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APPLICATION OF NEURAL NETWORKS FOR ASSISTING, CONTROLLING AND DESIGNING TECHNOLOGICAL PROCESSES

K. Żaba[1], B. Świątek[2], S. Nowak[1], A. Sury[3], M. Wojtas[4]

[1]Faculty of Non-Ferrous Metals, AGH University of Science and Technology, Cracow, Poland (krzyzaba@agh.edu.pl),

[2]Faculty of Electrical Engineering, Automatics, IT, Electronics, AGH University of Science and Technology, Cracow, Poland,

[3]Infoster Sp. z o.o., Cracow, Poland,

[4]Elsta Sp. z o.o, Cracow, Poland,

Abstract. *The methodology and examples of utilising neural networks for assisting, controlling and designing technological processes is presented in the paper. Examples concern the continuous melting, casting and rolling of aluminium and alloy rod intended for drawing for electrical wires. Neural networks allow to build dependencies between the performance parameter set, chemical composition of the processed material, and product properties. These functions are used for the process control and for determining the optimal work point of the technological line. The initial data constitute the analytical results of the metal chemical composition and process data collected by the specially built system of canvassing realisation parameters of all unit processes. The effectiveness and efficiency of the system was assessed.*

Keywords: *Neural networks, Continuous melting, casting and rolling line, Electrical wire.*

1. PROBLEM FORMULATION

The results of research concerning empirical dependencies between properties of the processed material and the chemical composition and parameters of the processes forming the technological line, are presented in the paper. The neural network technique was applied for the approximation of the experimental data.

The problem was solved in full consciousness that in multi-operational technologies in some cases only it is possible to predict properties after the selected operation stage (especially after the final operation) on the grounds of the properties before this operation and information of this operation parameters.

The most often the structure state before the operation, formed in successive operations should be also taken into account. This information can be given by the configuration and parameters of unit processes, it means by the processing history. For example, properties of the alloy, which is subjected to the precipitation strengthening after the drawing process, will depend not only on its chemical composition and deformation dimensions but also on the kind and parameters of the heat treatment before drawing, e.g. hyperquenching, natural aging and parameters of eventual artificial aging before drawing. A configuration of operations and their parameters are indirect information concerning the structure state differently reacting for deformations.

Likewise, in case of annealing of a material, which is not subjected to the precipitation strengthening, not only its chemical composition, temperature and time should be taken into account, but also the structure state - at least by giving its cold deformation value.

In consequence, two types of models were singled out.

1. Models taking into account the previous operations and the parameters of the operation after which the properties are determined:

PROPERTIES = f(chemical composition; parameters of the previous and actual unit process)

2. Models taking into account the initial property value before the selected operation and parameters of this operation:

PROPERTIES = f(chemical composition; the looked for parameter value before the operation, parameters of the operation)

In both cases the problems are multidimensional and non-linear.

The special program was developed for solving these problems. All technological stages, joining unit processes in groups, variables, connections and model designing within these variables are defined by the user. Models are remembered and can be improved by the new data introduction. The computational results are presented in numerical and graphite forms. The measuring data are introduced into the data base regardless of models designing and defining procedures. Models can be built for the already existing data in various configurations. Network parameters are determined at the stage of its training on the basis of the introduced measurement results. The neural network training occurs after each portion of experimental data and in this sense the program is of an adaptive character.

After defining of the models the selection of proper data from the data base and the network training program are activated. When the training is finished, the network structure is stored in the disc under the model name. The access to it is possible by introducing the name. The main monitor of the program is presented in Figure 1.

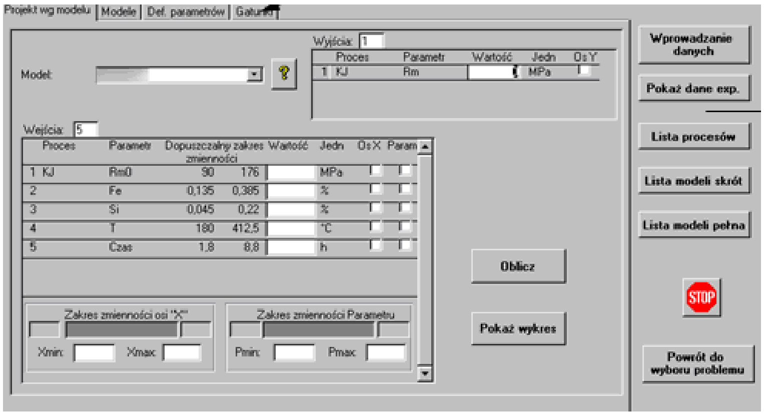


Figure 1. Main monitor of the program.

Training functions are organised in the monitor shown in Figure 2.

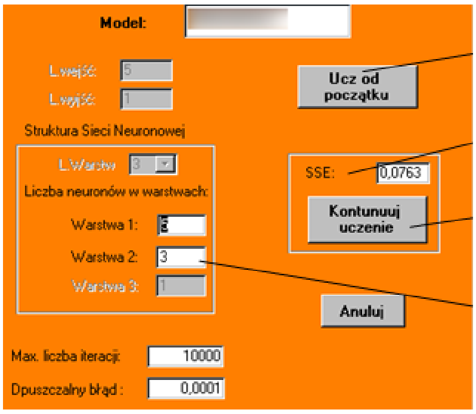


Figure 2. Neural network training (model building).

An example of solving the dependence: tensile strength (R_m) as a function of the annealing temperature (T) is presented in Figure 3.

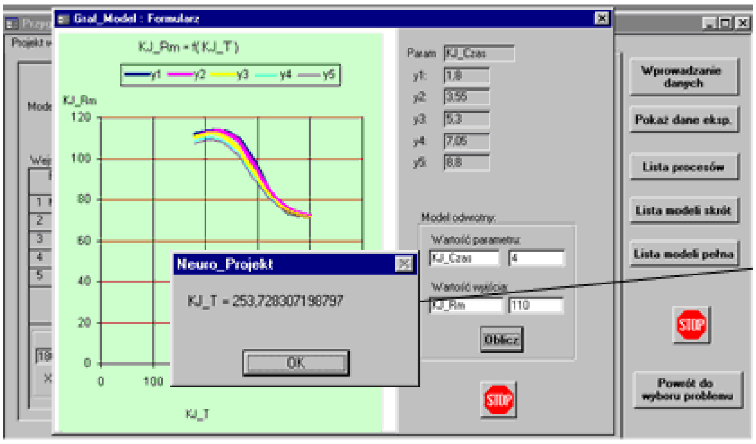


Figure 3. Presentation of the solution: $R_m=f(T)$.

2. ESSENCE OF MODELING BY NEURAL NETWORKS

Artificial neural networks (ANN) are effective tools for solving this type of problems mainly due to their ability of approximation of any multidimensional non-linear function. The approximated function is obtained in the network training process, and this feature singles it out from other technical systems [1-3]. Network training is based on presenting the training set it means the set of the process parameters values and the product parameters values. During the training process the network modifies its parameters in such a way as to find their relations. The result is in a form of the network model, being simultaneously the process model. The network excitation by values corresponding to process parameters causes that values corresponding to the product parameters occur at the output. The problem is presented schematically in Figure 4.

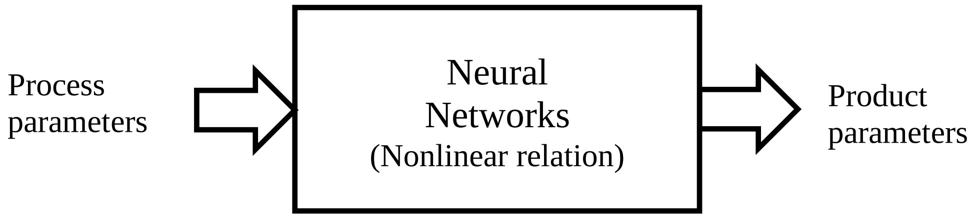
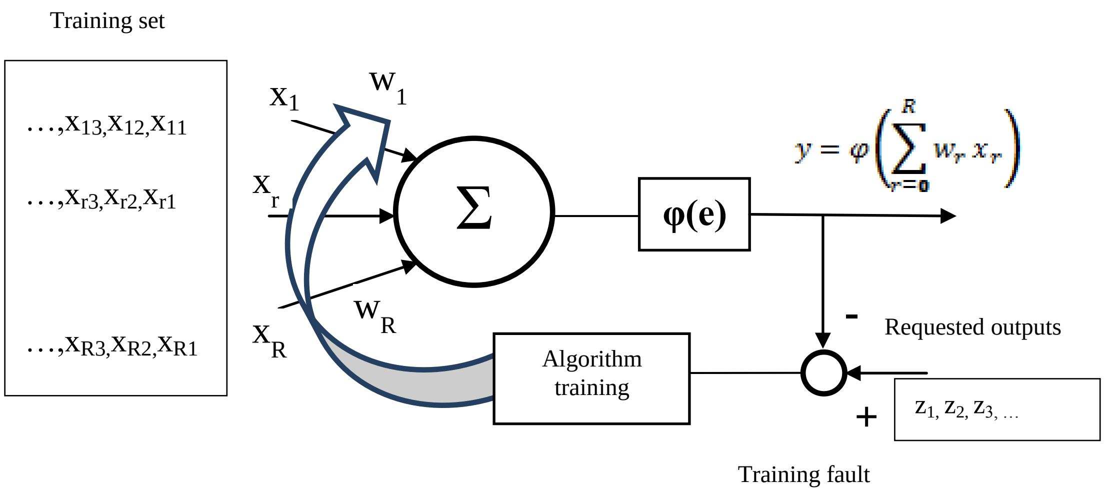


Figure 4. Processing of input data into output data by means of the neural network.

An attraction of a neural networks application is also caused by the possibility of their continuous adaptation. During the training process the network adapts itself to the new data. The model of the single artificial neuron and the way of training and answering computation is presented in Figure 5.



$$Q = \frac{1}{2}\sum_{k}\left(z_k - \varphi\left(\sum_{r=0}^{R} w_r x_r\right)\right)^2 . \qquad (1)$$

Figure 5. Neuron model.

During the training process the neuron modifies its balance to minimise the quality index (1). Training consists in looking for the minimum of function (1) by the iterative method of the steepest descent. The obtained algorithm is very simple and reduced to adding a certain part of input signals vector to the balance vector.

Unidirectional neural network is composed of layers containing neurons of the same type. The network topology (Figure 6) is very regular. Each layer input is joined with each neuron. Each input has the assigned balance. Each layer output is joined with each neuron of the next layer or can constitute the network output. This enables a generalization of the algorithm training single neuron into the whole network. In case of training multilayer networks the back-propagation algorithm is used.

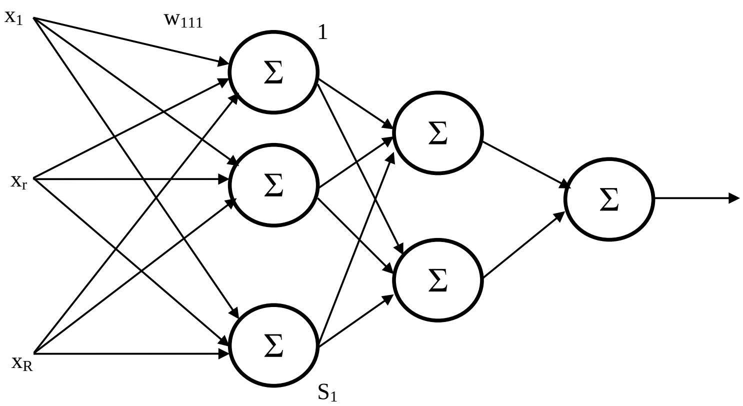


Figure 6. Neural network model.

Depending on the number of layers the network has not only the ability for approximating more and more complex functions but also for the identification of various shapes in a multidimensional space. This feature can be used for the determination of the process work point (set of optimal parameters). The two-layer network built of ideal perceptrons is able to recognize simplexes sets. Three-layer network built from the same elements identifies concave and disjoint sets. Giving at the network input the process parameters set and at the output the binary information: 1 – process without defects, 0 – process with defects, such trained network can be used either to the process control or to the determination – by the simulation method – of allowable changes of input parameters. Substituting ideal perceptrons by real neurons of e.g. sigmoidal transfer function causes that only some determination strictness of the transfer limit from one state into another is lost. The example of visualisation is presented in Figure 7.

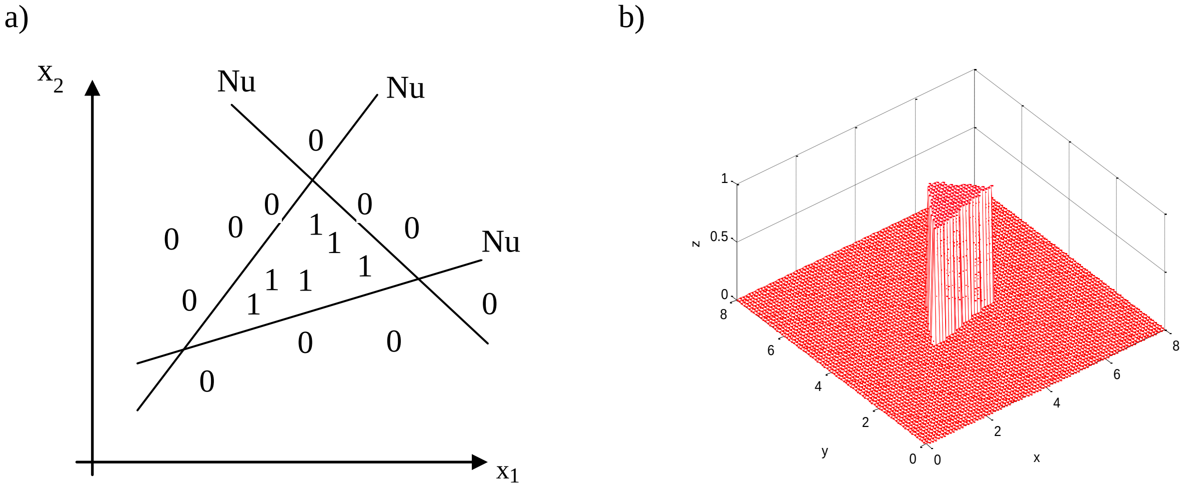


Figure 7. Example of the process, in which defects depend on two parameters and occur in the triangle shape
a) two-layer network, b) three-layer network.

3. EXAMPLES OF MODELS FOR VARIUS TECHNOLOGICAL PROBLEMS

3.1. Evolution of properties of AlMgSi alloys in production processes of self-supporting electrical wires.

Self-supporting electrical wires are produced from AlMgSi alloy. A charge for wire drawing, from which cables are twisted is a round wire rod of a diameter 9.5mm produced in the continuous casting and rolling line under conditions which warrant hyperquenching during rolling and cooling behind the rolling mill.

Wire and cable properties are formed by the chemical composition (basic additions content, according to the standard, is: ~0.4÷0.8%Mg and ~0.4÷0.8%Si), utilising effects resulting from deformations (drawing), precipitation strengthening (natural and artificial aging) and effects of the heat-plastic treatment. This treatment occurs during hot-rolling in the continuous casting and rolling line with simultaneous hyperquenching and also during drawing when the wire temperature obtains values from the range corresponding to the artificial aging conditions. Wire properties can undergo successive changes during an insulation placement. This operation is carried out at a temperature app. 160ºC and is followed by the next heat treatment in special lines at a temperature of 350ºC for 3÷4 minutes.

In the end the chemical composition, technological paths (alloys after another hyperquenching can be processed in various configurations of operations: natural aging - NA, artificial aging - AA, drawing - D, final heat treatment - FHT) and parameters of individual operations provide a chance of obtaining wires in the cable of a tensile strength to app. 380÷400MPa, elongation 3.5÷10%, resistance 30÷32.5nΩm and warrant the remaining exploitation features, including stability of properties at increased temperature, creep resistance and fatigue strength.

Examples of the possibility of forming properties are illustrated in Figure 8, where the dependence of the tensile strength and resistance on the basic alloying additions content for various technological variants is shown. Phase transformations occurring in the alloy cause that the determination of properties after a certain stage of processing (especially – the final) requires creation type 1 model. It means that it requires not only initial values before the operation and its parameters, but also information on the initial structure state, which reduces to the information on the configuration and parameters of previous operations.

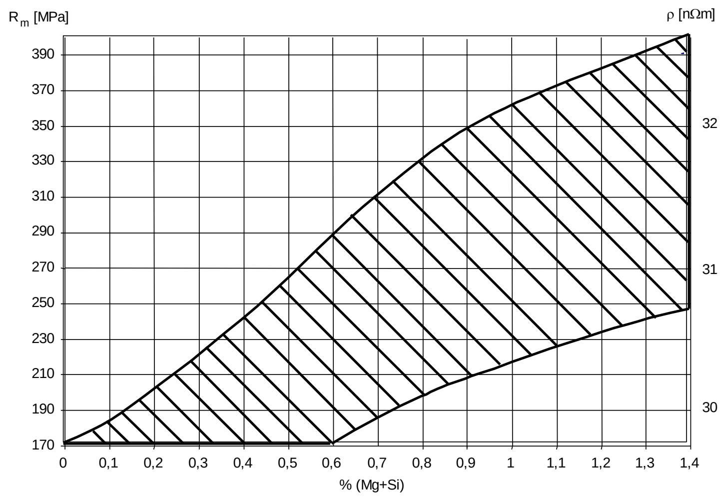


Figure 8. Dependence of tensile strength and resistance of wires on Mg and Si content for various technology.

If e.g. the aim is to design properties and to select process parameters in the technological line: NA-AA-D, the property function is of a form:

$$\textbf{\textit{Property (e.g. }}\boldsymbol{R_m}\textbf{\textit{)}} = \boldsymbol{f(\%Mg, \%Si; T_0, \varnothing_0; t_{NA}\ T_{AA}; t_{AA}; t_{he}; t_w, \varnothing_w; V_d)}$$

where:
-%Mg, %Si – percentage content of alloying additions,
-To – temperature of ingot before rolling mill (and hyperquenching),
-∅o – rod diameter,
-T_{NA} – natural aging time,
-T_{AA} – temperature of artificial aging of a rod,
-t_{AA} – artificial aging time,
-t_{he}, t_{ho} – heating and holding time at the assumed temperature of individual layers of coil (dependent on a coil mass and furnace characteristics),
-$\varnothing_w$ – wire diameter,
-V_d – drawing rate.

Due to the fact that models are taking into account the heating characteristics of a coil (via time of a temperature increase up to the assumed level) the information on the properties scatter caused by the layer position in a coil are obtained. The layer position in a coil is identified by the wire amount obtained to the determined moment.

One of the solutions for path NA-AA-D is presented in Figure 9. Diagrams present wire properties for alloys of the selected chemical compositions, made from rod hyperquenched in the line (ingot temperature was 520°C), and subjected to artificial aging at a temperature of 180°C.

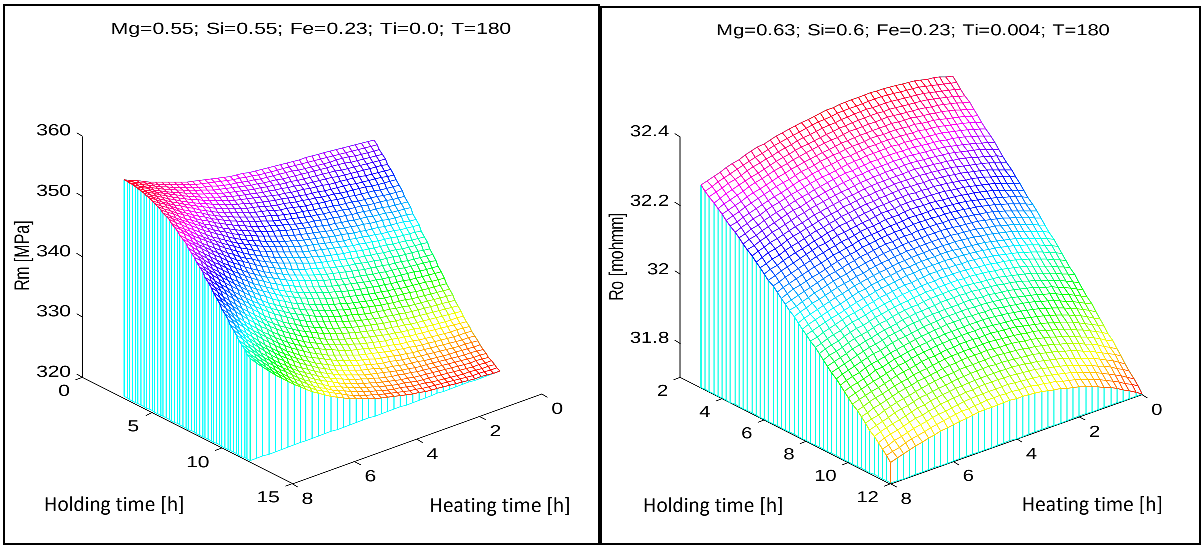


Figure 9. Solution example: strength and resistance of a wire from AlMgSi alloy as a function of heating and holding time at a temperature during the artificial aging of rod.

3.2. Properties of aluminium in rod production processes and its transformation into wires

The task is to create the function of controlling the continuous casting and rolling process in order to obtain required mechanical and electrical properties of the round aluminium rod.

The main elements of the line, with marked essential parameters and points at which their control is possible:

metal preparation, cannels and filter preparation, refining unit, casting machine, straightening machine, milling machine, induction heater, rolling mill, quenching chamber, wire shear, coilers.

The additions content and temperature during rolling are the most important parameters, on which the final rod properties depend. The 12 elements content is determined, in which the highest fraction belongs to iron and silica.

The strip temperature is a function of a liquid metal temperature, casting rate, crystalliser cooling conditions (pressure and discharge of cooling water and its distribution on the crystalliser perimeter), increased ingot temperature during eventual reheating in an induction furnace (ΔT), and conditions of the a strip cooling during rolling (pressure and consumption of cooling-lubricating emulsion). By changes of the casting conditions and the ingot temperature before the rolling mill the tensile strength can be changed within the range: 90÷150MPa. A field of mechanical properties changes is illustrated in Figure 10.

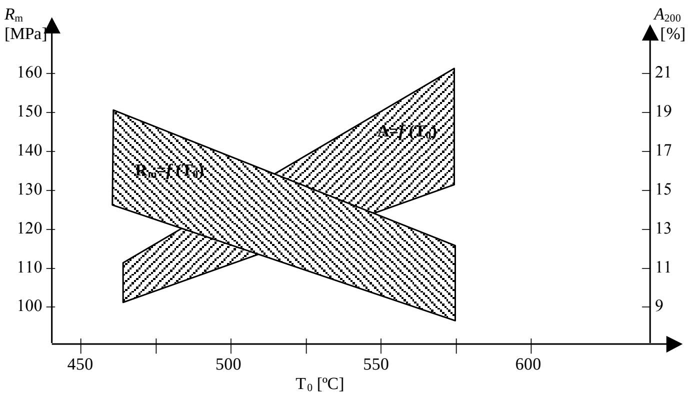


Figure 10. Strength and elongation of Al. rod as a temperature function for aluminium of a different purity and for various crystallisation and rolling conditions.

The model is of a form:

$$\boldsymbol{R_m;\ A_{250};\ \rho = f(\textit{chemical composition; casting conditions, rolling conditions})}$$

where:
-R_m – tensile strength;
-A_{250} – elongation in a tension test;
-ρ – resistance

When assuming that the most important final casting parameter constitutes the ingot temperature before the rolling mill the following model is obtained:

$$\boldsymbol{R_m;\ A_{250};\ \rho = f(\textit{chemical composition; ingot temperature, rolling parameters})}$$

Data collected during the exploitation allowed to build the model. Examples of network simulations are presented in Figure 11-12.

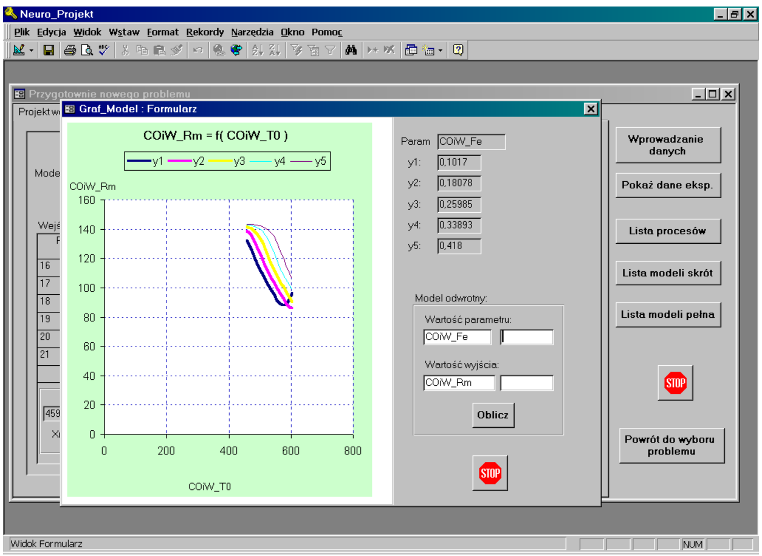


Figure 11. R_m=*f*(ingot temp.) for various Fe content.

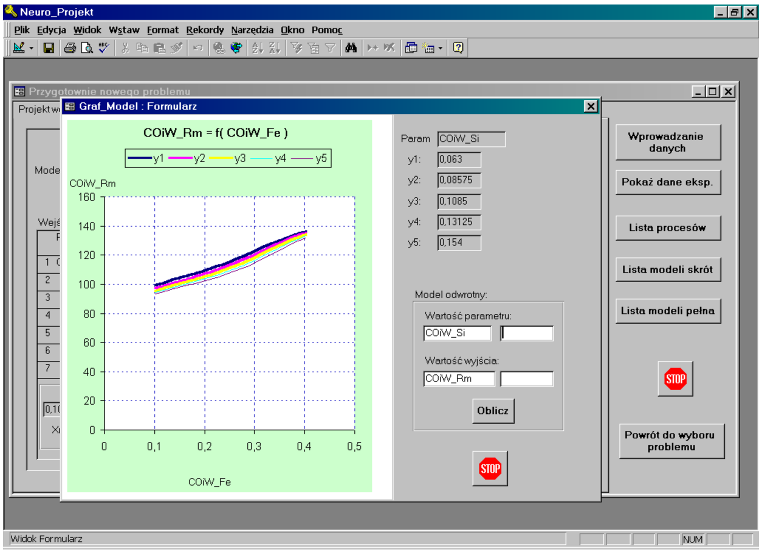


Figure 12. R_m=f(Fe content) for various Si content.

3.3. Rod annealing

In order to obtain product of strength <100MPa, the rod is subjected to soft-annealing. The problem is to select a temperature and heating time for the charge produced in the continuous casting and rolling line, being in a different initial state and differently reacting to a heat treatment. The following model was built:

$$R_m;\ A_{250};\ \rho = f(\text{chemical composition};\ R_{m(o)};\ T;\ \tau)$$

where:

-T – temperature of annealing;

-τ – time of annealing

Special experiments allowed to find the solution presented in Figure 13-14.

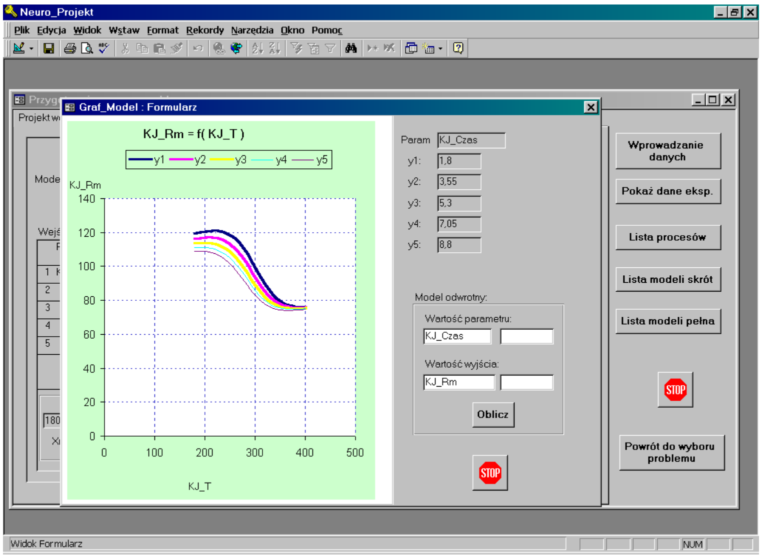


Figure 13. R_m=f(high temp.) for various times, R_{m0}=123MPa, Fe=0.3%, Si=0.15.

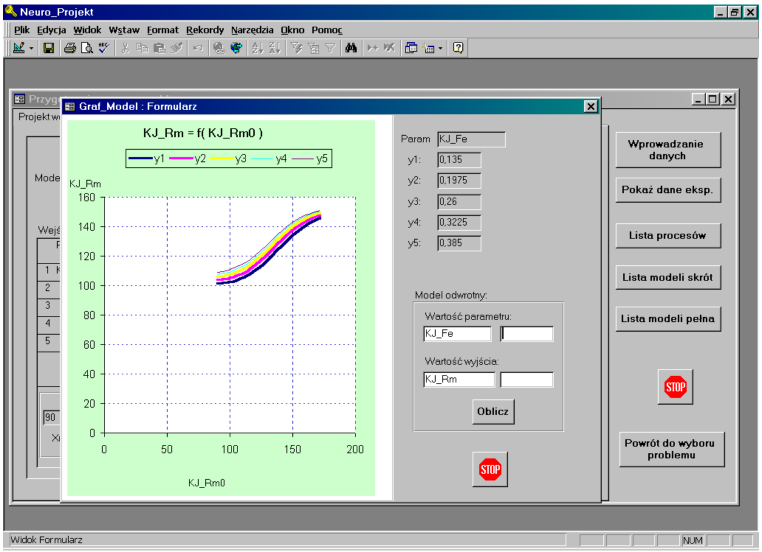


Figure 14. $R_m=f(R_{m0})$ for various Fe content, T=200°C, τ=2h, Si=0.15%.

3.4. Properties of strips made of AlMg alloys subjected to soft-annealing.

Strips were produced in the technological line:

melting – gaseous refining – semi-continuous casting – heating of ingots —hot rolling –cold rolling – annealing.

One of the variants was intermediate annealing. Kinetics of processes occurring in a material during heating (properties level after annealing) depend not only on a temperature but also on a chemical composition and this material energy state formed in individual operations, starting from the crystallisation, then hot-rolling up to cold-rolling (first of all).

In consideration of the kind of available data on parameters of individual processes (samples for investigations were taken from coils made in established conditions of casting, heating, hot- and cold-rolling) the following model was built:

R_m; R_{02}= f(%Mg, %Fe; %Si; strip thickness after hot-rolling; strip thickness after intermediate rolling; strip thickness after final rolling; temperature and time of heating)

A chemical composition was changed from app. 1.8% Mg to app. 3.2% Mg. This model was built for predominating quantitatively additions – Fe and Si. During a special experiment strips were annealed at temperatures: 200, 220, 250, 275, 300, 350ºC for 2, 5, 22 hours. R_m was estimated in a tensile test. Some examples of the neural network simulation results are presented in Figure 15-16.

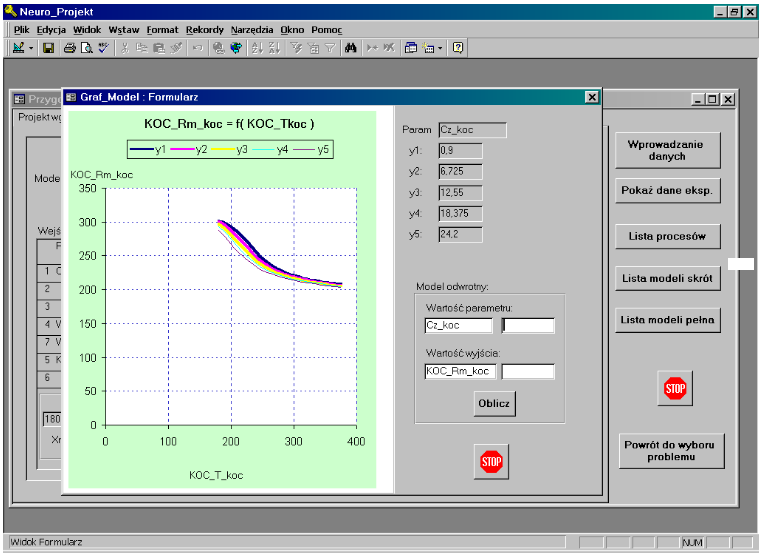


Figure 15. $R_m = f$(temp. FHT) for various times, Mg=2%, Si=0.35%, $\varepsilon_j=0.05$.

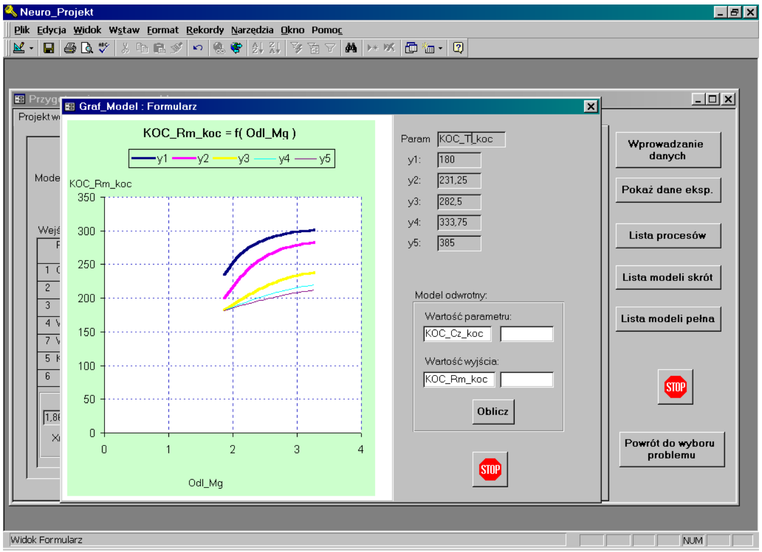


Figure 16. $R_m = f$(Mg content) for various τ=5h; temp. FHT=5h; [Si]=0.35%; $\varepsilon_j=0.05$.

3.5. Properties of aluminium strips subjected to soft-annealing.

The function describing property changes of the cold-rolled Al strip during annealing to the determined level of strength properties – is looked for. The strip is produced according to the scheme:

melting – gaseous refining – semi-continuous casting – ingot heating – hot-rolling – cold-rolling – annealing.

Samples for investigations were taken from coils made for the established ingot temperature and established conditions of carrying rolling processes, hot and cold. In consideration of the kind of possessed data it was possible to build the following dependence:

R_m;= f(%Fe; %Si; $R_{m(o)}$; strip thickness after hot-rolling; strip thickness after cold-rolling; temperature and heating time)

The chemical composition was changing from app. 99.7% Al to app. 99.5% Al. The predominating quantitatively additions Fe and Si were selected for building the model. In the experiment used for collecting data, annealing was performed at temperatures: 200, 220, 235, 250, 270, 290ºC for 1, 2, 3, 4 hours. R_m was determined in the tensile test. Strip thickness before rolling was 12mm and after hot and cold rolling was 1mm. Some examples of the neural network simulation results are presented in Figure 17-18.

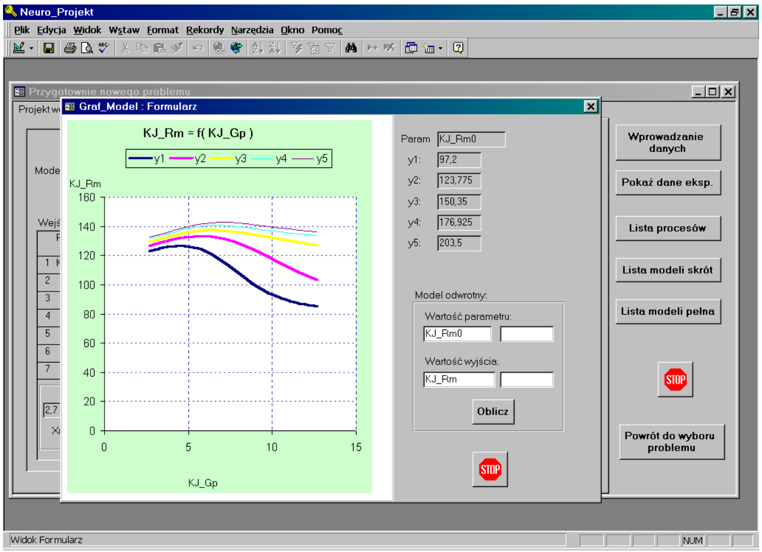


Figure 17. $R_m = f$(initial thickness) for various R_{m0}, Fe=0,26%, Si=0,15%, T=235ºC; τ=2h.

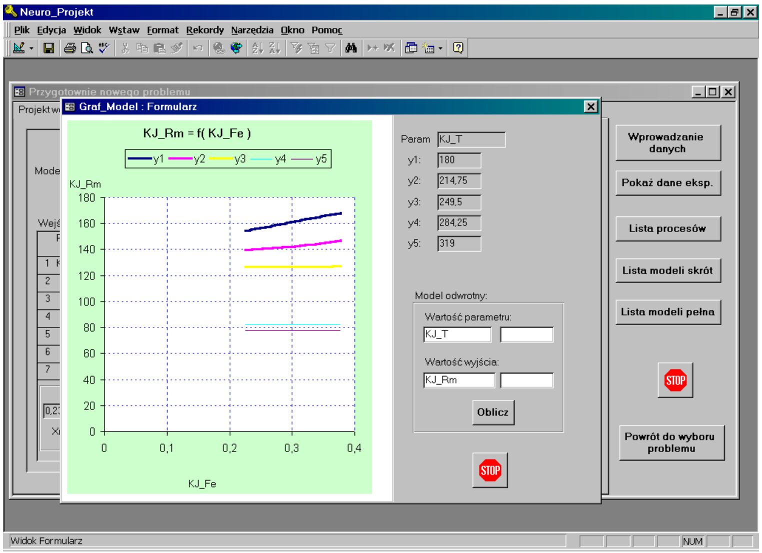


Figure 18. $R_m = f$(Fe content) for various annealing temperatures, R_{m0}=174MPa, Fe=0.26%, Si=0.15%; τ=2h, R_m=100Mpa.

3.6. Properties of copper rod produced in continuous melting, casting and rolling line (CONTIROD).

An example concerns a copper annealing ability. The test of a loaded elongation is used for assessing the possibility of copper resistance annealing in the drawing or enamelling line. The spring is made of wire ∅2mm, drawn from rod ∅8mm, annealed under standard conditions. The following function is looked for:

$$\Delta L_{spr} = f(\text{chemical composition; parameters of processes in the CONTIROD line})$$

Some examples of the neural network simulation results are presented in Figure 19-20.

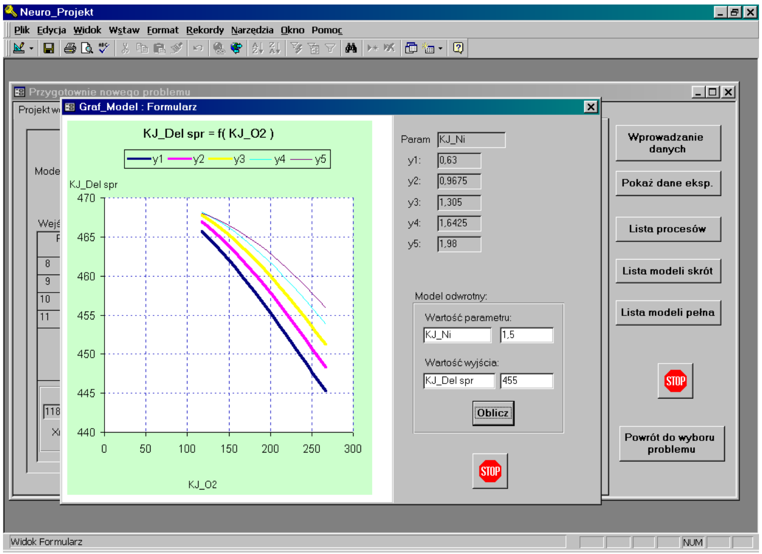


Figure 19. Elongation as the function of the oxygen content in rod.

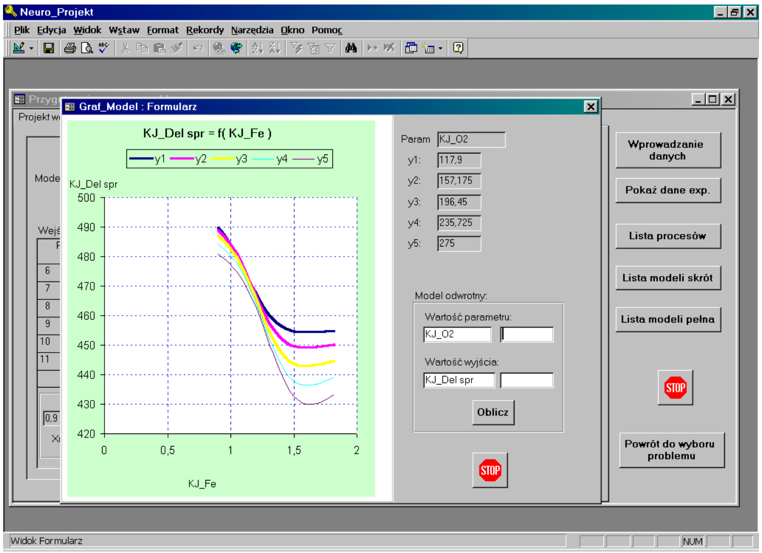


Figure 20. Elongation as the function of the iron content in rod.

3.7. Strengthening curves for material of diversified chemical composition and different initial state

The following function is looked for:

Properties after deformation (e.g. R_m, $R_{0,2}$) = f(deformation value, chemical composition, initial properties)

The example concerns the dependence $R_m=f(\varepsilon)$ for aluminium. A charge material for investigations carried out in order to collect data was the rod from example 1 of various level of initial values and a compact. A metal purity was changing from 99÷99.9% Al.
If there is a need of solution in the analytical form (formula), then values R_m, $R_{0,2}$, determined by means of the model for various deformations of composition and initial conditions can be approximated by function e.g. $A+B\varepsilon^n$ in the module of the classic approximation by the least square method.
Solutions performed by the neural network were presented in Figure 21-22. In Figure 21 they are presented in the classic system of coordinates $R_m(\varepsilon)$ for various Fe content and in Figure 22 the simulation results are in the system $R_m(R_{mo})$ for various Fe content.

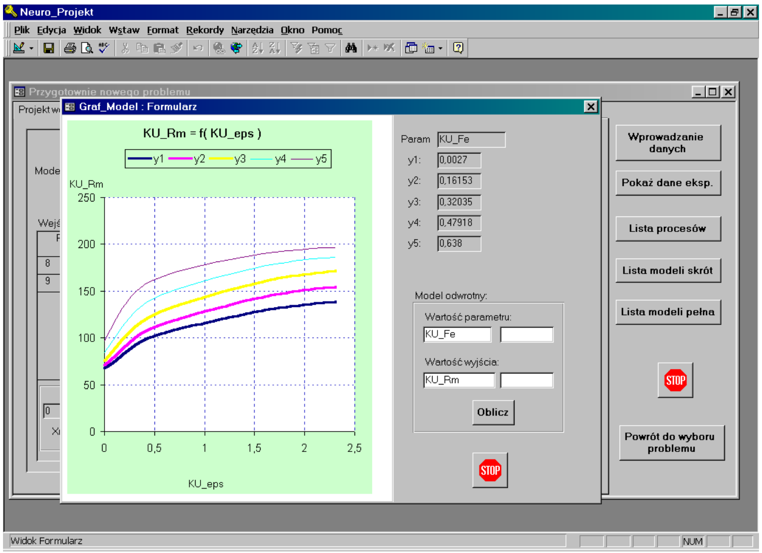


Figure 21. $R_m(\varepsilon)$ for various Fe content, Si=0.13%.

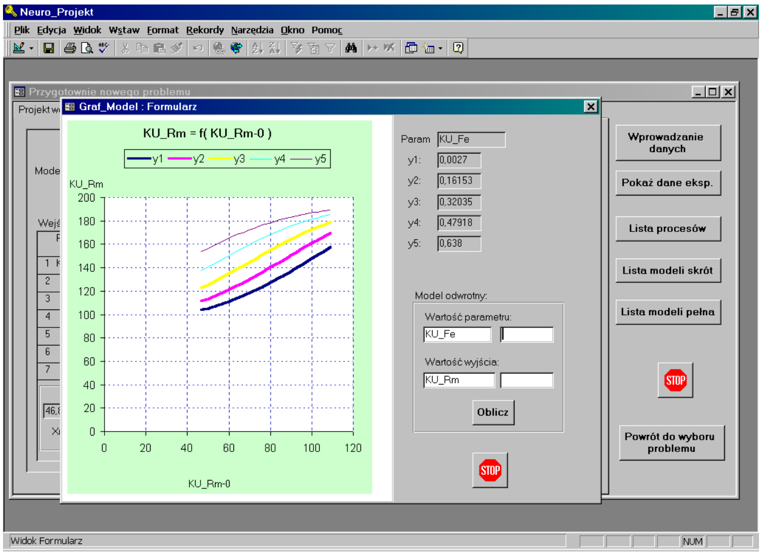


Figure 22. $R_m(R_{m0})$ for various Fe content, Si=0.13%, $\varepsilon_{(log)}$=2.2.

4. CONCLUSIONS

An attention should be directed toward the practical aspect of the presented simulation method. Both, the method and the designed by the authors program allow collecting new data portions, model adaptation and thus its systematic improvement. Due to that the method can be applied at the investigation stage, identification as well as in the process control.

5. REFERENCES

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