Recenzované vědecké články

Selected Aspects of Modelling in the Metallurgical Industry

Vybrané aspekty modelování v hutním průmyslu

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Selection of the right modelling tools is a key factor for ensuring the accuracy of the created model. For the case when the model should serve to predict the behaviour of the modelled system, it is necessary that the predictions reach the greatest possible consistency with the real system behaviour. One of the aspects for a suitable model selection is determination of the coefficient R. For creation of the models MATLAB and its tools of regression and of artificial neural networks were used. Neural networks provide higher match between the real and predicted values, while regression is more robust in terms of the values, which the neural network did not learn. The article shows the possibility of using both models in the foundries for an assessment of the heating and castings heat treatment efficiency. Thanks to the sufficiently accurate prediction it is possible to determine the heating gas consumption for the given type of heat processing and for the charged weight.

Key words*: artificial neural network; model; regression; robust*

Výběr správných modelovacích nástrojů je klíčem k přesnosti vytvořeného modelu. V případě, že model by měl sloužit k předpovědi chování modelovaného systému, je nezbytné, aby předpovědi dosáhly co největšího souladu s chováním skutečného systému. Jedním z aspektů vhodného výběru modelu je určovací koeficient R. Pro sestavení modelů byl použit MATLAB a jeho nástroje regrese a umělých neuronových sítí. Neuronové sítě poskytují vyšší shodu mezi reálnými a předpovězenými hodnotami, zatímco regrese je mnohem robustnější z hlediska hodnot, na které neuronová síť nebyla naučena. Prostředí MATLAB zahrnuje široké spektrum modelovacích nástrojů. Oba nástroje používané při práci poskytují srovnatelné výsledky, přičemž neuronová síť je mírně méně přesná. Pro posouzení vhodného modelu a jeho chování jsou klíčové jevy zobrazeny graficky. U neuronové sítě je důležité porovnání predikovaných a reálných dat. To lze posoudit pomocí grafu průběhu optimalizace nebo grafu predikce. Pro posouzení rozložení chyb byl využit histogram. V ekonomické praxi ve slévárnách mohou být oba modely použity k posouzení účinnosti ohřevu a tepelného zpracování odlitků. Vzhledem k dostatečně přesné predikci je možné stanovit spotřebu topného plynu pro daný typ tepelného zpracování a pro hmotnost vsázky. Model by měl tedy umožňovat porovnání ekonomických nákladů na tepelné zpracování ve srovnání s případnými sankcemi za nedodržení nasmlouvaného termínu u malokusových sérií, kdy na základě predikce ceny tepelného zpracování by mělo být možné určit, které náklady budou vyšší a podle toho pak zvolit ekonomicky výhodnější řešení.

Klíčová slova*: umělá neuronová síť; model; regrese; robustnost*

In the metallurgical industry, production costs are an important aspect of production. Foundry production, especially in the sphere of castings made from nodular iron and grey iron and steel castings, is a demanding production from the point of view of raw material, as well as energies. Since the foundry products usually – except few cases - are not the end-products but mostly only components of the final products, in most cases the margins of manufacturers are low. This means that the space for flexible production control in terms of order book is reduced.

The heat treatment of castings by annealing, quenching and tempering is one of the production stages. For these purposes, the heating furnaces are used; in most cases they are gas-fuelled. The target of foundries is to maximize charging of the furnaces with respect to their capacity. This, in view of the different heat treatment methods, cannot be always achieved due to the production terms.

In order to assess the heat treatment costs, a request to create a model for the gas consumption prediction based on the input parameters of the furnace charge was presented.

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1. Model Parameters

Heat treatment of castings in a heating furnace has determined the parameters that form simultaneously the inputs and outputs of the model [1].

The predictors of the model are the following:

- The weight of the charge gives the net weight of the processed products.
- The cycle length indicates the total heat treatment time.
- Initial temperature indicates the material temperature at the time of its putting into the furnace.
- The first rise rate indicates the temperature gradient in the first phase of heating.
- The first delay temperature indicates the temperature of the first dwell.
- The first delay time indicates the time of the first dwell at the temperature.
- The second rise rate indicates the temperature gradient in the second phase of heating.
- The second delay temperature indicates the temperature of the second dwell
- The second delay time indicates the time of second dwell at the temperature.
- The cooling rate indicates the temperature gradient in the cooling phase.
- The final temperature indicates the material temperature at the time of material pulling out from the furnace.
- Usage specifies the furnace capacity and real input ratio.
- Tv indicates the length (time) of the firing.
- The gas consumption for the entire processing cycle is the predicted value.

2. Classical Regression Analysis Methods

For the fast processing of basic regression models, MATLAB provides a tool of Regression analysis. This tool collects most of the regression tools that are available directly from the MATLAB command line. As a very advantageous tool it seems to be possible, for the initial analysis, to turn on all the available regression tools at the same time, and then, for further processing, to select the learned model that gives the best results. The method with the smallest quadratic error was the Gaussian process regression [2].

Gaussian process regression (GPR) models are nonparametric kernel-based probabilistic models. You can train a GPR model using the fitgpr function.

Consider the training set $\{(x_i, y_i); i = 1,2, \dots, n\}$ here $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$, drawn from an unknown distribution.

A GPR model addresses the question of predicting the value of a response variable y_{new}, given the new input vector x_{new}, and the training data. A linear regression model has the form $y = x^T\beta + \varepsilon$, where $\varepsilon \sim N(0, \sigma^2)$. The error variance σ^2 and the coefficients β are estimated from the data. A GPR model explains the response by introducing latent variables, $f(x\_i)$, $i = 1,2, \dots, n$, from a Gaussian process (GP), and explicit basis functions, h. The covariance function of the latent variables captures the smoothness of the response and basic functions project the inputs x into a p-dimensional feature space. A GP is a set of random variables, such that any finite number of them has a joint Gaussian distribution. If $\{f(x), x \in \mathbb{R}^d\}$ is a GP, then given n observations $x\_1, x\_2, \dots, x\_n$, the joint distribution of the random variables $f(x_1), f(x_2), \dots, f(x_n)$ is Gaussian. A GP is defined by its mean function $m(x)$ and covariance function, $k(x, x')$. That is, if $\{f(x), x \in \mathbb{R}d\}$ is a Gaussian process, then $E(f(x)) = m(x)$ and $Cov[f(x), f(x')] = E[\{f(x) - m(x)\}\{f(x') - m(x')\}] = k(x, x')$.

Now consider the following model. $h(x)T\beta + f(x)$, where $f(x) \sim GP(0, k(x, x'))$, that is $f(x)$ are from a zero mean GP with covariance function, $k(x, x') \cdot h(x)$ are a set of basis functions that transform the original feature vecto x in Rd into a new feature vector $h(x)$ in $R^p \cdot \beta$ is a p-by-1 vector of basis function coefficients. This model represents a GPR model. An instance of response y can be modelled as $P(y_i | f(x_i), x_i) \sim N(y_i | h(x_i)^T\beta + f(x_i), \sigma^2)$.

Hence, a GPR model is a probabilistic model. There is a latent variable $f(x_i)$ introduced for each observation xi, which makes the GPR model nonparametric. In vector form, this model is equivalent to $P(y|f, X) \sim N(y'H\beta + f, \sigma^2 I)$.

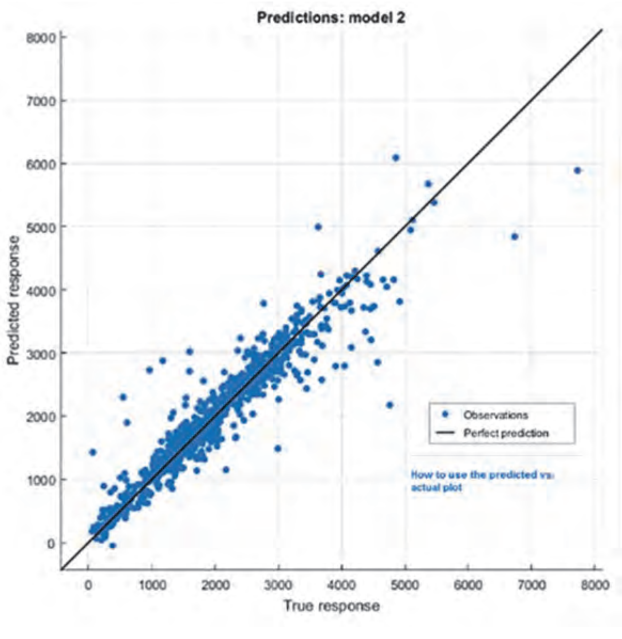

Fig. 1 Response – Prediction. Source: our own processing
Obr. 1 Odezva – Predikce. Zdroj: vlastní zpracování

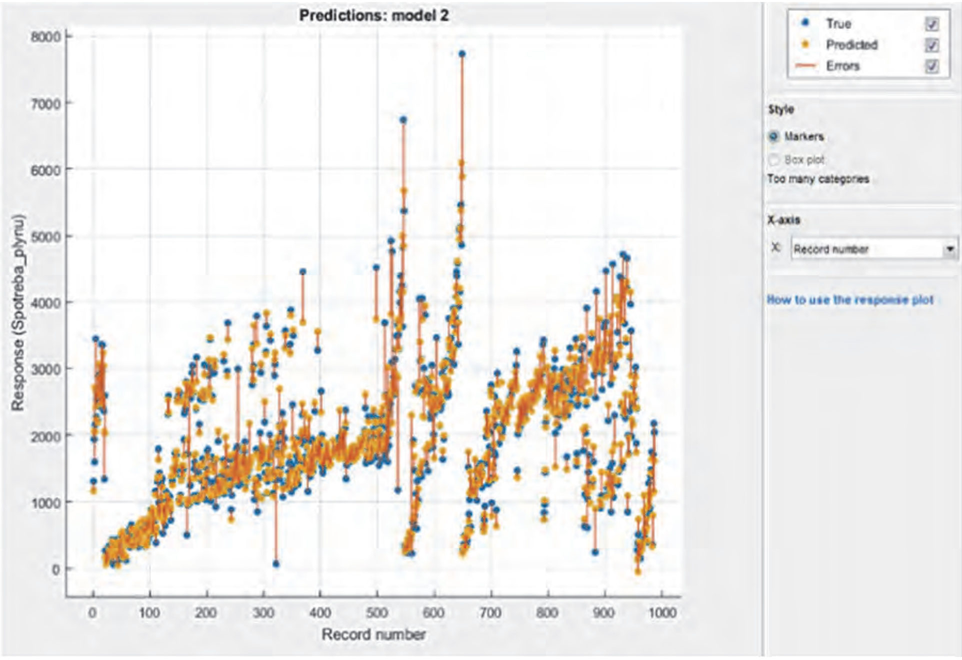

Fig. 2 Prediction, response and error value. Source: our own processing
Obr. 2 Předpověď, odezva a hodnota chyb. Zdroj: vlastní zpracování

The graphically expressed results are shown in Figs. 1 and 2. In Fig. 1 the blue points show the measured values (gas flow), the orange ones show the predicted results, and the connectors express the errors. Fig. 2 shows a graph of dependence of the real and predicted values for each gas flow value. The reached value of square sum root of errors RMSE = 303.75.

3. Use of a Neural Network for Used Gas Prediction

The artificial neural network (ANN) can be considered as a useful tool for creation of the model. In this case we are not able to formulate an analytical model of behaviour, especially due to the lack of the knowledge of the whole technological node [3].

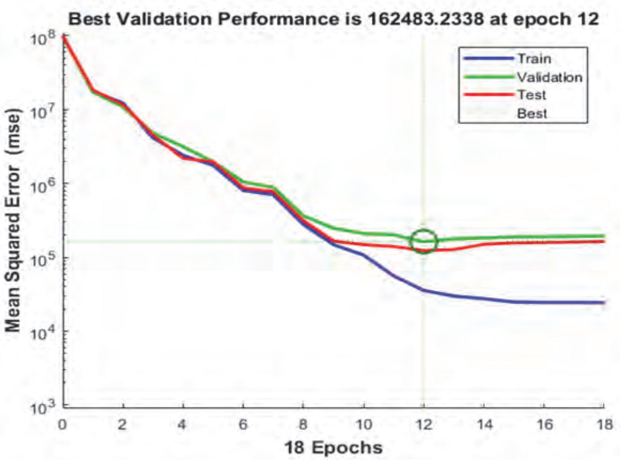

Fig. 3 ANN performance for each epoch. Source: our own processing
Obr. 3 Výkon ANN pro každou epochu. Zdroj: vlastní zpracování

Fig. 3 shows the dependences of the actual and predicted values for the training, validation, testing and summary sets. The obtained determination coefficient values are for the training set R = 0.98452 and for the test set R = 0.95762. As the sizes of the determination coefficient for those sets differ only in the hundredths, we can say that the resulting neural network will provide reliable predictions of gas consumption.

On the basis of histogram graph of errors as per Fig. 4, it can be stated that more than 500 instances have a prediction error less than or equal to -21.162 m^3 of gas.

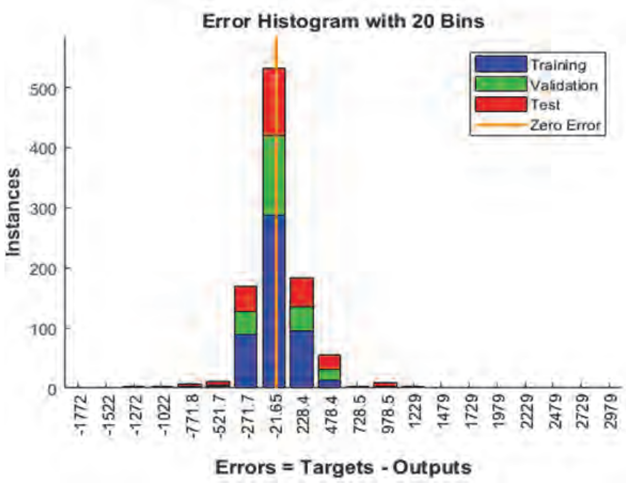

Fig. 4 Error histogram with 20 bins. Source: our own processing
Obr. 4 Histogram chyb pro 20 kategorií. Zdroj: vlastní zpracování

Fig. 5 shows that the network was trained during 18 periods, with the best performance achieved in the 13th stage. The value of the mean quadratic error was MSE = 162448 and therefore its square root value RMSE = 403.

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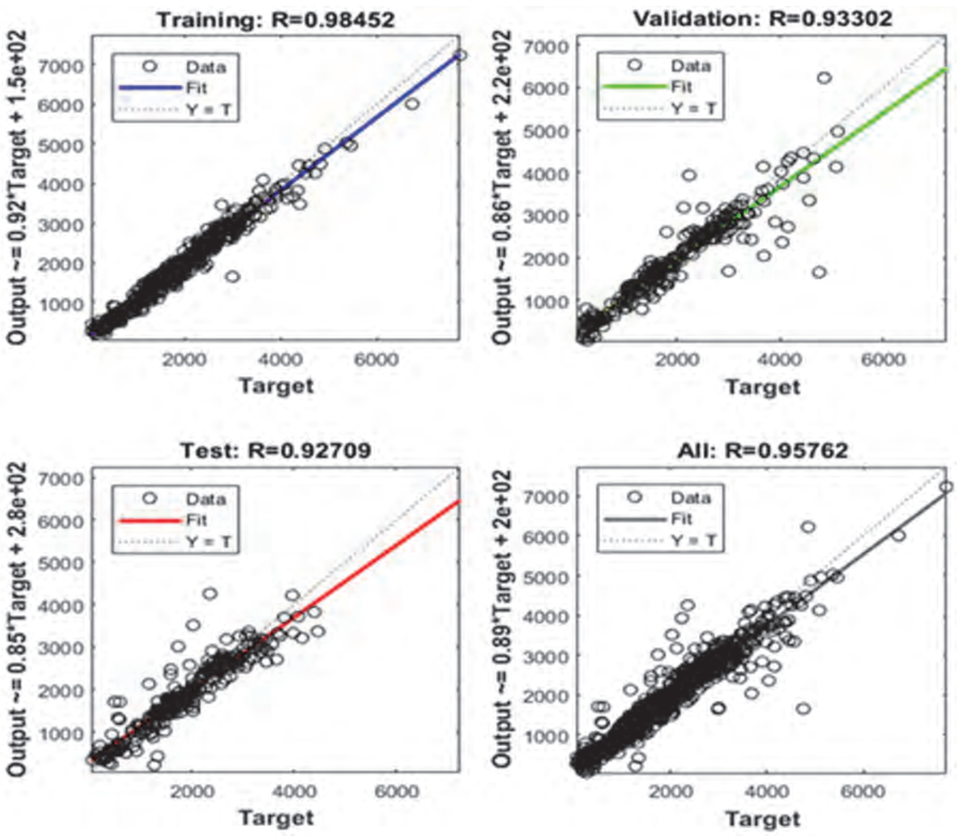

Fig. 5 Response – Prediction for ANN. Source: our own processing
Obr. 5 Odezva – Predikce pro ANN. Zdroj: vlastní zpracování

Conclusions

MATLAB's environment includes a wide variety of modelling tools. From the text above it is clear that both tools that were used at the work give comparable results; the neural network is slightly less accurate [4]. From a practical point of view, both models can be exported and used in economic practice in foundries for the assessment of efficiency of the heating and heat treatment of castings. Due to the sufficiently accurate prediction it is possible to determine the heating gas consumption for the given type of heat processing and of the charge weight. In this way the costs of heat processing for small batches (for time reasons) with penalty costs for non-compliance of delivery terms can be compared and then the economically more efficient way can be chosen [5].

Acknowledgments

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