

APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO IMPROVE STEEL PRODUCTION PROCESS

Igor Grešovnik^{1,2}, Tadej Kodelja², Robert Vertnik¹, Božidar Šarler¹

¹University of Nova Gorica

Kostanjeviška Cesta 16, Pristava, 5000 Nova Gorica, Slovenia

²Centre of Excellence for Biosensors, Instrumentation and Process Control

Velika pot 22, SI-5250 Solkan, Slovenia

gresovnik@gmail.com

ABSTRACT

The current work outlines application of a framework based on artificial neural networks and an integrated optimization module to adjustment of process parameters in steel production. The framework was originally developed for adjustment of parameters of material production processes in order to obtain the desired outcomes, and was primarily intended for use in the production of carbon nanomaterials in arc discharge reactors. Further development lead to more generalized procedures, applicable to a broad spectra of material production and processing. An example of optimizing the process parameters in continuous casting of steel on basis of expert knowledge and by the developed system is presented. Further steps are made towards modeling of the whole process chain in the steel plant, rather than just the casting process. Such models are in the development stage, and some preliminary results are shown where the model is used for performing some parametric studies.

KEY WORDS

Artificial neural networks, response approximation, continuous casting, steel manufacturing, optimization

1. Introduction

Continuous casting (process described in Section 3) enables large scale production of steel [14]. For efficient production, the process must run smoothly and without defects produced in the output material, which is controlled by the main process parameters such as temperature of the molten steel, casting speed, cooling in the mold, and spray cooling at different stages. Quality of the produced material must meet requirements prescribed by customers. Obtained material properties are result of both process parameters and chemical composition that is achieved when the steel is melted, and in turn chemical composition affects properties of the melt and solidified shell, as well as the solidifying process. A fair number of parameters must be properly adjusted in order to have efficient production of material with required properties.

A software framework has been developed for adjusting process parameters in material production in order to obtain the desired outcomes [22]. The framework was

initially intended for use in production of carbon nanomaterials in the arc discharge reactors, and has later been applied to continuous casting of steel. The framework functionality has been extended in order to provide support to different aspects of process design. In the present work, three example applications are shown. The framework is first applied to achieve desired outcomes in the continuous casting process. Further, it is applied to optimize process parameters in conjunction with numerical model of the process and engineering knowledge about the process. Finally, the framework was applied in order to predict outcomes of the whole chain of processes in a steel plant.

2. Software framework for neural networks modeling and optimization

The optimization part of the framework is designed as a stand-alone optimization system. Its development was centered around a library of optimization techniques for industrial problems where optimization is carried out on basis of computationally expensive numerical simulations whose results contain substantial level of numerical noise [1], [2]. This has been predominantly treated by algorithms based on adaptive approximation of the response functions. Successive approximations of sampled response over suitably sized domains enable exploitation of higher order function information. Restricted step approach is used to ensure global convergence, and adaptive sampling strategies play significant role in reducing the necessary number of evaluations of the response functions evaluated through expensive simulations.

Work was initiated as an attempt to re-implement the C library IOptLib [1]-[5] in a rigorous object oriented manner in order to more easily master complexity of the developed algorithms and to speed up the development process. In the future, framework will be extended in order to enable a straightforward inclusion and a seamless use of the third party optimizers. This requires careful design of abstraction levels and standardization of input/output and calling conventions, which is achieved by suitable wrappers, when third party software is incorporated. Further steps will be made towards more

unified treatment of different kinds of problems such as constrained / unconstrained or single objective / multiobjective optimization. Multidisciplinary approach is also considered in a way that different simulators may be used in different problem fields involved in a single definition of an optimization problem.

In many practical situations, process design parameters must be adapted quickly in order to produce results that comply with customer requests. With the classical approach to optimization of process parameters, long computational times needed for each run of the process simulation at trial design parameters can therefore limit applicability of process optimization in industrial environment. Alternative solution is to approximate the response of the observed system on basis of sampled response prepared in advance either by runs of numerical model or by measurements performed on previous designs used. Search for optimal design parameters is then performed on the surrogate model based on the approximated response.

In the current work, approximation based on neural networks has been applied. With this approach, evaluation of approximated response approximation is performed in two separate stages. In the training stage, the network is trained by using the sampled response (either measured or calculated by a numerical model). In the approximation stage, trained network is used for calculation of approximated response at arbitrary values of input parameters.

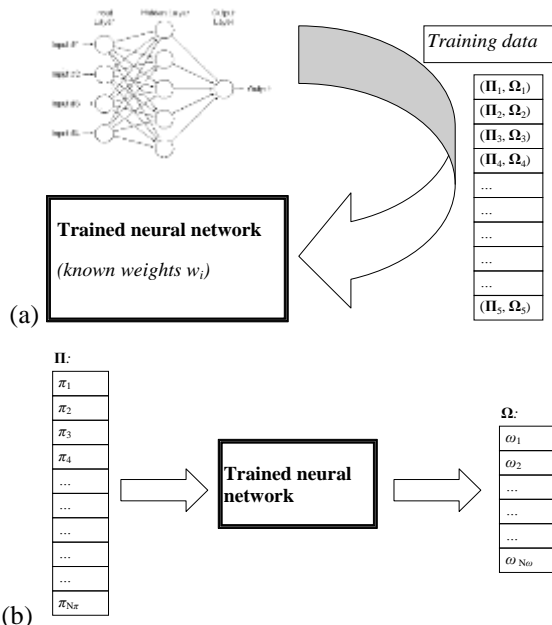


Figure 1: Two stages of application of the ANN-based system: a) building the approximation model by training the network on existent data, and b) evaluation of the approximate response by the trained neural network.

At the beginning, we have considered use of a commercial neural network approximation system for the approximation part of the framework. However, this turned inflexible and an in-house module was built based

on general purpose neural network libraries. It features modular design such that new underlying libraries can be easily utilized (open source libraries Aforge.Net [10] and NeuronDotNet [11] are currently used). This also provides good flexibility in integration with other software, designing training strategies, filtering training data, verification of results, testing different network layouts, etc. This is crucial when approximating behavior of material processing systems with a large number of process parameters. Data obtained from such systems is often inaccurate or even corrupted due to practical limitations in acquisition procedures. Response sampling can not be planned in advance but it is accommodated to production schedules in the factory, therefore information available may be deficient in some regions of parameter space in order to obtain good response approximation and therefore verification of results plays an important role.

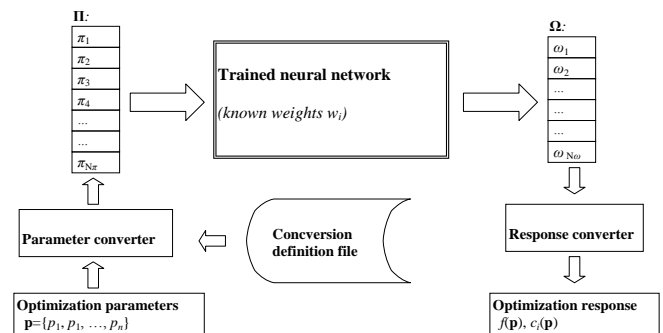


Figure 2: Evaluation of response functions based on approximated response, and integration of this step in optimization procedure.

Since the final goal is to optimize process parameters according to the design goals, we need to approximate the dependence of objective and constraint functions on optimization parameters. The described software system also supports a different approach where the neural network is trained with data that contains all influential parameters of the process and a number of rough output values sampled in the process. Specific optimization problems can then be defined on such approximated response by defining mapping between the optimization parameters and the input parameters of the neural networks, and mapping between the raw approximated output values and the higher level response functions (constraint and objective functions) of the optimization problem as they are defined. In this way we can solve differently defined optimization problems by using the same trained network, without the need to repeat the training procedure when the problem definition changes.

3. Process Description

The presented framework has been applied to optimization of process parameters of continuous casting process [12]-[17] in order to obtain the desired quality of produced steel billets. The industrial process considered is

outlined in [14]. Melted steel is poured into tundish, from which it flows to the mold where solidification begins. A partially solidified steel billet is transported from the mold by a series of supporting rolls. The billet is bent into horizontal position and solidifies from the surface towards interior, which is controlled by spray cooling and cooling of the rolls. At the end of this stage, the billet is cut and prepared for further processes.

Several requirements must be met in order that the process runs smoothly and without defects produced in the output material. At mold outlet the solidifying shell must be thick enough that the billet is not torn, which limits the affordable casting speed. In the region where bending occurs, the billet surface temperature must be high enough such that banding does not cause cracking of solidifying shell. On the other hand, the billet cross section must be fully solidified before the cut-off point in order to prevent the breakout of the molten steel.

The described process conditions are predominantly controlled by the temperature of the molten steel, casting speed, cooling in the mold, and spray cooling at different stages. Together with the chemical composition, this affects the properties and quality of the produced continuously cast billets.

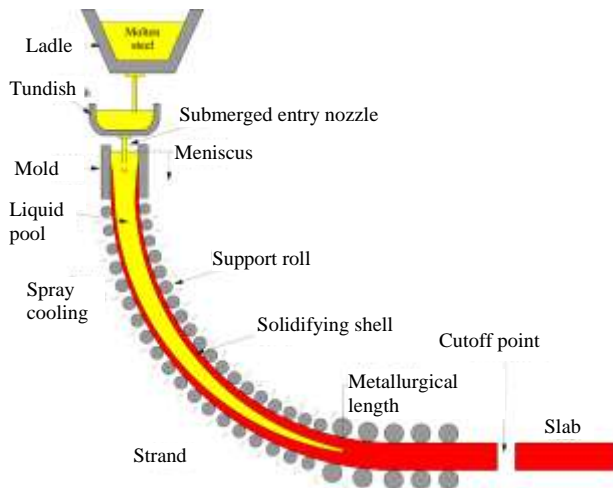


Figure 3: Scheme of the continuous casting process [14].

A calibrated numerical model has been used to calculate the process outcomes at any given set of process parameters (example is depicted in Figure 4).

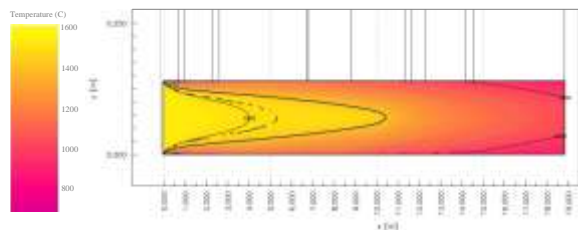


Figure 4: Numerical simulation results, temperature field along billet cross section [14].

4. Applications

4.1 Identification of Optimal Composition and Process parameters of Continuous Casting of Steel

Two test cases have been discussed. In the first test case, the numerical model was used for generation of test training data set for a neural network. A total of 240 corresponding sets of output values were generated for chosen combination of 19 influential parameters. These consisted of chemical composition parameters (concentrations of alloying elements Cr, Cu, Mn, Mo, Ni, Si, V, C, P, S), billet dimension, casting temperature, casting superheat, casting speed, temperature difference of cooling water in the mould, cooling flow rate in the mould, cooling water temperature in sprays, cooling flow rate in wreath spray system, and cooling flow rate in first spray system. Metallurgical length (see Figure 3), shell thickness at the end of the mould and billet surface temperature at straightening start position were considered on the output side.

Sampled data has been used to train a two layer artificial neural network with sigmoid activation function. It turned that sufficient quality of approximation has been achieved, which was verified by leaving different random combinations of training samples out of the learning process, and then checking approximation errors in these points. After training, the network state was saved in order to serve for approximation of the selected process output values dependent on input parameters. An optimization procedure has been used on the approximate model, with the objective to achieve favorable process behavior with respect to the metallurgical length, shell thickness and billet surface temperature. Problem that was solved is defined in the following way:

$$\min_{\mathbf{x}} f(\mathbf{x}) = \sum_{i=1}^{N_o} \left(\frac{o_i(\mathbf{x}) - o_i^*}{l_i} \right)^2, \quad (1)$$

where \mathbf{x} is a set of optimization parameters, including mass concentrations of alloying elements and process parameters (see Table 1), $o_i(\mathbf{x})$ are the observed output quantities calculated by numerical simulation of the process at given input parameters, o_i^* are the corresponding target values of these quantities, and l_i are their corresponding scaling lengths that are used to compensate for different magnitudes of the observed quantities and to weight their importance. The scaling lengths are typically determined as lengths of intervals of acceptable values of the corresponding quantities. If necessary, they can be shrunk by a factor proportional to relative importance of the corresponding output quantities.

Results are listed in Table 1. It must be mentioned that this first example is of an academic nature, since chemical composition of steel is usually narrowly prescribed by the customer. It is used to demonstrate the ability of the applied methodology to deal with larger numbers of

process parameters, as well as its potential to identify beneficial changes in chemical compositions in certain cases.

A global-local approach has been used where in the first stage, a near-optimal set of parameters was found by examination of all data points and choosing the point with the smallest value of the minimized function as

initial guess in the second stage (listed in Table 1 as starting guess). In the second stage, fine optimization was performed by the modified Nelder-Mead algorithm[5].

Table 1
Optimized process parameters.

Description & units	Range in the training set	Starting guess	Optimal value
2: Chromium concentration [wt%]	0.1 - 1.15	1.0	1.05
3: Copper concentration [wt. %]	0.075 - 0.175	0.1	0.125
4: Manganese concentration [wt. %]	0.375 - 1.725	0.9	0.75
5: Molybdenum concentration [wt. %]	0.01 - 0.45	0.03	0.025
6: Nickel concentration [wt. %]	0.075 - 0.2	0.15	0.1
7: Silicon concentration [wt. %]	0.18 - 0.6	0.3	0.275
8: Vanadium concentration [wt%]	0.025 - 0.155	0.155	0.025
9: Carbon concentration [wt. %]	0.07 - 0.61	0.51	0.415
10: Phosphorus concentration [wt. %]	0.0075 - 0.0225	0.0125	0.015
11: Sulfur concentration [wt. %]	0.01 - 0.0525	0.035	0.0275
12: Billet dimension [mm]	140 - 180	180	140
13: Casting temperature [C]	1515 - 1562	1521	1534
14: Casting superheat [C]	15 - 59	40	43
15: Casting speed [m/min]	1.03 - 1.86	1.13	1.74
16: Temperature difference of cooling water in the mould [C]	5 - 10	7	8.1
17: Cooling flow rate in the mould [l/min]	1050 - 1446	1308	1134
18: Cooling water temperature in sprays [C]	18 - 33	26	19
19: Cooling flow rate in wreath spray system [l/min]	10 - 39	10	18
20: Cooling flow rate in 1st spray system [l/min]	28 - 75	31	48

Table 2
Observed output values of the process.

Description & units	Range in the training set	Starting value	Target value	Optimal value
0: Metallurgical length [m]	8.6399 - 12.54	11.19	10.31	10.3137
1: Shell thickness at the end of the mould [m]	0.0058875 - 0.0210225	0.0167	0.0124	0.01259
2: Billet surface temperature at straightening start position [C]	1064.5 - 1163.5	1114	1121	1120.3296

4.2 Optimization of Process Parameters of Continuous Casting of Steel

The second example is oriented towards optimizing the process parameters at a fixed chemical composition of steel. Optimization criteria and constraints are set in order to maximize productivity while at the same time keeping amount of defects in the produced billets within the acceptable range. The problem was solved for the CrV4

steel grade with the following chemical composition: 1.03% Cr, 0.205% Cu, 0.875% Mn, 0.045% Mo, 0.145% Ni, 0.3% Si, 0.14% V, 0.515% C, 0.014% P, 0.01% S, whereby mass fractions of elements are specified in mass percentage.

Five parameters were considered in optimization: casting temperature T_c , casting speed v , difference between inlet and outlet temperature of cooling water in the mold ΔT , flow rate in the wreath cooling spray system (positioned

immediately after the mold) Q_w , and flow rate in the first spray cooling system Q_1 :

$$\mathbf{x} = \{T_c, v, \Delta T, Q_w, Q_1\}, \quad (2)$$

A set of 10,000 training input/output pairs was generated by running numerical simulator with randomly chosen parameters within the prescribed parameter ranges. Parameter ranges were adjusted according to process limitation of the caster. For each parameter set, a set of

$$\begin{aligned} & \min_{\mathbf{x}} \left(-v - k_T T_s + k_d (d_s - d_{s,desired})^2 + k_l (l_m - l_{m,desired})^2 \right) \\ & \text{subject to:} \\ & d_{s,lower} < d_s < d_{s,upper} \\ & T_{s,lower} < T_s \\ & l_{m,lower} < l_m < l_{m,upper} \end{aligned}, \quad (3)$$

with the following constants:

$$\begin{aligned} d_{s,lower} &= 11\text{mm}; d_{s,upper} = 14\text{mm}; d_{s,desired} = 12\text{mm} \\ T_{s,lower} &= 1110^\circ\text{C} \\ l_{m,lower} &= 9\text{m}; l_{m,upper} = 11\text{m}; l_{m,desired} = 9 \end{aligned}, \quad (4)$$

The above problem definition is based on the attempt to optimize the production rate of the caster (which is proportional to the casting velocity v) and on expert knowledge about the ranges of output quantities that assure smooth process with no significant defects [12]. Shell thickness at the end of the mold is limited below because the solidified shell must provide mechanical support to the molten steel, but billet surface temperature should not be too low because this would cause difficulties in bending the billet. Metallurgical length is bounded above by the length from the mold to the straightening start position, until which the cross section of the billet should be completely solidified. It is limited below, because if the billet is completely solid much before the straightening start position, this would cause problems in bending the billet. Due to requirements for sufficient formability after casting, it is more desirable that the surface temperature is higher at the straightening start position. There is a known lower bound above which the surface temperature should be kept.

Optimum was obtained at $T_c = 1516\text{ C}$, $v = 1.793\text{ m/min}$, $\Delta T = 7.35\text{ C}$, $Q_w = 21.4\text{ l/min}$, and $Q_1 = 43.7\text{ l/min}$. Optimal values of output quantities are listed in Table 3.

Table 3
Results of the optimized casting parameters.

Description & units	Starting value	Optimal value
Metallurgical length [m]	10.25	10.95
Shell thickness at the end of the mould [m]	0.0115	0.01325
Billet surface temperature at straightening start position [C]	1112.4	1156
Casting speed [m/min]	1.54	1.793

three output quantities was calculated and stored for later use in training the ANN model: the metallurgical length l_m , thickness of the solidified shell at the end of the mold d_s , and billet surface temperature at the straightening start position, T_s .

The optimization problem has been defined in the following way:

In both optimization examples, feed forward artificial neural networks with back propagation were used to build the models. Different combinations of layouts and training parameters, decided on the basis of past experience ([7]-[9]) and some additional experimentation were tried. More than 20 trainings with both NeuronDotNet and Aforge libraries were performed in each case, trying out different parameters. Good results were achieved by using ANN with one hidden layer containing 20-40 neurons. Both libraries performed similarly in terms of final results, while NeuroDotNet was slightly faster. The learning rate, which determines the learning speed, was set to 0.3. Momentum, which determines how much of the previous corrective term should be applied in the current training, was set to 0.6.

4.3 Modeling of the Whole Production Line in a Steel Plant

While modeling and optimization of a casting process alone makes sense in counteracting specific difficulties of this specific process, it is difficult to relate economy of production in a steel plant to performance of a single process. Production cost and final properties of the products depend on the whole chain of subsequent processes. This typically consists of casting, reheating, multiple stage rolling, and cooling. These processes are interdependent in the sense that the outcome of one process influences the performance of the following process. If only a single process within the chain is considered, any modification in optimization parameters should be followed by verification of how this affects the subsequent processes and thus overall performance.

An alternative approach is to model the whole chain of processes rather than a single process. At the current stage of development, there exist limitations that prevent

achievement of sufficient accuracy of numerical models of the whole process chain in order to use such models directly in optimization procedures. The approach that we envisage is to build a neural network-based model of the process chain on basis of measured data gathered and stored in production line over longer time. Data used include final outcomes such as tensile strength, maximal elongation and shrinkage, flow limit and hardness, measured after production with different process parameters. Figure 5 outlines preliminary results in form of parametric study that shows dependence of the final hardness of produced steel (at the end of the process chain) on carbon mass fraction. Different curves correspond to different points in parameter space around which variation of the observed parameter is performed.

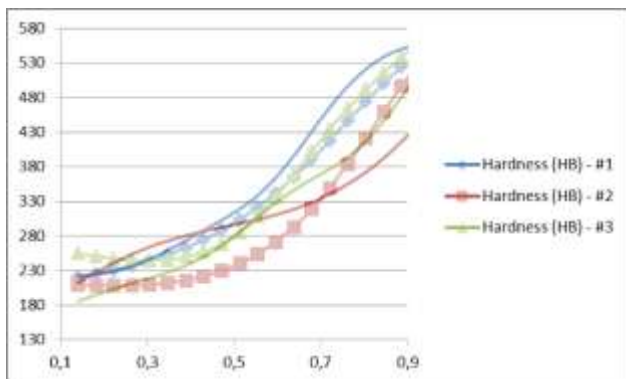


Figure 5: Steel hardness after rolling as a function of carbon mass fraction, calculated by the ANN model. Solid curves correspond to 24 parametric model, and dotted curves correspond to 35 parametric model.

At the current stage, results of the model have been examined by experts from steel manufacturing industry, who confirmed that the trends exhibited in various parametric studies are consistent with expectations. Verification of results was also performed in a standard way by using part of the measured data as validation data that was excluded from training. Training was performed on 2500 data sets obtained from the steelwork's database, of which 100 were used for validation. Errors obtained in validation points were of order of one to five per cent relative to the whole range of the corresponding output values. Additional difficulty is in the nature of data where sets are grouped in clusters around some standard steel qualities commonly used in industry. Work is currently continuing towards more thorough investigation of response and error analysis, which will also be accompanied by larger data when available from the production line.

5. Conclusion

Two applications of optimization system that utilizes artificial neural networks – based model of continuous casting of steel were presented. Further development will be directed to approximation of response for a series of processes and eventually the complete process chain (including casting, heat treatment and rolling). This would

have better practical value because final product properties (that are also widely tested in production facilities) are achieved only after the last processing in the chain. This is also more challenging due to a large number of influential parameters that need to be considered, difficulties associated with accurate modeling of a chain of processing procedures, and possibility of defects in available data. Sensible results have been obtained in modelling of the complete production line, however further effort must be invested in order to ensure that the obtained models are reliable and accurate enough to use them as support in deciding about process parameters settings in a real industrial environment.

Acknowledgement

The financial support of the Slovenian Research Agency in the framework of the project L2-3651, Štore Steel company and COBIK is kindly acknowledged. The Centre of Excellence for Biosensors, Instrumentation and Process Control (COBIK) is an operation financed by the European Union, European Regional Development Fund and Republic of Slovenia, Ministry of Higher Education, Science and Technology.

References

- [1] I. Grešovnik, IoptLib User Manual, URL <http://www2.arnes.si/~ljc3m2/igor/ioplib/doc/optlib.pdf>.
- [2] I. Grešovnik, The Use of Moving Least Squares for a Smooth Approximation of Sampled Data. *Journal of Mechanical Engineering*, 9, 2007, 582-598.
- [3] I. Grešovnik, Optimization shell Inverse, URL <http://www2.arnes.si/~ljc3m2/inverse/index.html>.
- [4] I. Grešovnik, Investigative Generic Library, URL <http://www2.arnes.si/~ljc3m2/igor/iglib/>.
- [5] I. Grešovnik, Simplex Algorithms for Nonlinear Constrained Optimization Problems. *Technical report*, 2009, URL <http://www2.arnes.si/~ljc3m2/igor/doc/rep/optalgsimplex.pdf>.
- [6] R. Rojas, Neural Networks – A Systematic Introduction. *Springer-Verlag*, Berlin, 1996.
- [7] I. Belič, Neural Networks and Modelling in Vacuum. *Vacuum*, 80, 2006, 1107-1122.
- [8] I. Belič, B. Poniku & M. Jenko, Neural network for AES spectra peak base background removal. *14th European Conference of Surface and Interface Analysis*, 2011.
- [9] L. I. Belič, I. Belič, B. Erjavec & J. Šetina, Neural Network Modelling of Cold-cathode Gauge Parameters. *Vacuum*, 71, 2003, 505-515.
- [10] Aforge.Net, 2012. URL <http://www.aforgenet.com/>.

- [11] NeuronDotNet, 2012. URL <http://neurondotnet.freehostia.com/>.
- [12] W. D. Bennon & F. P. Incropera, A Continuum Model for Momentum, Heat and Species Transport in Binary Solid-liquid Phase Change Systems - I. Formulation. *International Journal of Heat and Mass Transfer*, 30, 1987, 2161-2170.
- [13] N. Saunders, X. Li, P. Miodownik & J. Ph. Schille, Using JmatPro to Model Materials Properties and Behavior. *Journal of Metals*, 55, 2003, 60-65.
- [14] R. Vertnik, Heat and Fluid Flow Simulation of the Continuous Casting of Steel by a Meshless Method. *Ph.D. thesis*, University of Nova Gorica, 2010.
- [15] B. Šarler & R. Vertnik, Meshfree Local Radial Basis Function Collocation Method for Diffusion Problems. *Computers and Mathematics with Application*, 51, 2006, 1269-1282.
- [16] R. Vertnik & B. Šarler, Meshless Local Radial Basis Function Collocation Method for Convective-diffusive Solid-liquid Phase Change Problems. *International Journal of Numerical Methods for Heat & Fluid Flow*, 16, 2006, 617-640.
- [17] R. Vertnik & B. Šarler, Simulation of Continuous Casting of Steel by a Meshless Technique. *Int. J. Cast. Met. Res.*, 22, 2009, 311-313.
- [18] A. Z. Lorbiecka, R. Vertnik, H. Gjerkeš, G. Manojlović, B. Senčič, J. Cesar & B. Šarler, Numerical Modeling of Grain Structure in Continuous Casting of Steel. *Tech Science Press*, 8, 2009, 195-208.
- [19] R. Vertnik, M. Založnik & B. Šarler, Solution of Transient Direct-chill Aluminium Billet Casting Problem With Simultaneous Material and Interphase Moving Boundaries by a Meshless Method. *Engineering Analysis with Boundary Elements*, 30, 2006, 847-855.
- [20] B. Šarler, R. Vertnik, S. Saletić, G. Manojlović, & J. Cesar, Application of Continuous Casting Simulation at Štore Steel. *BHM Berg-und Hüttenmännische Monatshefte*, 150(9), 2005, 300-306.
- [21] R. Vertnik, B. Šarler, Z. Buliški, & G. Manojlović, Solution of Transient Temperature Field in Continuous Casting of Steel by a Meshless Method. *Proc. 2nd International Conference of Simulation and Modelling of Metallurgical Processes in Steelmaking*, Graz-Seggau, 2007, 223-228.
- [22] I. Grešovnik, T. Kodelja, R. Vertnik & B. Šarler, A software Framework for Optimization of Process Parameters in Material Production. *Applied Mechanics and Materials*, 101-102, 2012, 838-841.
- [23] C. A. Santos, J. A. Spim & A. Garcia, Mathematical Modeling and Optimization Strategies (Genetic Algorithm and a Knowledge Base) Applied to the Continuous Casting of Steel. *Engineering Applications of Artificial Intelligence*, 16, 2003, 511-527.