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Innovative Training Network

TOMOCON

Deliverable Title

General Methodology for Tomography-assisted Control

Description

This deliverable summarizes briefly the main control issues and open questions connected with the applications of tomography based control. An important source for this summary is the experience with TOMOCON industrial demonstration cases. Starting from this summary this deliverable further outlines the general principles of fundamental control concepts and strategies that can be used to cope with these issues.

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Introduction

Unlike conventional sensors, industrial tomography "can see" what is going inside industrial processes and this opens new ways to control them. In some cases these new control ways mean that tomography has the enabling potential to allow the control of processes where the process control has played just a marginal role till now. An example of such process is the crystallization process where the role of control has not been significant in industry and it has been limited to laboratory-scale research and development. This has been due to the lack of adequate sensor technology and other issues limiting crystallization process controllability like fast solidification with highly dynamic and nonlinear nature. In other cases this means that using tomography it will be possible to enhance existing controls with new capabilities. For example, the standard control loops used in continuous casting like mould level control and stopper position servo control can be augmented with additional control loops that are more directly related to the product quality.

Prospective tomography applications in process control are numerous and although they share certain common features they differ in many aspects. To keep the scope of the research as general as possible the TOMOCON project included a set of four demonstration plants: Continuous casting, batch crystallisation, microwave drying and inline fluid separation. Each of them represents somewhat different control challenges and issues. Taken as a whole this set allows a fairly general treatment of the topic of the methodology of tomography assisted control.

In this report we will briefly characterise the features of the demonstration plants and the respective control issues. Subsequently we will generalize the treatment to the outline of general guidelines for selection of control methods for tomography assisted control. To keep this report reasonably short the main focus will be on the continuous casting process while in the case of other demonstration processes the focus will be mainly on the control issues and requirements in which they differ from the continuous casting process.

Demonstration processes to be controlled – modelling and control issues

Continuous casting

Continuous casting is a very important process that is used to produce about 95 % of the world's steel production. In this report continuous casting will be used as the main example to elucidate the modelling and control issues as well as to demonstrate the potential benefits that can be obtained using tomography based control. The principle

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operation of a continuous caster is shown in Fig. 1. Liquid steel or other metal flows from the ladle to the tundish and from there via a submerged entry nozzle (SEN) into the mould. The flow rate is there controlled by a stopper rod or a sliding gate. In the water cooled mould a solid steel shell is formed and the partly solidified strand is further transported on rolls and cooled by water sprays until it is solidified completely.

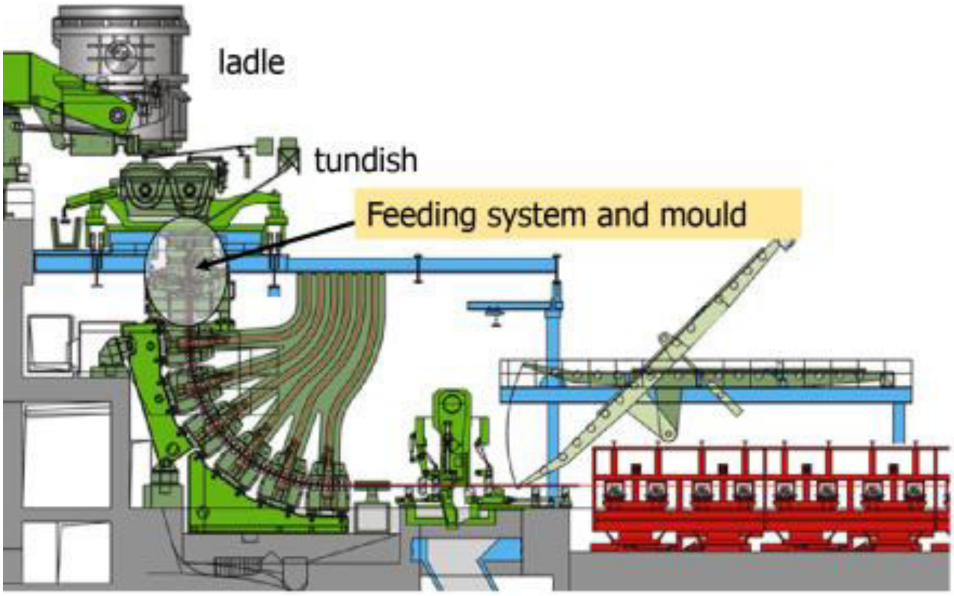

Fig. 1. Schematic diagram of the continuous casting process

The quality of the final product is closely related to the flow regime in the SEN and in the mould. Unstable flows in the mould can lead to surface defects or slag entrapment. Electromagnetic actuators (electromagnetic brakes or stirrers) are often used to control this flow. For several steel grades argon gas is injected into the SEN to prevent nozzle clogging and to float inclusions. If argon is used it is further necessary that the flow field in the mould does not hinder the rise of bubbles towards the free surface.

The continuous casting process is marked by several intricate phenomena that govern the process from beginning to end; these include turbulent fluid flow, electromagnetic effects, particle entrapment, and thermal-mechanical distortion (Thomas, 2002). One of the main challenges when dealing with the continuous casting process is creating mathematical models to describe the many coupled interactions that occur in this process. There have been numerous advances in the modelling of different aspects of the process; however, the topic still remains open for further development. As more mathematical models are developed to describe the interactions in the process, the question arises as to how to utilise these models for the purpose of controlling the process. In the following report it will become clear that the challenge of controlling the continuous casting process is not only limited by the need to model the process accurately, but also by the sensors used in the process. The harsh conditions of the process severely limit the use of

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traditional sensors. One of the methods to solve this challenge is the use of nonconventional sensors that are based on tomography. This report will discuss the general methodologies needed to build a tomography-based control loop that will be applied on the continuous casting process.

Modelling of continuous casting process

Finite-difference models have been proven to produce reliable mathematical models that are able to describe the interactions that occur in the continuous casting process. However, due to the complexity of the whole process, it is not possible to model the entire process all together, instead the different phenomena are uncoupled, and assumptions are made in order to model them in isolation. There has been significant interest in modelling the heat transfer and solidification process that occurs in continuous casting; models are used to predict to temperature distribution and the solidifying steel shell (Thomas, 2018). These models have been successfully implemented in control loops in order to control the temperature fields in both the mould and the secondary cooling zone (Belavý *et al.*, 2015; Hulkó *et al.*, 2016). Furthermore, the fluid flow in both the mould and the nozzle has been successfully modelled using either the finite-difference methods or the finite-volume methods to solve both the continuity equation and the Navier-Stokes equations (Thomas, 2018; Zhang et al., 2007). These models will be of particular interest for our work in the TOMOCON project due to the types of sensors we will be implementing in the continuous casting process. The Contactless Inductive Flow Tomography (CIFT) will allow us to reconstruct the velocity fields in the mould, while the Mutual Induction Tomography (MIT) will allow us to reconstruct the two-phase flow of the SEN nozzle with the argon gas. An example reconstruction from the Mini-Limmcast facility is shown in Fig. 2.

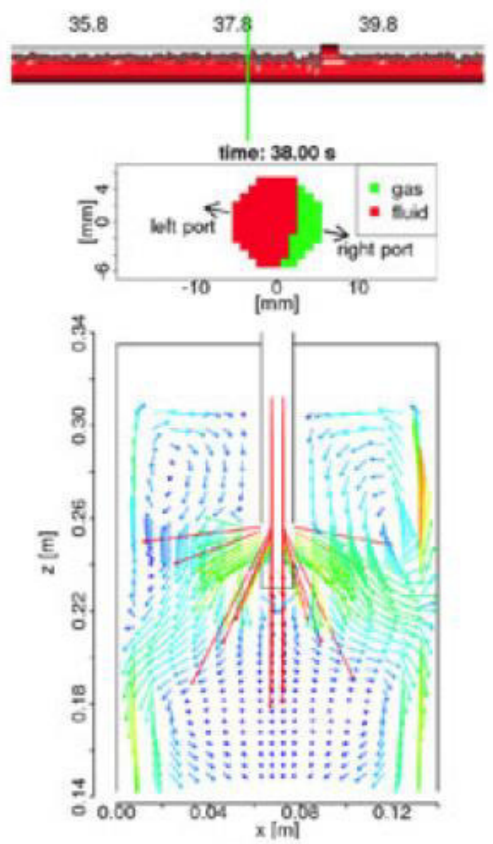

Figure 2: Reconstructed images from CIFT and MIT sensors from Wondrak, *et al.*, 2011.

Due to the nature of the process and the sensors, a distributed parameter model is an adequate representation of the process. Distributed parameter

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modelling will be used in the virtual demonstrator – a model using CFD solver based on finite-volume method that will be created within the framework of the TOMOCON project.

This virtual demonstrator will be used for controller testing however its applicability to controller design remains an open question at this moment. Probably a more promising approach is to perform an attempt to obtain a reduced order model and to use it for the purpose of the control loop. It is common practice in the field of control to obtain a quick estimate of specific phenomena for the development of online control (Thomas, 2018). Although it might seem counter-intuitive to not take advantage of both the spatial and temporal information obtained from the sensors, it might be interesting to see if a lumped parameter model will be sufficient in controlling the loop. In the following sections an idea based on a lumped parameter model using the raw data coming from the CIFT sensors will be discussed.

Electromagnetic Flow Actuation

Due to the importance of the fluid flow in the mould in improving steel cleanliness, it has become common practice to use electromagnetic actuators to somewhat control the flow in the mould. These actuators can be classified under the terms electromagnetic stirrers and electromagnetic brakes (EMBr) (Gerber, 1997). The concept behind electromagnetic stirrers is creating a rotating magnetic induction field to eventually create an electromagnetic force that is applied to the steel liquid. Electromagnetic brakes on the other hand generate a static magnetic field which creates Lorentz forces in order to break the fluid motion. This phenomenon has been modelled frequently in many researches; in Haiqi, 2008 where a finite-volume model was implemented using the theory of computational fluid dynamics and magneto-hydrodynamics. It was shown that both the magnetic induction intensity and the position of brake region affect the fluid flow in the mould. As the magnetic field is increased, both the recirculating flow velocity and the impingement intensity become weak. Cukierski & Thomas, 2008 attempted to investigate the effects of varying the depth of the submerged entry nozzle (SEN) and the electromagnetic brake field intensity to see the combined effect. It became clear that increasing the EMBr field strength at a constant SEN depth reduced the downward velocity of the jet and decreased the top surface velocity along with other effects. Increasing the SEN depth without EMBr has a similar effect as increasing the EMBr field strength. However, increasing the SEN depth with EMBr had an opposite effect as above.

Although various researches have been conducted on the modelling and analysing the effect of electromagnetic actuators on the mould, it seems that there is gap when it comes to utilizing these electromagnetic actuators in a control loop. One of the few papers that attempt to incorporate an electromagnetic actuator (Dekemele *et al.*, 2016) designed a control loop using an electromagnetic stirrer. The electromagnetic stirrer was used to both

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brake and accelerate the liquid steel in the mould in order to keep the flow speed at an optimal range. A sensor was used for the drag force in order to measure the flow at a certain point in the mould. System identification was used to model the process in which both a PI controller and a controller based on MPC were designed for the control loop. In the end, it appeared that the MPC controller outperformed the PI controller, however, at a cost of much more aggressive control efforts which may later on lead to issues such as saturation and rate limiting.

Techniques used in classical (not-tomography based) control of continuous casting process

If tomography sensors are not used, the control can be based just on the knowledge about the relationship between single measurable variables and product quality. It turns out that one of the most important measurable variables is the molten steel level in the mould (Kitada et al., 1998). It is necessary to decrease the fluctuation of this level in order to avoid potential defects. Consequently most of the published papers related to the continuous casting control are focused on mould level control. It can be stated that the notion continuous casting control as used in the literature is mostly just another way to say mould level control, i.e. control of a single lumped variable.

In many cases a reduced model is used to describe the fluctuations in the mould, and a simple mould level sensor is used for the control loop designed to control the mould level. In Smutný *et al.*, 2005 a PI controller with a variable gain was implemented to control the mould level, by adding a dithering signal it proved robust enough to achieve its objective. A comparison between linear and non-linear cascaded controllers based on PIDs was also conducted (Graebe, 1994). Furthermore, more advanced controllers such as H-infinity were also designed and compared to the traditional PID controller in Kitada *et al.*, 1998. It was proven that the proposed H-infinity controller outperformed the PID in disturbance rejection and robust stability.

A common phenomenon that was being observed on the mould level was the bulging disturbance; bulging disturbance is mostly created by the supporting rollers that tend to push the liquid steel upward periodically (Kim *et al.*, 2011). Various control methodologies were proposed to compensate for this disturbance such as an adaptive sine estimator based disturbance observer (Kim *et al.*, 2011). This observer was combined with a phase lead adaptive fuzzy controller. Both simulation and experimental results proved that the controller was able to reduce the bulging disturbance effect on the mould level. A similar attempt at suppressing the disturbance was done using a basic PI controller with an additional adaptive compensation that adapts the gain and prediction time to compensate for the disturbance (Fortmueller & Re, 2006).

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Another controllable variable that affects product quality is the temperature field. This control task has some similarity with tomography based control because the underlying dynamics is also described as a distributed parameter system and the model that is used for designing the controller is usually conceived as a distributed parameter system. In Belavý *et al.*, 2015 the temperature fields were described using partial differential equations, and a finite element method was used to solve these equations and model the process. The author was able to create a lumped-input/distributed output (LDS) based on the FEM modelling for the purpose of creating the controller. The main concept behind LDS is the decomposition of the control synthesis into time and space control tasks. A robust control system for the LDS was created using an IMC structure. A similar approach is used in Hulkó *et al.*, 2016 where a model based on nonlinear partial differential equations was used for the control of secondary cooling in the continuous casting process. The control synthesis was also designed using the lumped input/distributed output method. In this case a single-parameter constrained Model Predictive Control (MPC) was designed to generate the input signals into the secondary cooling zone. This methodology of lumped input/distributed output (LDS) has the potential to be useful also for our specific control task particularly in regards to the velocity fields measured by the CIFT in the mould structure. The structure of this control is shown in Fig. 3.

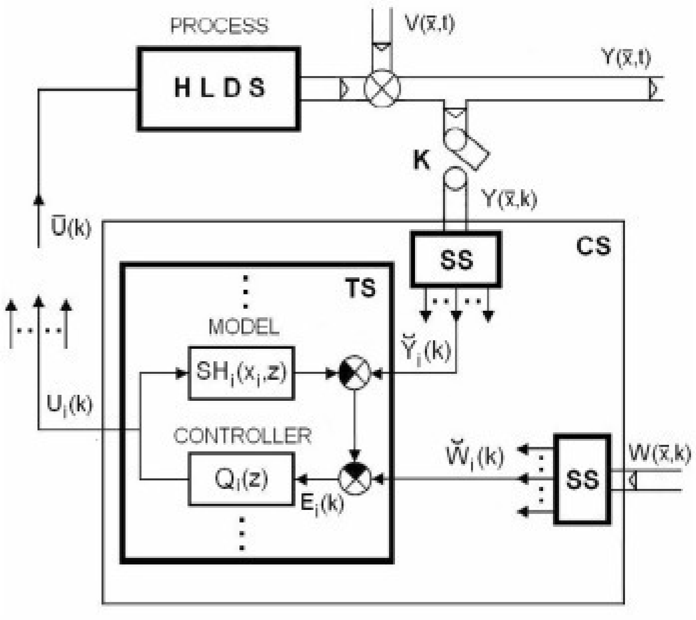

Figure 3: Distributed Parameter Feedback Control System as proposed in Belavý *et al.* 2015

Microwave Drying of Porous Materials

Microwave heating is an attractive technology for drying porous materials for example in food and pharmaceutical industries. It brings a significant benefit due to the possibility of volumetric and selective heating. With that significant energy and time saving as compared to conventional, convective and radiative heating can be achieved. However if the moisture distribution is non-uniform, efficient use of microwave drying requires

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intelligent control of distributed microwave sources. This control can achieve more homogeneous moisture distribution in the material. For efficient control, process tomography sensors could be employed since they are real-time and non-invasive measurement systems. Figure 4 illustrates the Microwave Drying demonstration along with its control system and sensors.

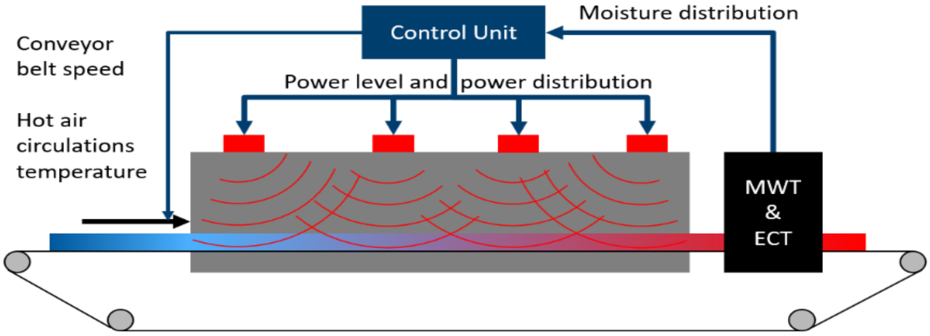

Figure 4. Microwave drying process (Figure courtesy of TOMOCON - KIT Demonstration Planning Meeting 2017-11-29)

Tomography sensors used for microwave drying process

In the Microwave Drying demonstration, both Electrical Capacitance Tomography (ECT) and Microwave Tomography (MWT) sensors are qualified for moisture distribution measurement. The information about the moisture distribution is then used to control microwave antennae power drivers. We have written Matlab/Netgen code to develop the forward model for ECT and the COMSOL Multiphysics based forward model for different geometrical configurations of MWT. Using numerical simulations, we can test different types of sensor geometries for ECT and desired radiation sources with different receiver parameters for MWT. These test runs will be used in designing the prototype sensors for laboratory tests and for the final demonstration.

Microwave drying control system and objectives

The objective of designing the control system for the Microwave drying process is to keep the moisture distribution of the material at a desired level and as homogeneous as possible. The controller uses the estimated moisture distribution to derive the input of power drives and possibly the belt speed and hot air circulation temperature to satisfy the control objective.

Batch Crystallization

Batch crystallization is a wide-spread industrial process to purify substances and transform dissolved compounds to solid products. Prominent examples are crystallization of

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sugar or salt, concentration of fruit or coffee extracts, purification of bulk or fine chemicals, production of pharmaceuticals, zeolites and more. Crystal product quality should be according to set specifications in order to avoid expensive reprocessing steps. Prior to the 1990s, crystallization from solution process control was limited because of a lack of accurate in situ monitoring sensors as well as limited knowledge of processing factors of crystallization (Gao *et al.*, 2017). Crystallization control is essentially product quality control, i.e. how to operate the process to obtain the desired product quality in terms of crystal characteristics such as particle shape, particle size distribution (PSD). As it has already been stated in the introduction, the role of process control in crystallization has not been considerable in industry and it has been limited to laboratory-scale research and development. This is due to the fast solidification process, highly dynamic and nonlinear nature and lack of adequate sensor technology.

Remarkable advances have occurred in crystallization process and control over the recent years following the process analytical technology (PAT) concept by The US Food and Drug Administration (FDA) in 2004. PAT instruments are used to ensure final product quality by utilizing novel sensors for in situ monitoring, analysing, and controlling process parameters (Nagy *et al.*, 2012). One of the major drawbacks of PAT instruments is their limited applicability in harsh operating conditions of the industrial environments (Li *et al.*, 2008). It is envisaged that the next generation of tomography-based monitoring instruments such as electrical resistance tomography (ERT) and ultrasound tomography (UST) will be robust enough to satisfy these requirements for widespread application in industrial plants.

Tomography sensors used for the batch crystallization process

Novel tomographic measurement based on ERT/UST could be applied in the most typical crystallization processes. Combining measurement results from process tomography with a control system can provide a significant benefit to many industrial processes. However, simultaneous monitoring, control and implementation of feedback control of crystallization processes based on tomographic measurement (ERT/UST), hitherto, has not been reported and it has been limited to just monitoring of the processes.

In-line spectroscopy techniques are difficult to use in fast solidification and dense crystallization slurries and provide only local measurements such as species concentration, flow rate or suspension density, which are not representative throughout the reactor volume. Tomographic methods provide a means for suspension density measurement, measuring the spatial concentration and distribution of particles (Pertig *et al.*, 2011; Bolton & Primrose, 2005) offer real-time mixing visualization as well as flow distribution monitoring in various industries (Rodgers & Kowalski, 2010; Sharifi & Young, 2013; Gradov *et al.*, 2018)

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Inline Fluid Separation

This demonstration does not consider the classical principle of gravitational separators but an advanced concept of flow splitters. This concept has superior features. Apart from a gross reduction in investment costs and footprint the same separation quality can be achieved much faster and hence production times in the chemical and mineral oil industries can be accelerated by orders of magnitude. The principle is simple in concept. Fluids of different density are set into circular motion by a swirl element in a slim flow channel. Centrifugal forces up to 100 times the gravitational acceleration separate the phases. Hence, the lighter one swirls to the centre of the originating vortex structure and is there being extracted by a so-called pick-up tube.

However, practical application of this conceptually simple principle poses significant challenges like transient and non-linear waviness of the interface and vortex stability for changing inlet phase fractions. High turbulence intensities back-mix the separated fluids and high shear rates produce small droplets that are difficult to separate. In liquid-liquid separation this may even lead to development of emulsions, which are difficult to break because of coalescence hindering by charged interfaces.

In this case the tomography based control may play the role of enabling technology and it is developed for the first time ever in the TOMOCON project. Wire-mesh and Electrical Capacitance Tomography sensors measure inlet flow conditions (flow regime, phase fractions) upstream and vortex parameters (interface, dispersion state) downstream the swirl element at high speed.

Tomography Data Analysis

One of the main challenges of implementing a tomographic-based control loop is the integration of the data from the tomographic sensors in a manner that the controller can fully interpret and calculate a suitable control action based on these data. This task is very nontrivial and the controller designer may easily get to a similar position as a lucky lottery winner that became rich and does not know what to do with so much money. Tomography data are very rich however it is not always obvious how to make sensible use of them for the control purposes. The nature of the data provided by tomographic sensors is both spatial and temporal; however, classical control theory depends on the concept of lumped parameter systems. Therefore, various data analysis methods need to be considered to see the most suitable method for our process.

Raw Measurement Data

Data analysis methods applied to process tomography can be categorised under two methods: raw measurement data, and the visualization of the process in the form of 2D or

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3D images (Romanowski *et al.*, 2005). In Zhou *et al.*, 2001 principal component analysis (PCA) was used on the raw data to relate the material concentration to principal components of raw data. Therefore, calculating the phase concentration of the two-phase flow was possible without reconstructing the image. Another example is Seleghim & Hervieu, 1998 where the time topology of flow was recreated by plotting signals corresponding to the peripheral impedance measurements, thus avoiding the reconstruction of the image. A similar methodology was also successfully implemented for the purpose of controlling the phase distributions in solid-liquid mixing (Tabe *et al.*, 1999) where principle component analysis (PCA) was used to perform feature extraction from a sequence of images, and then a neural network was trained to map the key features into a scalar quantity as a controlled variable. Therefore, a traditional controller can be designed to control the complex process.

As previously mentioned, the use of raw data instead of the reconstructed images can be proven to be useful for our demonstrations. Reconstructing images from tomograms usually involve solving an inverse problem that is ill-posed, which adds a degree of uncertainty in the reconstructed image. Furthermore, the time taken to reconstruct the image may also be an issue in the future for the control loop as many processes including most of the demonstrations feature comparatively fast dynamics.

A possible methodology to use the raw data in the case of the CIFT sensors used in connection with the continuous casting process can be seen in the figure below. The velocity field in the mould is usually reconstructed from the measured magnetic field from the CIFT

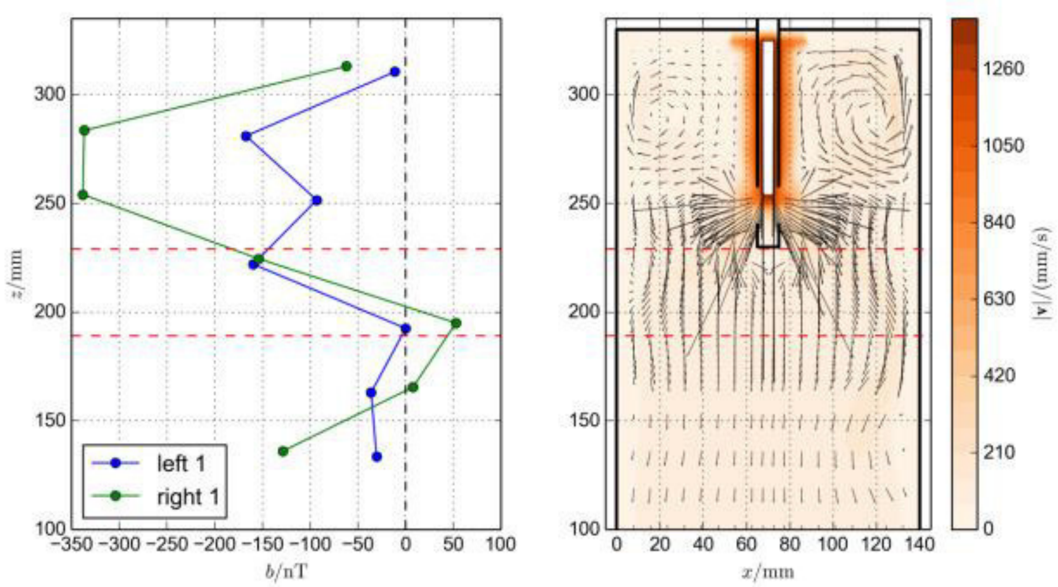

Figure 5: Measurements and Reconstruction of CIFT images (from from Wondrak *et al.*, 2011)

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sensors. It has been shown that different flow patterns in the mould translate to a specific pattern in the magnetic field. For example, the double roll pattern (which is the optimal flow pattern) has a specific S shape in the magnetic field. Therefore, a similar approach as the above researches can be conducted where various flow patterns are identified from the raw data, and the controller can take a decision based on these patterns without reconstructing the whole velocity field in the mould. This is illustrated in Fig. 5.

Image Reconstruction

The concept of using the reconstructed image should also be addressed alongside the raw data. However, it is preferable that the reconstruction of the data is not blind, but rather we should investigate methods to interpret the data while reconstructing it. This idea relies on adding knowledge about the phenomena to the stage of image reconstruction (Romanowski *et al.*, 2005). There have been two common methodologies for the incorporation of prior information with the reconstruction of the images: Parametric modelling and state estimation. An example of parametric modelling based on tomography

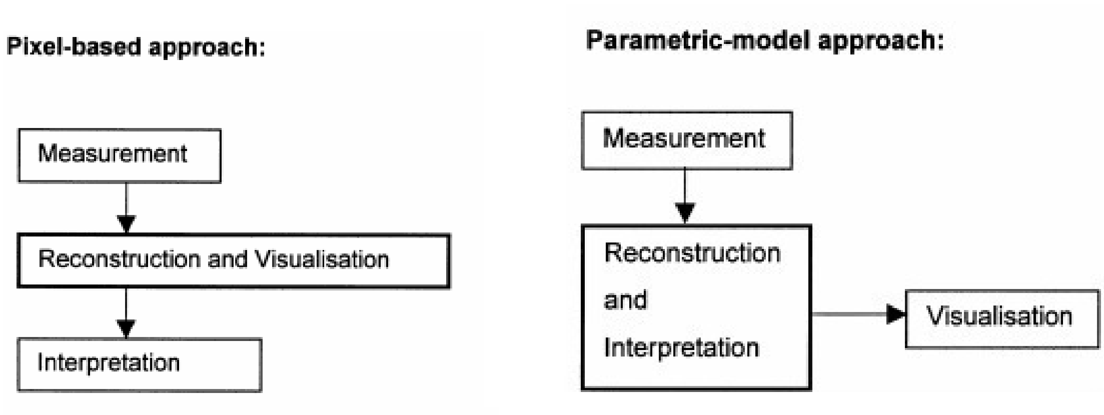

Figure 6: Comparison of pixel-based approach and parametric-approach from West & Williams, 2000

was implemented in West *et al.*, 2000 where a parametric representation of the tomogram was used for the application to a hydrocyclone. The tomogram was built upon basis functions that would suit the geometry of the problem. A comparison between the conventional pixel based approach image reconstruction and the parametric-model approach is illustrated in Fig. 6.

Another example for the parametric approach (Grudzien *et al.*, 2006) implements Markov chain Monte Carlo (MCMC) methods applied to Bayesian modelling in order to implement direct characteristic parameters estimation avoiding the blind reconstruction of the image. Although the parametric approach allows the inverse problem to be better posed by restricting the number of parameters, it has not been commonly used in previous

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literature on tomographic-based control. As mentioned in Grudzien *et al.*, 2006 the algorithms used to implement parametric modelling can be time-consuming, therefore being unsuitable for real time control.

Furthermore, another method for solving the inverse problem in image reconstruction is state estimation. This has proven to be very useful in cases of time-varying targets because the state-estimation approach incorporates a target evolution model in the reconstruction (Seppänen *et al.*, 2009). The reconstruction algorithm allows for state predictions given by the evolution model, this is updated with the information provided by the measurements. In Seppänen *et al.*, 2009 the evolution model was described as a convection-diffusion model where both the velocity field and the conductivity distribution was reconstructed using an extended Kalman filter using measurements coming from an Electrical Impedance Tomography (EIT). A similar approach was implemented in Soleimani *et al.*, 2007 where state estimation was used to solve the inverse problem using both Electrical Capacitance Tomography (ECT) and Electromagnetic Induction (EMT). The linearized Kalman filter was used to improve the temporal resolution of the reconstructed images. The state-estimation approach appears to be more suitable for the task of designing a controller as the state space model can be utilised in the mathematical derivation of the controller. Furthermore, a tomographic-based control loop has been developed using state-estimation in Ruuskanen, 2003. A Linear Quadratic Guassian (LQG) controller was designed using impedance tomographic measurements and was successful in controlling the concentration profile of a pipeline.

Proposed Control Strategies

At least two important points are clear from the previous sections. First, the design of the control loop is heavily coupled with the implementation of the tomographic sensors. Both structures cannot be considered in isolation and the way the tomographic data are interpreted and processed will have significant impact on the controller structure.

For instance if the tomography data are condensed to one numerical characteristics (e.g. jet angle in continuous casting) we will have a standard control task of controlling single-input single-output system. The control structure can then be the basic feedback structure. If the tomography data in continuous casting are evaluated by classifying various flow patterns as outlined above we have linguistic variable as controlled system output. An adequate controller is then some kind of rule based system, probably with fuzzy inference rules as there may be some ambiguity in classification of flow patterns.

Second, a very significant part perhaps even the majority of application areas of tomography enhanced control is essentially real time product quality control (in the selected demonstration it is the case of continuous casting, batch crystallization and fluid separation).

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That means, mostly we do not have controlled variable(s) with specified set-point(s) but certain product quality requirements. These requirements must be translated into standard control engineering terms and control objectives i.e. by finding appropriate numerical characteristics that can be obtained from tomography and whose desired value or range of values can be specified.

Controller design is always connected with models of the controlled plant and its sensors and actuators. This connection can be very strong and evident if the model is an explicit part of the controller. In this case we speak about model based control and the most notable example of such control is model predictive control where the model is used to calculate optimal future control actions. This connection is somewhat weaker but still important if the controller is designed on the basis of the model but the model is not explicitly present in the controller. For instance, PID controller tuning parameters can be calculated on the basis of the model but the model itself is not an explicit part of the PID controller.

Tomography allows distributed sensing and as such it is well suited for treating the controlled process as a distributed parameter system. That means, in principle the control can be based on or designed using distributed parameters model. However it is not the only alternative. The controller can be based on or designed using classical lumped parameter models or it can be knowledge based control using fuzzy or neural models. Lumped parameter models can be obtained by three ways: simplification or approximation of the distributed parameter model (typically this will result in a state space model); simplified first principles reasoning, mass and energy balances etc. or as a result of system identification.

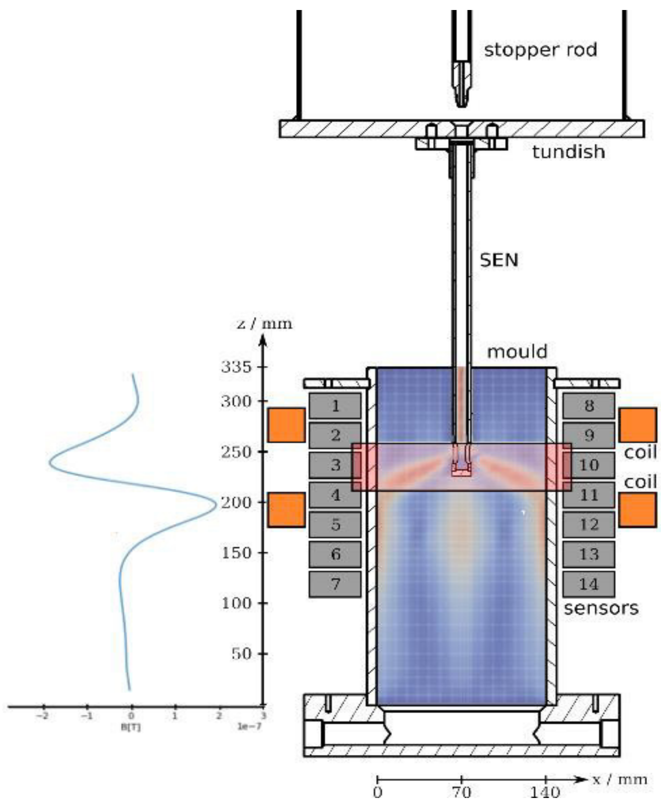

Figure 7: Mini-Limmcast facility

Speaking about the design based on a distributed parameters model it should be noted that it would be more exact to speak about the controlled processes as about lumped input distributed-output systems because the number of the actuators remains finite even if

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tomography based measurement is used.

This can be well illustrated using the structure of the Mini-Limmcast facility for experiments with continuous casting as shown in Fig. 7. There is a maximum of three manipulated variables even in the fullest conceived configuration where CIFT tomography sensing is used to observe the flow in the mould and ECT/MIT tomography is used to observe the flow and bubble distribution in the submerged entry nozzle. These manipulated variables are: stopper rod position, magnetic field of electromagnetic brake and argon gas flow. This restricts the degrees of freedom in manipulating the state of the controlled system even if its state dimension can be regarded as infinite from the system theoretical point of view.

There are several monographs that provide theoretical treatment of the control of distributed parameters systems described by partial differential equations (e.g. Christofides, 2001). However, the real attempts to design a controller in the context described above (distributed parameter model, distributed sensing, lumped actuation) are very rare and at the end they mostly finish with some kind of lumped parameter approximation even if they declare themselves as based on distributed parameter modelling.

An example of this approach can be the paper (Belavý *et al.*, 2015) that was already mentioned above (see Fig. 3). In this paper, the distributed output to be controlled was the temperature field in the steel casting mould. That means, the measurement did not use tomography but the nature of the control task bore a high degree of similarity to the tomography based control. The controller based on the lumped-input/distributed output (LDS) model was implemented and it was shown that this controller is effective in controlling the plant described by distributed parameters. However, the decomposition of the control synthesis into time and space control tasks introduced a number of uncertainties into the model. This further increased the demands on control robustness, which was achieved by internal model control design. Most importantly the declaration that the control is based on a distributed parameters model basically meant that the plant was modelled using multiphysics modelling software and the numerically simulated responses were approximated by standard low order transfer functions using system identifications methods i.e. a very classical lumped parameter model (or set of models) was used at the end. These transfer functions were then used in the controller (see Fig. 3).

Control based on the distributed parameter model is also reported in Villegas *et al.*, 2009. The objective was to control the moisture content in a batch fluidised bed dryer. An electric capacitance tomography (ECT) was used to measure the moisture content. Also in this case most aspects of the controlled plant behaviour were modelled using lumped parameter models based on mass and energy balances. However a distributed parameter model was used to describe the permittivity distribution. The controller was designed to

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keep the distributed permittivity around a desired shape using optimal control tools. This approach, where distributed parameter modelling is used just to describe those aspects of the plant behaviour whose distributed parameter modelling is really essential while the rest is modelled using lumped parameters, seems to be generally promising to be used with the demonstration plants. Such models can be tractable analytically and suitable for use in the context of model based control.

A more detailed elaboration and evaluation of the potential of this approach will be subject of further research connected with the modelling of the demonstration plants. This research is now at the stage that CFD and/or multiphysics simulation models are being built. Among other purposes these models may serve as virtual demonstrators for testing the control strategies using an appropriate co-simulation scheme: typically controller simulated in Matlab/Simulink connected with model implemented e.g. in OpenFoam environment.

In principle, these simulation models could also be used to obtain lumped parameters control-oriented models in a similar way as done in Belavý *et al.*, 2015 i.e. using system identification methods applied to the results from numerical simulation. However, it will probably be more fruitful if system identification methods are applied directly to the data obtained from experiments with real demonstration plants.

This approach of using identification methods applied to experimental data is currently being evaluated with the continuous casting demonstration. It has been found that the appropriate value of the jet angle guarantees desirable flow pattern (double roll) at least if the flow is single phase (no argon). This angle can be obtained from CIFT images. For identification purposes it is also possible to use Ultrasound Doppler Velocimetry (UDV) measurements to obtain the value of this angle. This angle can then be used as a way to translate the product quality requirements to control engineering terms. The control objective is to keep this angle constant with no angle oscillations.

A set of measurements with responses to various strengths of magnetic field of the electromagnetic brake was performed. The objective is to apply system identification in order to obtain classical discrete time input output polynomial model (ARMAX) that could be used as a basis for controller synthesis or as a part of model based controller. Currently the potential of this approach remains an open question. The first experimental data set turned out to provide just limited identification relevant information and new measurements more specifically focused on the dynamics of the response of angle value to the step changes of the magnetic field of the electromagnetic brake will have to be performed.

Other demonstration cases are at a similar stage of development. In the case of microwave drying process the control objective is naturally defined in the standard control engineering terms: it is necessary to keep the moisture distribution of the material at a desired level and as homogeneous as possible. In the case of other demonstrations some

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translation from product quality requirements to control engineering specifications is necessary.

In some cases, application specific control structures will be necessary. This is the case of crystallization process. Semi-batch antisolvent sucrose crystallization is considered with ethanol used as an antisolvent. This process is monitored by an advanced tomographic measurement system. It is envisaged that by extracting one or two global control variables, an adaptive control strategy based on the real-time process information can be implemented to run the crystallization into desired product quality. Adaptive control has the capability to correct the effects of changes in operating conditions due to disturbances. Manipulated control variables could be antisolvent addition rate as well as the number of crystals (direct nucleation approach).

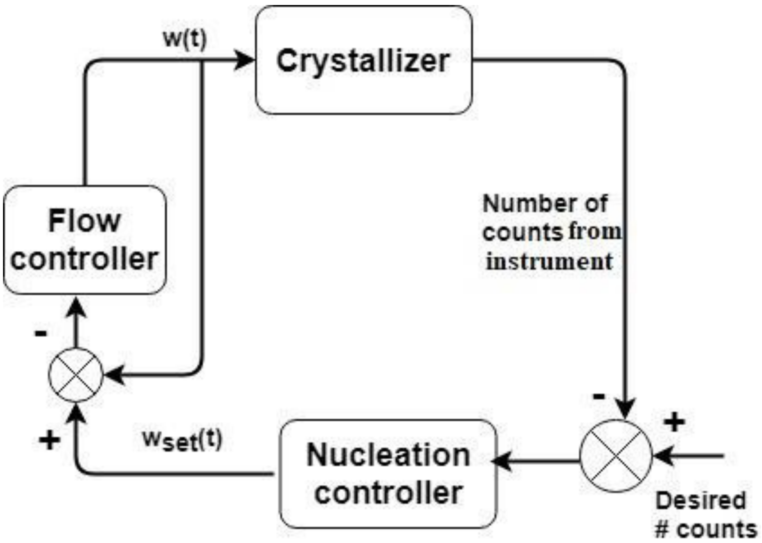

Fig. 8 Block diagram of the DNC approach. *w*(*t*) is the actual antisolvent flowrate into the crystallizer. w_set (*t*) is the antisolvent flowrate set-point given by the DNC to the pump. Adapted from Abu Bakar *et al.*, 2009.

A promising approach could be direct nucleation control (DNC) (Abu Bakar *et al.*, 2009) which maintains the number of particles at a predetermined range during the crystallization. This robust method is based on the idea that the lower is the number of crystals in the system; the larger is the size of the final products. The number of crystals can be measured through tomography measurements (e.g. ultrasonic attenuation) and a feedback control strategy can be implemented to control the amount of nuclei present. This can be achieved by the addition of an antisolvent to generate nuclei up to a desired number of counts. This special control structure is outlined in Fig. 8.

A specific control structure will be necessary also for the microwave drying process. It is evident from Fig. 4 that the measurements are delayed as the tomography sensor is located at the system output. This necessitates the use of an appropriate dead time compensation scheme. This compensation can be based on the classical Smith predictor structure or it is possible to make use of the fact described in Normey-Rico & Camacho, 2007 that a dead-time compensator structure is intrinsically computed in the model predictive

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control law. However, an open issue that will have to be a focus of further research in both variants is the fact that the control objective is basically disturbance rejection (the desired moisture distribution must be achieved regardless of the moisture distribution at process input) and both Smith predictor and dead time compensation intrinsic in the model predictive control offer more significant improvement if the main objective is set-point tracking.

To sum up, apart from specific control structures that will be needed in some cases it can be stated generally that the following model and controller structures are most likely to be used. First, if it turns out that it is viable to obtain a simplified analytical model where just some essential parts are modelled as distributed parameters, it may be possible to use model based strategies. As even these simplified models will be nonlinear and exhibit other control challenges simple standard linear model predictive control cannot be expected to satisfy all of the control requirements. That is why, simplified nonlinear versions of MPC are preferable such as MPC based on Wiener–Hammerstein models, MPC with nonlinear prediction and linear optimization and MPC based on switched linear models. This approach can also be combined with system identification and neural networks can be used to model the nonlinearity. The uncertainties in the model can be handled via adaptive or robust control. Adaptive control is generally likely to achieve better control performance however there is some risk that the adaption process can fail while the robust control is generally safer from this viewpoint however at the expense of nominal control performance.

Second, knowledge based control can be used if simplified analytical modelling is not viable. However, this does not necessarily need to be a universal panacea because the fact that it is not possible to obtain a reliable analytical model of the plant does not automatically mean that it will be possible to obtain a good fuzzy model. If the controlled plant behaviour as sensed by the tomography sensor can be converted to some semi qualitative terms like e.g. the shape of the flow pattern this knowledge based control can have the character of a rule based system, possibly with fuzzy inference rules. Alternatively, machine learning based approaches like reinforcement learning may be a good alternative.

Third, since all demonstration cases exist as physical plants available for experiments, the use of system identification methods applied to the experimental data is a promising approach. Depending on the particular case all categories of models like classical polynomial input output models, state space models as well as fuzzy and neuro-fuzzy models can be used. Depending on the category of the identified model both model based and model free control approaches can be used.

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