LUBOMIR KLIMES [1], JOSEF STETINA[1]

CHALLENGES IN NUMERICAL MODELLING OF CONTINUOUS STEEL CASTING – VERY FAST GPU DYNAMIC SOLIDIFICATION MODEL AND ITS USE IN CONTINUOUS CASTING CONTROL

Abstract

Dynamic solidification models of continuous casting are very demanding from the computational point of view. The extensive progress of parallel computing on graphics processing units (GPUs) in last years serves a great opportunity to use GPUs for computing of dynamic solidification models of continuous casting. A GPU, which is usually equipped with several hundred processors, can enable a substantial speed-up of solidification models due to high parallelism. The paper describes the development of the parallel GPU dynamic solidification model with the use of CUDA computing architecture and NVIDIA Tesla GPU. Its computing performance is then compared with commonly used non-parallel models. Consequently, the GPU model is used for model-based predictive control with an emphasis on violent changes in the casting speed. This approach utilizes the GPU model for real-time prediction of the temperature field for various control strategies. The proper control strategy is then chosen according to the evaluation of the thermal behaviour of cast blank and other criteria. The results show that parallel computing and GPUs are great tools to enhance the computing performance of dynamic solidification models. Due to the significant speed up in order of tens, new opportunities for real-time control of casting have become available.

Keywords

Continuous casting of steel, dynamic solidification model, GPU computing, parallel computing, model-based predictive control

1. Introduction

A rapid development of computers during in last decades has enabled a wide use of dynamic solidification models of continuous steel casting in steelworks and metallurgy companies in the world. These models are used in various ways [1–6], e.g., for off-line simulations (allow metallurgists to perform simulations and analyses of casting processes) or for real-time (on-line) control and optimization of casting. Especially, on-line models are required to operate in real time and process real data [7]. Owing to requirements on real-time operation capabilities, on-line dynamic solidification models are rather simple but relatively fast. On the other hand, off-line models allow for more detailed and accurate simulations but they need significantly longer time to perform required calculations. However, control of continuous steel casting and its optimization by means of dynamic solidification models usually require features of both the on-line and off-line models, i.e., the rapid computation ability for

[1] Brno University of Technology, Faculty of Mechanical Engineering, Technicka 2896/2, 616 69 Brno, Czech Republic, {klimes, stetina}@fme.vutbr.cz

real-time responses and control as well as the ability to compute a sufficiently accurate transient temperature distribution of cast blank.

Recently, a novel computing approach has been introduced for computations of highly parallelizable problems. This technique is called GPGPU (general-purpose computing on graphics processing units) and, instead of the state-of-the-art CPU computing, utilizes computing on graphics cards, GPUs. Such a GPU consists of a rather large number (hundreds or ever thousands) of relatively simple processors. Therefore, GPUs and GPGPGU offer a huge performance for computations of various problems in science and engineering. Recently, GPGPU techniques have been utilized, in particular, for computing in molecular dynamics [8], image processing [9] and Monte Carlo simulations [10]. In spite of this, only several scientific papers related to technical problems have been published by other researchers, see, e.g. [11]. Nowadays, the optimal control of continuous steel casting is a crucial task for every steelmaker. A pertinent control of casting, in particular of the secondary cooling nozzles, is a major issue in continuous casting since it is linked with productivity and quality. Researchers and engineers have used various approaches for that purpose, e.g., PI or PID controllers [1], heuristics and meta-heuristics [2, 3] or fuzzy logic [6]. However, various problems can appear when these techniques are utilized in practice [12].

The motivation for authors of the paper was to overcome these problems related to both the calculation of the dynamic solidification model and to the control method of continuous casting. The authors of the paper have recently published their results on a very fast dynamic solidification model running on GPU [13, 14] and on the model-based predictive control for real-time control of continuous casting [12] which is mainly based on the use of the developed GPU dynamic solidification model. The results show that GPGPU computing and the concept of model-based predictive control seem to be great tools for modelling and control of continuous casting. For further details, we refer readers to [12–14]. The aim of this article is to summarize these results and performed research and to present these valuable tools to specialists in continuous steel casting at the ECCC 2014 conference.

2. Dynamic solidification model for continuous casting and its GPU implementation

In these days, dynamic solidification models for continuous steel casting use the state-of-the-art CPU computing, i.e., all calculations of the model are performed by the central processing unit. However, dynamic solidification model based on particular numerical methods is a parallelizable computational problem that can be computed more efficiently with the use of GPGPU techniques and graphics processing units (GPUs) [15]. The GPGPU technique is based on splitting a computational problem into parts that are independent and can be therefore computed concurrently in parallel fashion. Hence, a GPU consists of a large number of simple computing units which are intended to process an identical code, but on different data. The number of computing units of a GPU can be between several hundred and several thousand dependent on a particular type of GPU.

In continuous casting, transient heat transfer and the solidification of cast blank may be modelled by the Fourier-Kirchhoff equation [16]

$$\frac{\partial H}{\partial t} = \nabla \cdot (k \nabla T) + v_z \frac{\partial H}{\partial z} \tag{1}$$

where H denotes the volume enthalpy, T is the temperature, t is time, k is the thermal conductivity, v_z is the casting speed and z is the longitudinal spatial coordinate in the casting direction. As can be seen from Eq. (1), fluid flow and mass transfer inside a cast blank are usually neglected due to a rather large viscosity of the melt. The volume enthalpy used in Eq. (1) is due to the latent heat of solidification which releases during the casting process [16]. The volume enthalpy can be defined as

$$H(T) = \int_0^T \left(\rho c - \rho L_{\mathrm{f}} \frac{\partial f_s}{\partial \theta} \right) \mathrm{d}\theta \tag{2}$$

where ρ is the density, c denotes the specific heat, L_{f} stands for the latent heat and f_{s} is the solid fraction.

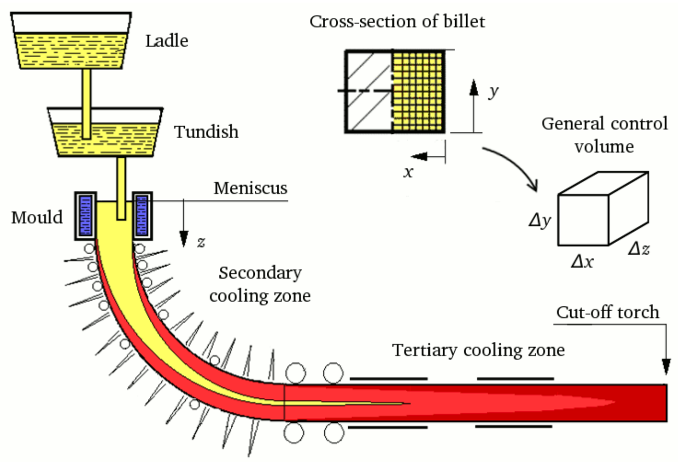

Fig. 1 Scheme of continuous casting model

Fig. 2 GPU NVIDIA Tesla C2075

The developed dynamic solidification model for continuous casting of steel billets presented in the paper is derived from Eq. (1) including necessary initial and boundary conditions which are used to set up the heat withdrawal from the billet, e.g., from the mould and within the secondary spray cooling. The numerical implementation of the model is based on the use of the control volume method and the explicit time discretization [13]. The explicit time discretization of the model is crucial for the parallel model computing and it allows for running the model on GPUs. Main principle of GPU model utilizes concurrent calculations, i.e., computations related to different control volumes (within one time iteration) are calculated concurrently by various computing units on GPU [13, 14]. The CUDA C/C++ computing architecture provided by the producer of GPU NVIDIA was used for the implementation of the model. The model calculates the unsteady temperature field of entire cast billet from the pouring level inside the mould, within the secondary and tertiary cooling zones with cooling nozzles to the cutting point where the torch cuts billets allowing a next processing stage, see Fig. 1. The mesh density, which is represented by the number of control volumes, can be arbitrarily chosen according to an intended use of the model.

3. Computing performance of CPU and GPU dynamic solidification models

The computing core of the developed model is running in MATLAB for both the CPU and GPU model. In the case of the CPU model, the core was implemented as a MEX file which enhances the computing performance. In the case of the GPU model, the computing core was implemented in CUDA C/C++. For all benchmarking tests, the GPU NVIDIA Tesla C2075 having 448 computing units and 6 GB of RAM memory was selected, see Fig. 2. The

CPU model was run on a computer with Intel Core 2 Quad CPU with 4 cores, each running 2.4 GHz and 6 GB of RAM memory. The computing performance between the developed GPU solidification model and the identical model running on CPU representing the state-of-the-art computing was compared and is shown in Fig. 3. Note that due to the significant differences in the computing time of the models, Fig. 3 had to be displayed in logarithmic scale rather than in linear (standard) one. The results of computing performance benchmarks are presented for six computational mesh densities of cast blank, but providing identical casting conditions in order to have comparable results [13]. The numbers of mesh nodes were 10^5, $2{\cdot}10^5$, $5{\cdot}10^5$, 10^6, $2{\cdot}10^6$ and $3{\cdot}10^6$. One can deduce from Fig. 3 that GPGPU computing can serve a very significantly enhancement and it greatly improves the performance of the dynamic solidification models. For the coarsest mesh with $2{\cdot}10^5$ of mesh nodes, the GPU solidification model calculates all the computations in less than 3 seconds which is about 30-times faster than the standard CPU solidification model. However, with an increasing mesh density, the significance of parallelism and computational performance of GPU is even more powerful – with the mesh including $3{\cdot}10^6$ the GPU model is even 50-times faster than the model running on CPU architecture. The details about computing times and corresponding speedups for various mesh densities in the range between 10^5 and $3{\cdot}10^6$ can be seen in Fig. 3. The presented benchmark results unambiguously show the enormous computing power of GPUs and its possible use in modelling of continuous steel casting [13].

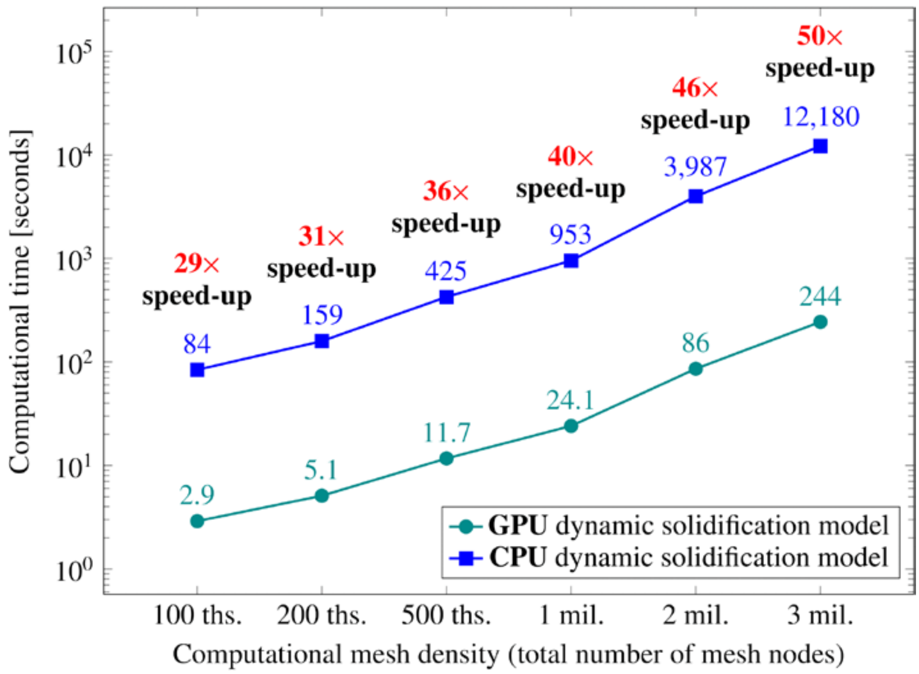

Fig. 3 Results of benchmark tests comparing the performance of GPU and CPU models

4. Real-time model-based predictive control by means of GPU solidification model

Various techniques and approaches can be used for optimal control and optimization of continuous steel casting [1, 3, 5, 6]. In the paper, the model-based predictive control approach (MPC) [17,18] is examined by means of the developed GPU model. The MPC has been recently utilized in various technical applications [17–19]. The idea of a MPC system is that the MPC utilizes the computer model of the controlled process to predict and estimate *beforehand* the behaviour and future evolution of the system. Afterwards, the MPC system evaluates the results of these input changes and tries to respond to them. This behaviour is in fact an opposite strategy than in case of PID systems which control a process according to what had already happened in past.

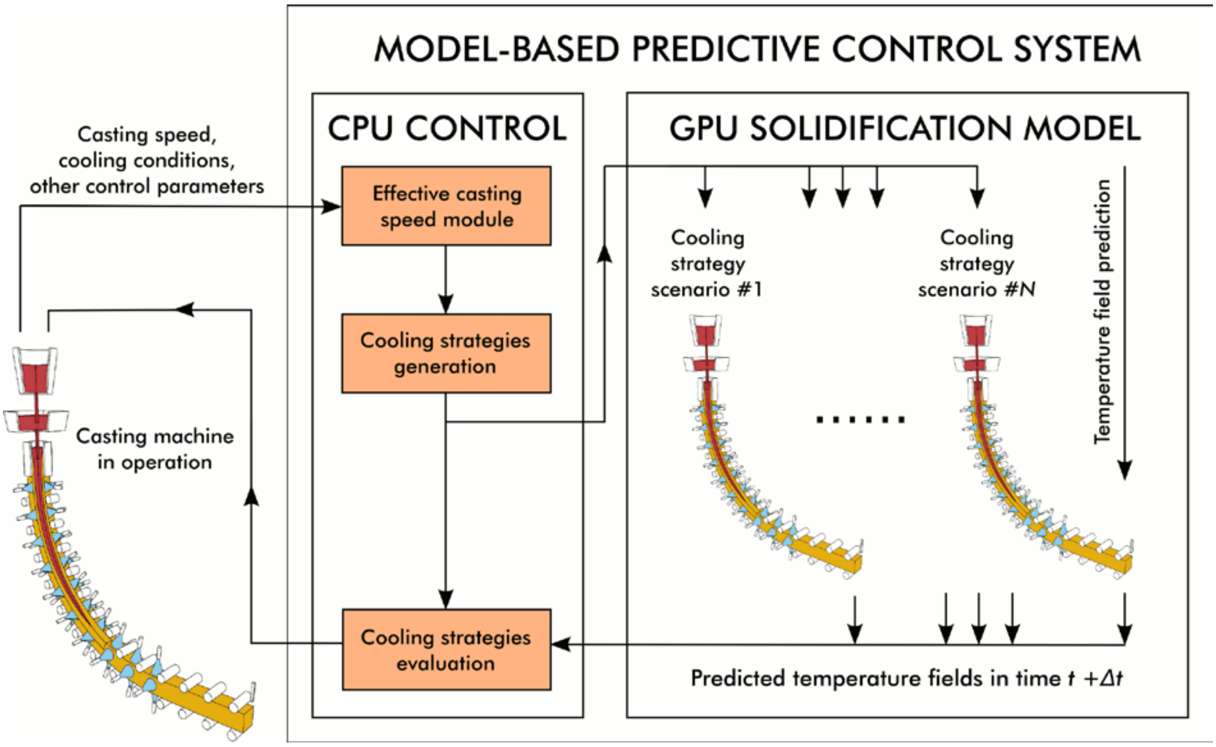

Fig. 4 MPC system for continuous steel casting utilizing very fast GPU solidification model

The propounded MPC system for continuous steel casting described in the paper is based on the use of the developed very fast GPU dynamic solidification model to predict the behaviour of the casting process. The scheme of the MPC system for continuous steel casting is shown in Fig. 4. The propounded control system is designed as a scenario-based system. In each predefined step in time, the MPC control system acquires all necessary casting parameters (casting speed, water flow rates in the secondary spray cooling, pouring temperature, etc.). Based on these evaluated data, the MPC system proposes a predefined number of control strategies to control the casting under actual casting conditions. Each of control strategies is a possible control strategy of the caster, in particular specifying water flow volumes within the secondary spray cooling. The control strategies are proposed according to experts' experiences, the traditionally-used cooling curves (dependency of the flow volume through cooling nozzles as a function of casting speed) and taking into account the effective casting speed [12, 20] of all cooling zones within the secondary cooling. The effective casting speed is actually related to the residential time which the cast blank divided in artificial slices spends within each of the secondary cooling zone. This approach is mainly worth when the casting speed varies in time [12]. In this case the cooling according to the real casting speed can lead to inappropriate cooling, especially in cooling zones that are more far from the pouring level [20]. Fig. 5 illustrates the use of the effective casting speed in case of fluctuating real casting speed. It shows that the effective casting speed fairly realistically characterizes very variable casting conditions. Notice that the effective casting speed causes smoothing of the real casting speed, especially in case of cooling zones that are more far from the pouring level [12].

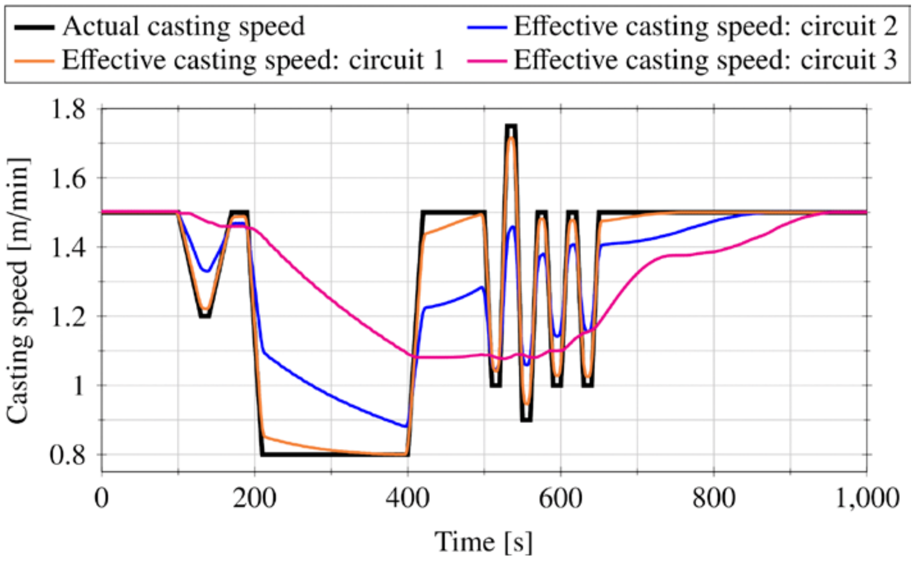

Fig. 5 Effective casting speed and its smoothness effect for three cooling zones with different distances from the pouring level

Once the control strategies are generated, the MPC system for all of them calculates the future temperature field of cast blank for a certain time horizon. Owing to the developed very fast GPU model, all these calculations are possible to do in real time (within tens of seconds). The MPC system then evaluates the predicted results and determines the resultant control strategy to be applied in the real casting process. The resultant control strategy is chosen so that it ensures to maintain the surface temperatures in specified temperature ranges (to avoid surface defects) and to keep the metallurgical length in a predefined range. The loop of the MPC system is thereby closed and the system continues with the next control iteration [12]. Note that the criteria for the selection of the resultant cooling strategy can be arbitrarily modified according to requirements of metallurgists.

5. Use of MPC system in case of abrupt change of casting speed and discussion

The functionality and use of the developed model-based predictive control system were tested in case of a casting situation with an abrupt drop of the casting speed [12]. The drop was simulated as a 6 minute-duration drop from the casting speed of 1.5 m/min to 0.8 m/min, see Fig. 6. For that purpose, the developed very fast GPU dynamic solidification model was used in the following configuration: the casting machine with 6 spray cooling zones within the secondary cooling including the total number of 180 spray cooling nozzles of several types. The casting machine was supposed to cast 200 × 200 mm of a low-carbon steel billets, which are routinely cast with the casting speed of 1.5 m/min. In the steady state casting conditions, the abrupt drop of the casting speed described above was assumed to occur, see Fig. 6.

Also notice that the effective casting speeds for the cooling zones No. 2, No. 4, and No. 6 are plotted in Fig. 6 (the corresponding curves for zones No. 1, No. 3, and No. 5 were omitted due to the lucidity of the figure). From the figure one can see the smoothness effect of the effective casting speed which implies that the spray cooling in the last zone No. 6 would not be as intensive as in the cooling zones closer to the pouring level. The MPC system was used to regulate the spray cooling within the cooling. The aim of the cooling strategy and the criterion for the casting control was to maintain the predefined temperatures on the surface of cast billet as close as possible to the corresponding temperatures for the case with steady-state casting conditions, i.e., the case with no change of the casting speed. In other words, the surface temperature courses in steady-state casting conditions were assumed to be optimal and the aim of the control was to regulate the casting so that

$$\left\| T - T^{*} \right\|_{2} \rightarrow \min \qquad (3)$$

where T is the actual surface temperature to be controlled and T^{*} is the corresponding steady-state surface temperature considered as an optimum.

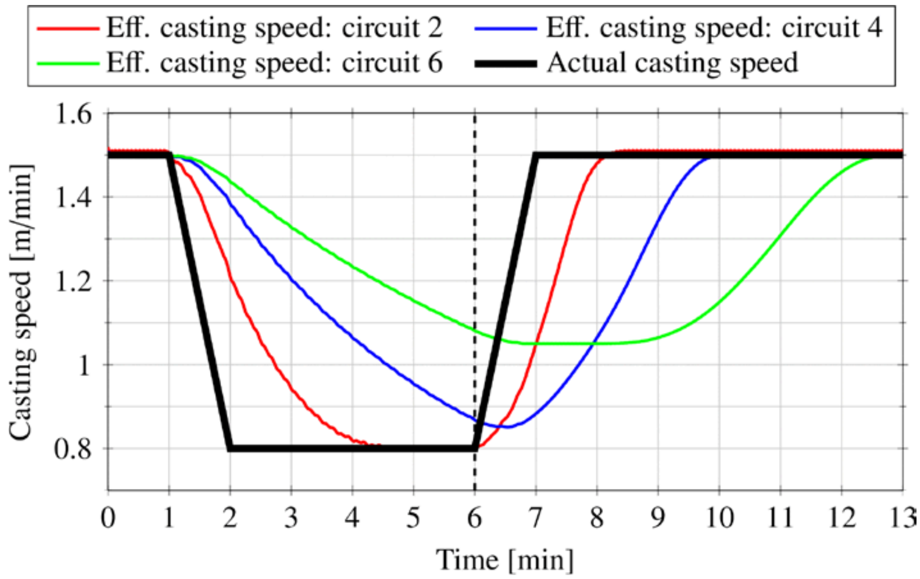

Fig. 6 Use of the MPC system for case with abrupt change of casting speed: time evolution of the casting speed and of the corresponding effective casting speeds

As for the case of the abrupt change of the casting speed, the MPC system was set up to propose 15 cooling strategies with various cooling intensities of spray cooling within the secondary cooling. The cooling strategies generated by the MPC system were proposed taking into account the cooling setup used in the steady-state casting conditions as well as the effective casting speeds providing the information about real casting conditions, but filtered by the smoothness effect. The MPC system then in real time calculated the temperature fields which would be attained under the proposed cooling strategies. The GPU dynamic solidification model was set up for the computational grid with 10^6 nodes and all these computations of future thermal behaviour for all the proposed cooling strategies were computed in less than one minute by means of GPU NVIDIA Tesla C2075 [12].

The controlled surface temperatures on the top surface for three (for the lucidity of the figure) selected representative cooling strategies calculated by the MCP system are shown in Fig. 7. These cooling strategies are denoted as CS-1, CS-2, and CS-3 and show the thermal behaviour of cast billet in the cooling zones No. 4, No. 5, and No. 6. The temperature courses are plotted in a moment when 5 minutes elapsed from the drop of the casting speed, i.e., in time of 6 min. corresponding with Fig. 6. Fig. 7 also shows how the surface temperature would be in the case of no change in cooling. One can readily see from Fig. 7 that a substantial subcooling of the billet surface would occur within secondary cooling in case of no change of the cooling setup, i.e., in case of no control system used. The proposed cooling strategy CS-1 applied to control the casting would also result in unadvisable cooling because it would lead to a rather subcooling, see Fig. 7. On the other hand, the proposed cooling strategy CS-2 seems to be also quite inappropriate since it would conversely cause an undesirable overheating, mainly in cooling zones No. 5 and No. 6. However, the cooling strategy CS-3 seems to be a fairly feasible cooling strategy since this setup of cooling would maintain the controlled surface temperature very close to the optimal surface temperature. Hence, the cooling strategy CS-3 is then taken as the optimal cooling strategy to be applied to the real casting process. The control system then proceeds to the next time instant, retrieves the data from the caster again and the whole procedure is repeated in a loop to control the casting process [12].

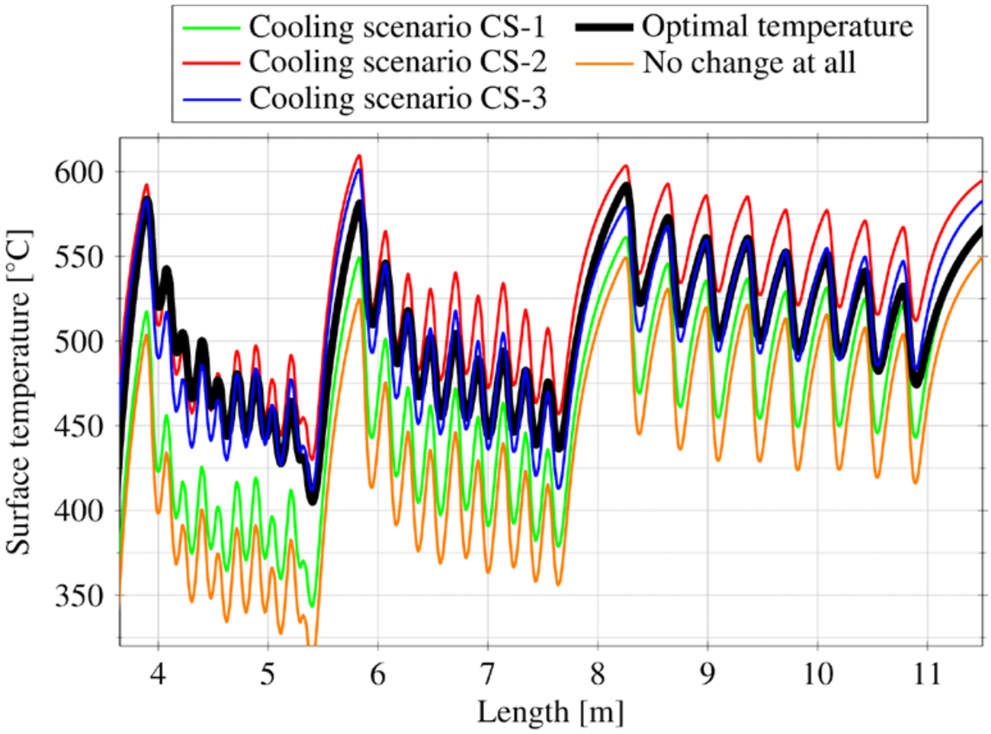

Fig. 7 Results of the MPC for the case of abrupt change of casting speed: controlled surface temperatures of cast billet

Conclusion

The paper summarizes the research and its results performed in the field of continuous casting of steel. The very fast GPU dynamic solidification model running on graphics processing units was developed. The comparison of the computing performance between the ordinarily used CPU models and the developed GPU model shows that the GPU model can offer even 50-times faster computing of the temperature field of cast blanks. The GPU model was then utilized as a numerical sensor for the optimal casting control. For that purpose, the model-based predictive control approach was utilized and implemented. The control system is designed as a scenario based utilizing the concept of effective casting speed for the proposal of the cooling strategies. The use of the control system was demonstrated for the casting situation with an abrupt change of the casting speed. The presented results show that the developed MPC can provide a fairly good casting control and is a promising tool for the real-time casting control.

Acknowledgement

This work was supported by research and scientific activities of NETME Centre, regional R&D centre built with the financial support from the Operational Programme Research and Development for Innovations within the project NETME Centre (New Technologies for Mechanical Engineering), Reg. No. CZ.1.05/2.1.00/01.0002 and, in the follow-up sustainability stage, supported through NETME CENTRE PLUS (LO1202) by financial means from the Ministry of Education, Youth and Sports of the Czech Republic under the „National Sustainability Programme I".

References

[1] B. Petrus, K. Zheng, X. Zhou, B. G. Thomas and J. Bentsman, Real-time model based spray-cooling control system for steel continuous casting, Metallurgical and Materials Transactions B (2011), p. 78

[2] M. S. Kulkarni and A. S. Babu, Managing quality in continuous casting process using product quality model and simulated annealing, Journal of Materials Processing Technology (2005), p. 294

[3] N. Cheung and A. Garcia, The use of a heuristic search technique for the optimization of quality of steel billets produce by continuous casting, Engineering Applications of Artificial Intelligence (2001), p. 229

[4] Y. J. Xia, F. M. Wang, C. R. Li and J. L. Wang, Simulation of thermomechanical behaviour during continuous casting process based on MiLE method, Journal of Central South University (2012), p. 2403

[5] C. A. Santos, J. A. Spim and A. Garcia, Mathematical modelling and optimization strategies (genetic algorithm and knowledge base) applied to the continuous casting of steel, Engineering applications of artificial intelligence (2003), p. 511

[6] T. Mauder, C. Sandera and J. Stetina, A fuzzy-based optimal control algorithm for a continuous casting process, Materiali in tehnologije (2012), p. 325

[7] B. G. Thomas, Modeling of the continuous casting of steel – past, present, and future, Metallurgical and materials transactions (2002), p. 795

[8] J. A. Baker and J. D. Hirst, Molecular dynamics simulations using graphics processing units, Molecular Informatics (2011), p. 498

[9] K. E. A. van der Sande, T. Gevers and C. G. M. Snoek, Empowering visual categorization with the GPU, IEEE Transactions on Multimedia (2011), p. 60

[10] Y. Uejima, T. Terashima and R. Maezono, Acceleration of a QM/MM-QMC simulation using GPU, Journal of Computational Chemistry (2011), p. 2264

[11] W. S. Fu, W. H. Wang and S. H. Huang, An investigation of natural convection of three dimensional horizontal parallel plates for a steady to an unsteady situation by a CUDA computation platform, International Journal of Heat and Mass Transfer (2012), p. 4638

[12] L. Klimes and J. Stetina, Unsteady model-based predictive control of continuous steel casting by means of very fast dynamic solidification model on GPU, Materiali in Tehnologije (2014), *in press*.

[13] L. Klimes and J. Stetina, Parallel dynamic solidification model of continuous steel casting on GPU, Proceedings, 22nd International Conference on Metallurgy and Materials METAL, Brno, Czech Republic (2013), 6 p.

[14] L. Klimes and J. Stetina, Transient heat transfer problem with phase changes solved by means of GPGPU with CUDA and MATLAB, Proceedings, 19th International Conference on Soft Computing MENDEL, Brno, Czech Republic (2013), p. 397
[15] J. D. Owens, M. Houston, D. Luebke, S. Green, J. E. Stone and J. C. Phillips, GPU computing, Proceedings of the IEEE (2008), p. 879
[16] D. M. Stefanescu, Science and Engineering of Casting Solidification, Springer, New York (2009)
[17] P. Tatjewski, Advanced Control of Industrial Processes: Structures and Algorithms, Springer, New York (2007)
[18] A. Ivanova, Model predictive control of secondary cooling modes in continuous casting, Proceedings, 22nd International Conference on Metallurgy and Materials METAL, Brno, Czech Republic (2013), 6 p.
[19] S. J. Qin and T. A. Badgwell, A survey of industrial model predictive control technology, Control Engineering Practice (2003), p. 733
[20] Z. Dou, Q. Liu, B. Wang, X. Zhang, J. Zhang and Z. Hu, Evolution of control models for secondary cooling in continuous casting process of steel, Steel Research International (2011), p. 1220