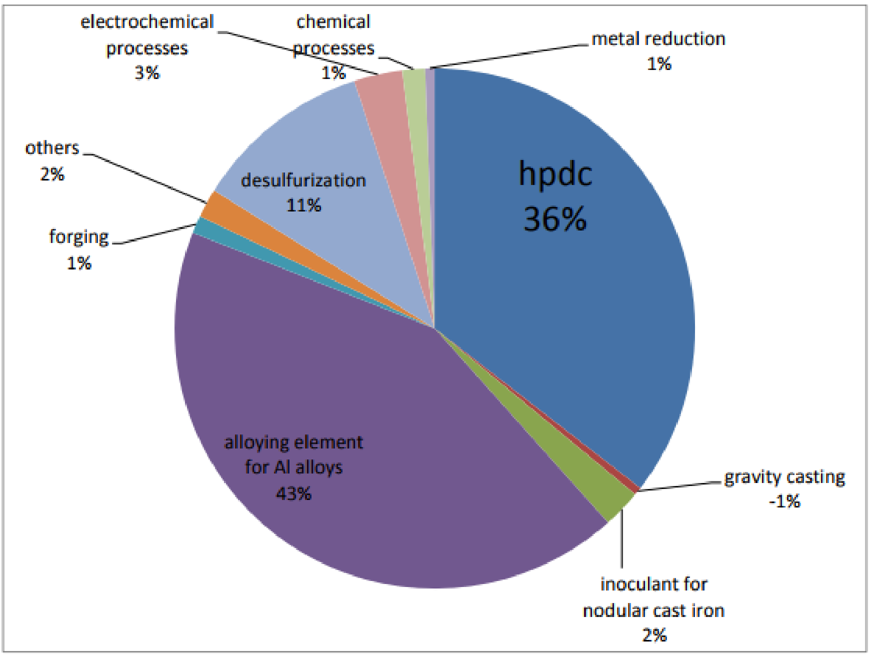


Figure 2.1 : Market share of magnesium in the year 2000 [6]

[6] M. I. Khan, Y. Frayman, and S. Nahavandi, "MODELLING OF POROSITY DEFECTS IN HIGH PRESSURE DIE CASTING WITH A NEURAL NETWORK," *Methodology*, pp. 1-6.

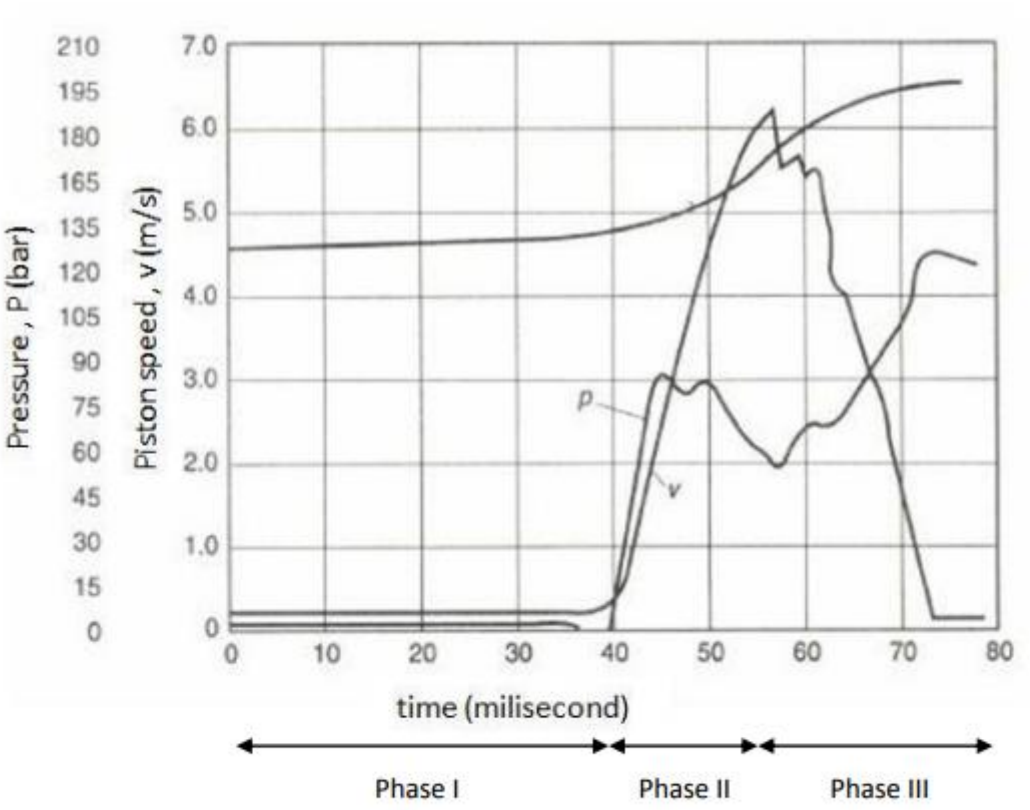


Figure 2.3 : Speed – pressure diagram of high pressure die casting process [3]

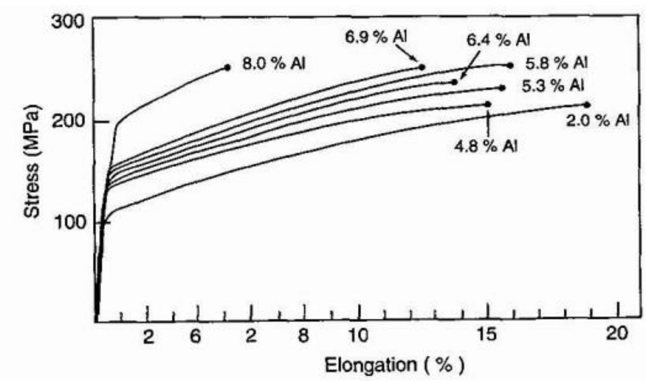


Figure 10. Nominal stress-strain curves of high pressure die casts AM-alloys with varying Al-content (10).

10. Aune, T.K. and Westengen, H., Proc. Conf. 'Magnesium Properties and Applications for Automobiles', SAE 1993, paper 930418

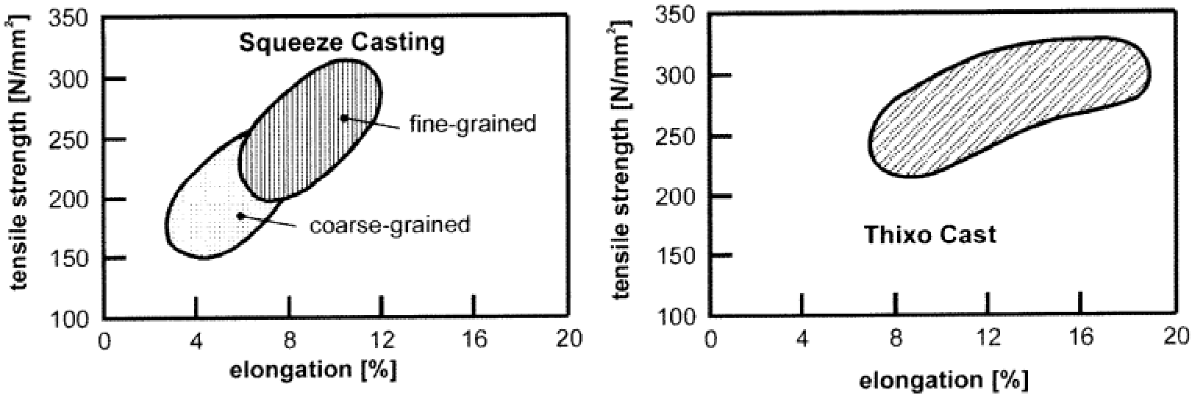


Fig. 7. Relationship between tensile strength — elongation areas for squeeze cast and thixo cast AZ91 T4 material [5].

[5] H. Kaufmann, Endabmessungsnahes Gießen: Ein Vergleich von Squeeze-Casting und Thixocasting, Giesserei 81 (1994) 11.

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Review

Mechanical Properties of Magnesium-Rare Earth Alloy Systems: A Review

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Tel.: +65 65166358; Fax: +65 67791450

Table 2.3 Summary of the physical and mechanical properties of various implant materials in comparison with human bone [23, 36].

	Density (g/cm^3)	Elastic modulus (GPa)	Tensile strength (MPa)	Fracture toughness ($MPa^{1/2}$)	Total Elongation (%)
Cortical bone[⊖]	1.8-2.1	3-20	35-283	3-6	1.07-2.10
Cancellous bone[⊖]	1.0-1.4	-	1.5-38	-	-
Magnesium alloys	1.74-2.0	41-45	150-400	15-40	2-20
Titanium alloy (TiAl6V4)	4.4-4.5	110-117	830-1025	55-115	10-15
Stainless steel (316L)	7.9-8.1	205-210	480-620	50-200	30-40
Co Cr alloys	8.3 9.2	230	450 1000		
Synthetic hydroxyapatites	3.1	70-120	40-200	0.7	-

[⊖] Different values are due to different races, age, testing conditions etc.

[23] M.P. Staiger, A.M. Pietak, J. Huadmai, and G. Dias, *Magnesium and its alloys as orthopedic biomaterials: A review.* Biomaterials, 2006. **27**(9): p. 1728-1734.

[36] F. Witte, N. Hort, C. Vogt, S. Cohen, K.U. Kainer, R. Willumeit, and F. Feyerabend, *Degradable biomaterials based on magnesium corrosion.* Current Opinion in Solid State & Materials Science, 2008. **12**(5-6): p. 63-72.

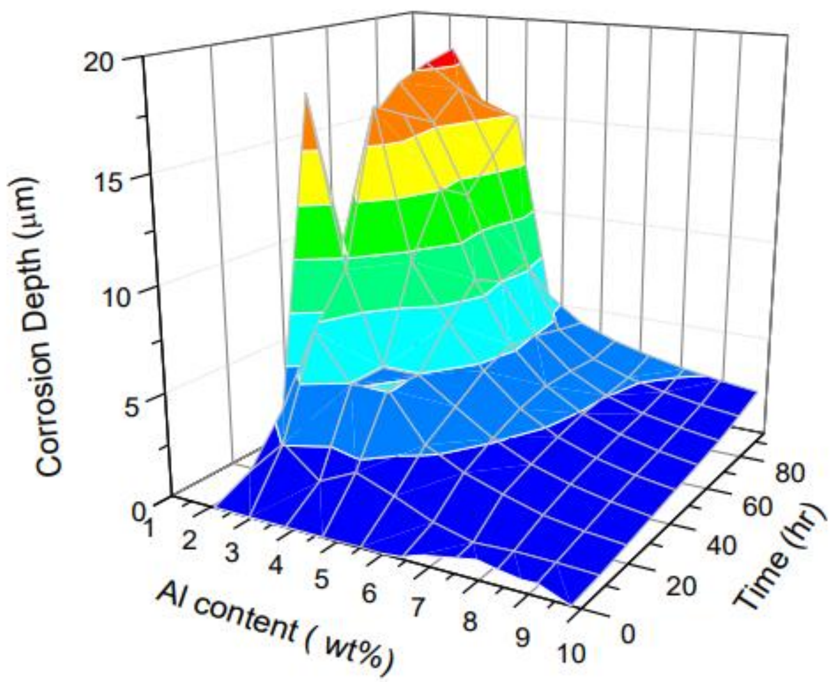


Figure 3. 8 - The relationship between corrosion depth on α-grains and their Al content as a function of corrosion exposure time.

Table 1. 4 - List of comparative corrosion rates of Mg alloys.

Corrosion Resistance	Medium	Method	Ref
AZ80 > AZ91 > AZ31	NaCl	EIS	[84]
AM60 > AZ31	NaCl	Weight Loss	[85]
AZ91 > AM50	Na_2SO_4	EIS	[43]
Pure Mg > AZ91 > ZE41	NaCl	Weight Loss, Hydrogen	[53]
Pure Mg = AZ31 >AZ91 > AM30 > AM60 > ZE41	NaCl	Hydrogen	[53]
WE43 > ZE41 > AZ91	NaCl	Weight Loss	[75]
ZK60 > AM60 > AZ31 > AZ91	NaCl	EIS, Electrochem	[20]
AE42 > ZAC8506 > AZ91	NaCl	Weight loss	[41]
AZ91 > AZ61 > AZ31	NaCl	Weight Loss	[86]
AZ91 > AM60 > AM20	NaCl Air	Weight loss	[30]
ZK31 = WE54 > EZ33	NaCl + NaOH	Electrochem, EIS	[71]
NZ30 > AZ91	NaCl	Weight Loss	[74]
AZ 31 > AZ 61 > AP 65 > Mg	$Mg(ClO_4)_2$	EIS	[87]

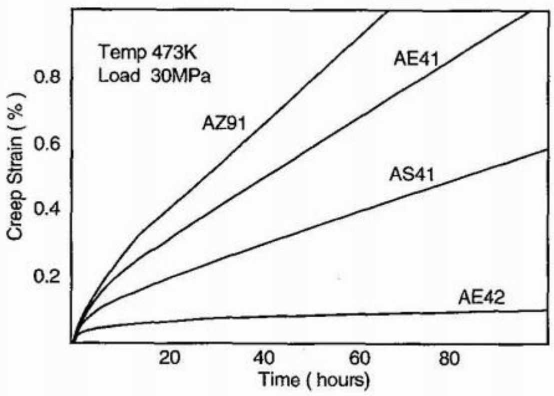


Figure 12. Creep strain vs. time for various alloys at 200 °C, load 30 MPa (12).

12. Aune, T.K. and Westengen, H., Proc. Conf. 'Magnesium Alloys and Their Applications', Garmisch-Partenkirchen, DGM 1992, 221

Tab. 5.2: Final basic choice of the thermophysical properties of magnesium alloy AZ31

Temperature (in K)	Thermal conductivity (in W/(m K))	Specific heat (in J/(kg K))	Temperature (in K)	Solid fraction
293	76.9	1040	733.00	1.0000
323	83.9		823.23	0.9530
373	87.3		837.34	0.9018
423	92.4	1042	849.27	0.8022
473	97.0		855.79	0.6984
523	101.8		860.59	0.6002
573		1148	865.09	0.4992
733	124.0		869.12	0.3982
837	118.7		873.00	0.3015
849	113.4		877.49	0.2019
869	92.2		882.92	0.1024
883	76.3	1414	886.48	0.0497
896	71.0		896.00	0.0000

Table 1. Castability Index for Mg Die-casting Alloys [13]

	Castability Index , I_C		
ALLOY	**Thin-walled castings**	**Medium-walled castings**	**Thick-walled castings**
AZ91	20	20	20
AM50	25	24	35
AS21	39	38	49
AE42	50	50	60
AJ52x	32	24	35
AJ51x	38	32	42
AJ50x	42	37	45

*The lower the number the better the castability.
** For AJ51x, the freezing range is 104°C and the normalized condivity value is 119 W/mK.

Argo, et. al., "PROCESS PARAMETERS AND DIECASTING OF NORANDA'S AJ52", 2002.

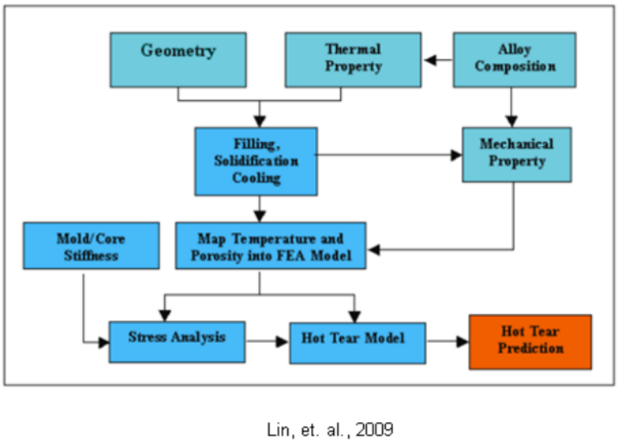


Figure 22. Hot tearing modeling approach [26]

26. Lin, Z., Monroe, C.A., Huff, R.K., and Beckermann, C., "PREDICTION OF HOT TEAR DEFECTS IN STEEL CASTINGS USING A DAMAGE BASED MODEL", Modeling of Casting, Welding, and Advanced Solidification process-XII, TMS, 2009

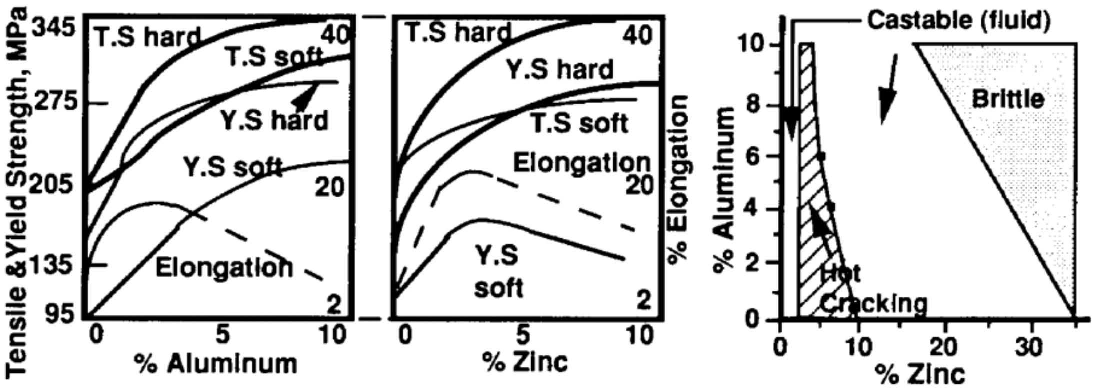


Fig. 2.4. Effects of Al and Zn on the mechanical properties and castability of Mg [13].

[13] M. Ö. Pekgüleryüz, M. M. Avedesian, DGM Conference "Magnesium Alloys and Their Applications", 1992, Garmisch-Patenkirchen, Germany, p. 213.

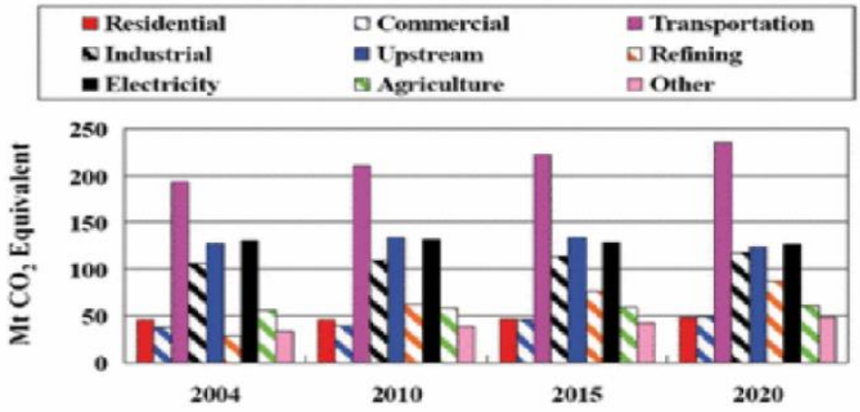


Figure 1. 2 - Canadian green house gas emissions by sector [3].

3. D. Karman, G. Rideout, W. Bailey, A. Green, P. Eggleton "Transportation Emissions: Sources and Regulations" Air Quality Management, Springer Netherlands (2014) 203-235

4. DESIGN OF EXPERIMENTS (DOE) STUDY

4.1 DOE Matrix Based on the Magnesium-Zirconium Phase Diagram

Pure magnesium (99.9% Mg) and magnesium-15 wt% zirconium grain refiner master alloy were used for the experiments. Three different parameters were varied to study grain refinement efficacy – wt% total zirconium addition (0.25, 0.5, and 1 wt %), pouring temperature (705 and 815ºC), and settling time (0 and 30 min). The experimental DOE matrix is shown in Table 4.1. This is a full factorial experiment in one three-level factor and two two-level factors. A total of 12 grain refinement experiments were carried out. A pure magnesium hockey puck sample was also poured for comparison.

Table 4.1 Experimental DOE matrix

Expt. No	wt% Zr	Temperature (˚C)	Settling Time (min)
1	0.25	705	0
2	0.25	705	30
3	0.25	815	0
4	0.25	815	30
5	0.50	705	0
6	0.50	705	30
7	0.50	815	0
8	0.50	815	30
9	1.0	705	0
10	1.0	705	30
11	1.0	815	0
12	1.0	815	30

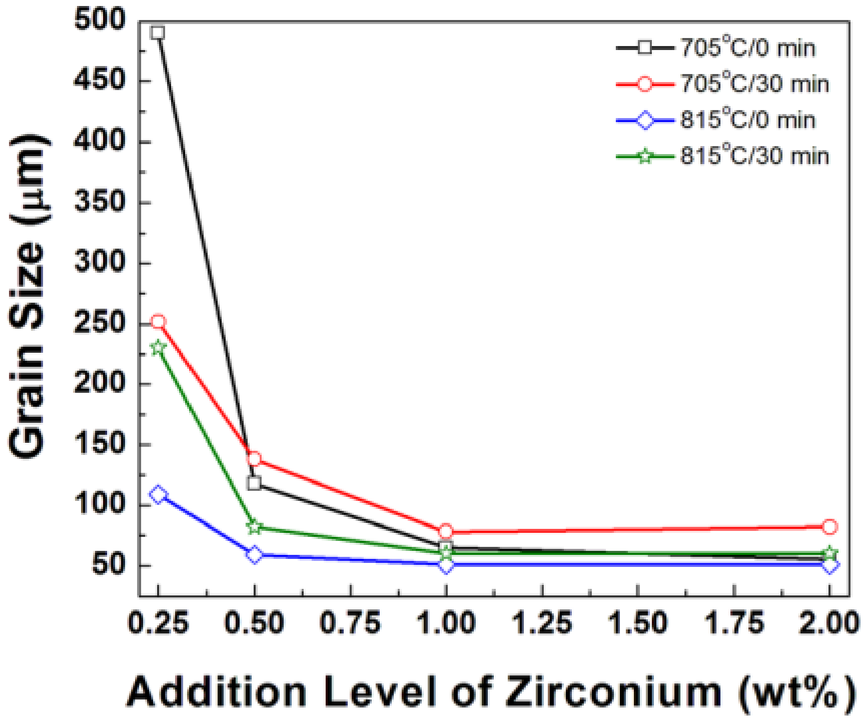


Fig. 4.15 Measured grain size vs. zirconium addition.

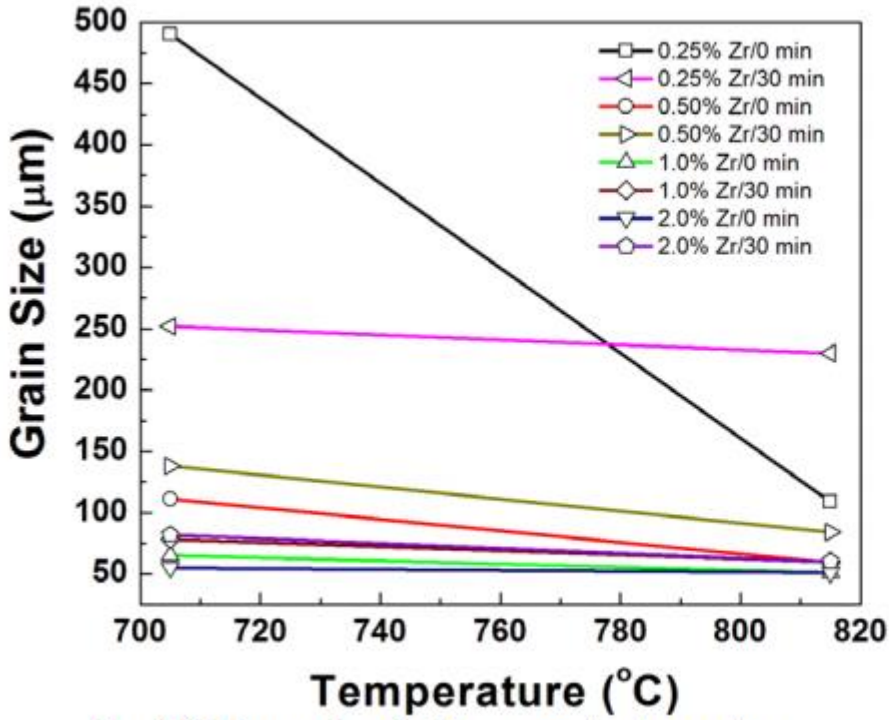


Fig. 4.16 Measured grain size vs. pouring temperature.

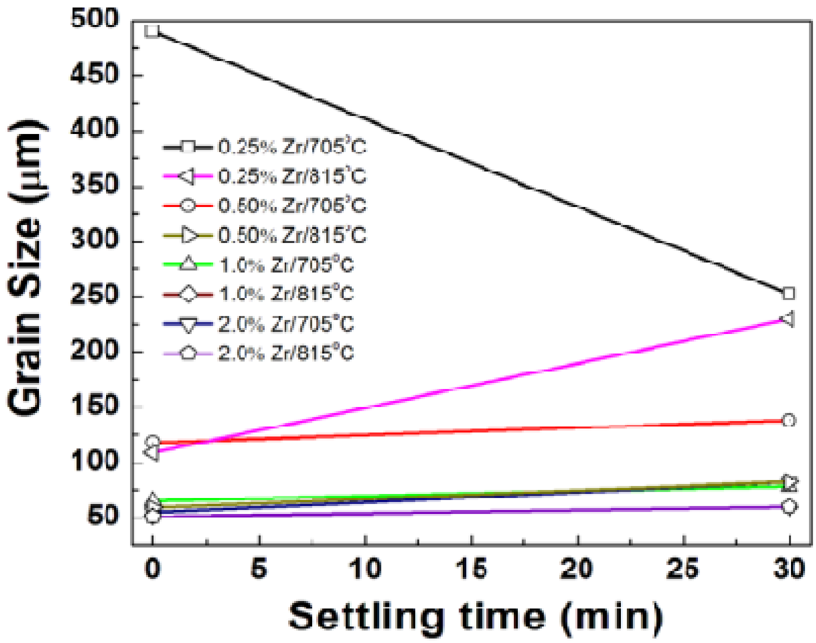


Fig. 4.17 Measured grain size vs. settling time.

AN ANALYSIS OF THE GRAIN REFINEMENT OF MAGNESIUM BY ZIRCONIUM

by

PARTHA SAHA

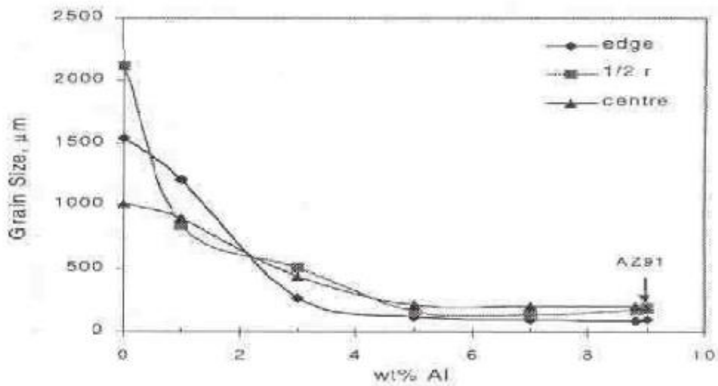
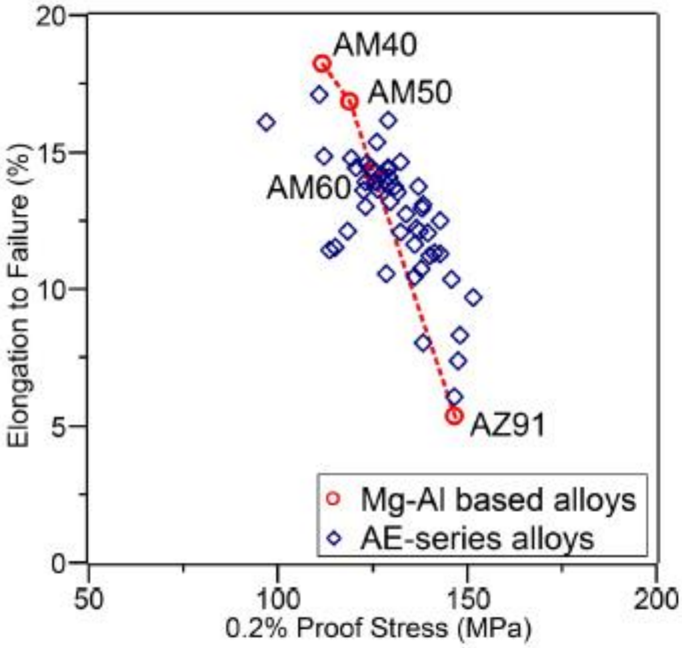


Figure 2 - Grain Refining Effects of Al in Pure Mg [12]

[12] Y.C. Lee, A.K. Dahle, and D.H. StJohn, "Grain Refinement of Magnesium", Magnesium Technology 2000, TMS, pp. 211-218.



Elongation to failure and 0.2% proof stress of magnesium-aluminium based alloys and AE-series alloys [34].

[34] Magontec. Mechanical properties of die-cast magnesium alloys. Unpublished raw data.

Table 3.2: Measured compositions (wt.%) by (ICP-AES).

Alloy	Mg	Al	Mn	Zn	RE (Ce + La)
AM40	Bal.	4.44	0.21	0.05	<0.01
AM60	Bal.	6.26	0.29	0.1	<0.01
AZ91	Bal.	8.88	0.19	0.74	<0.01
AE44	Bal.	3.67	0.31	<0.01	2.5 + 1.33

Table 3.3: Casting parameters for HPDC magnesium alloys in this research.

Casting Parameter	Parameter Value
Melt Temperature	740 °C
Oil Heaters in Both Halves of the Die	250 °C
Accumulator Pressure	110 kg/cm^2
Ram Velocities, Slow Speed	Approximately 0.36 ms^{-1}
Ram Velocities, High Speed	Approximately 2.2 ms^{-1}
Average Die Fill Time	600 ms
Die Open Time	4 s

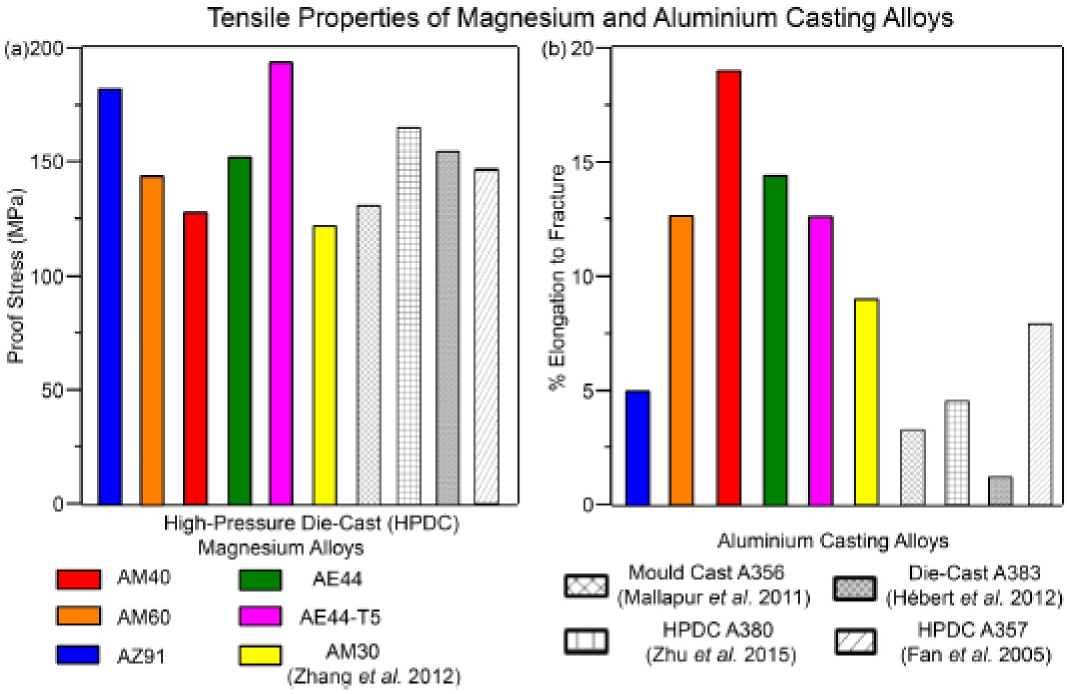


Figure 8.2: Comparison of (a) proof stress and (b) % elongation to fracture of magnesium and aluminium casting alloys. The proof stress of magnesium alloys is measured by the 0.45% offset method while the proof stress of aluminium alloys is measured by the conventional 0.2% offset method. Data of magnesium alloy AM30 [1] and aluminium alloys [2-5] are taken from the literature.

[1] Zhang JH, Liu SJ, Leng Z, Liu XH, Niu ZY, Zhang ML et al. Structure stability and mechanical properties of high-pressure die-cast Mg-Al-La-Y-based alloy. Materials Science and Engineering A 2012; 531: p. 70-5.

Performance Evaluation of High-Pressure Die-Cast Magnesium Alloys

Mark Easton, Suming Zhu, Mark Gibson, Trevor Abbott,
Hua Qian Ang, Xiaobo Chen, Nick Birbilis, and Gary Savage

Table 1 Chemical compositions (wt%) of the alloys in this study determined by Inductively Coupled Plasma—Optical Emission Spectroscopy

Alloy	Al	Si	Ca	Sr	Sn	Mn	Zn	Ce	La	Nd	Pr	Y
AZ91	8.88	–	–	–	–	0.19	0.74	–	–	–	–	–
AM60	6.26	–	–	–	–	0.29	0.1	–	–	–	–	–
AS31	3.52	0.56	–	–	–	0.27	–	–	–	–	–	–
AJ52[a]	5.2	–	0.07	1.86	–	0.25[a]	–	–	–	–	–	–
MRI153A	8.32	–	1.01	0.09	–	0.22	0.75	–	–	–	–	–
MRI153M	7.73	–	1.06	0.30	–	0.25	–	–	–	–	–	–
MRI230D	6.49	–	2.00	0.43	0.95	0.28	–	–	–	–	–	–
AXJ530	4.49	–	3.44	0.17	–	0.25[a]	–	–	–	–	–	–
AE42	3.45	–	–	–	–	0.31	–	1.45	0.60	0.41	0.1	–
AE44-4	3.73	–	–	–	–	0.30	–	2.47	1.21	0.51	0.1[a]	–
AE44-2	3.95					0.15		2.82	1.32			
AM-HP2+	0.05	–	–	–	–	–	0.42	0.99	1.65	0.96	–	0.08

Where the amount is not listed the composition is below the detectable range usually 0.01 wt%
[a]Note that it was planned to make AJ62, but the Al content was measured to be 5.2%, in other words AJ52

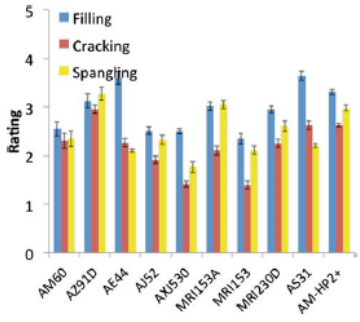
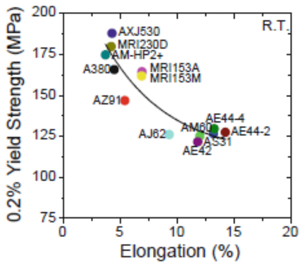


Fig. 2 Average ratings for cracking, filling and spangling for the selected Mg die casting alloys using the specially designed castability die



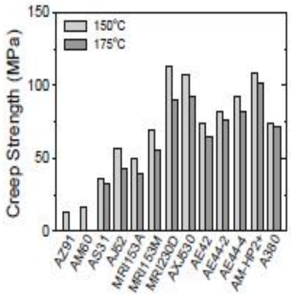


Fig. 4 Creep strength (stress to produce 0.1% strain at 100 h) at 150 and 175 °C for the selected Mg alloys. Al die-casting alloy A380 is included for comparison

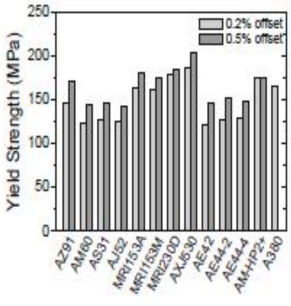


Fig. 5 Room temperature yield strength determined by 0.2% offset and 0.5% offset for the selected Mg die-casting alloys. Al die-casting alloy A380 is included for comparison

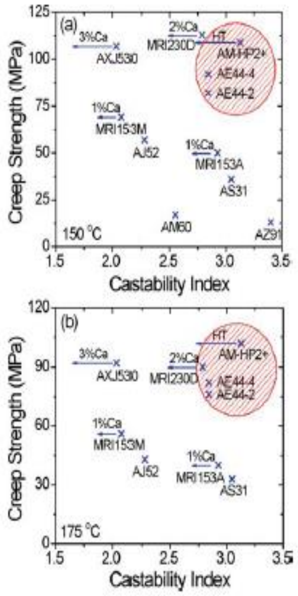


Fig. 8 0.1% creep strength at **a** 150 °C and **b** 175 °C plotted against castability index (average index of filling and cracking) for the selected Mg diecasting alloys. The *arrows* show decreases in the castability related to melt handling (MRI153M, MRI230D and AXJ530) and hot tearing resistance (AM-HP2+)

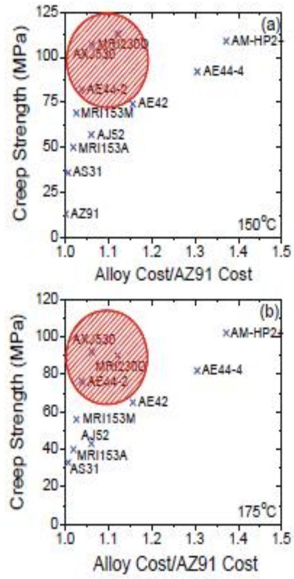


Fig. 10 0.1% creep strength at **a** 150 °C and **b** 175 °C plotted against material cost relative to that of AZ91 for the selected Mg diecasting alloys. The *circled areas* indicate alloys with high creep resistance yet low cost