Advanced Process Control of Distributed Parameter Plants by Integration First Principle Modeling and Case-Based Reasoning

Part 1: Framework of DPP Control with Initial Uncertainty

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***Abstract* — A tight integration between model-based approach and Case-Based Reasoning (CBR) as data-driven AI technology for advanced process control of periodical industrial plants described by parabolic Partial Differential Equation (PDE) is considered. Via First Principle Model Parametrization using batch parameters as main features instead thermo-dynamical parameters, a discrete virtual Version Space (VS) is proposed as a Case Base for modified CBR. An open loop control is accepted with small sub-optimality and it is derived for each point of VS. In this way, the big part of the model driven calculations are transferred in predominant off-line procedure.**

For the on-line control remains a modest volume of data-driven CBR calculations. This significantly reduces the requirements for computer power and resources for design, commissioning, and maintenance. The proposed control strategy could be seamlessly incorporated into the existing SCADA- or DSC-based industrial control systems. Some simulation results are presented.

Keywords – Case-Based Reasoning; First Principle Model; Partial Differential Equation; Process Control; Simulation

I. Introduction

The market pressure for higher competiveness combined with the increasing ecological requirements, restrictions, and penalties, and also the clear trend toward digitalization according the Industry 4.0 conception impose the necessity to discover new ways for innovative engineering decisions not only in advanced sectors but in the traditional technologies as well. No doubt that one of the most promising way for innovation is the application of AI in a relevant form. The real achievements of AI in variety of domains show that there developed methods, platforms, and tools represent a significant resource of innovative knowledge. It could be successfully implemented in classical technologies too.

The present study is oriented in this direction taking into account that relation gain/losses with AI technologies implementation could be business acceptable.

This investigation is focused on finding efficient data-driven approach for model-based suboptimal control of industrial plants, which behavior could be described by Partial Differential Equations (PDEs) in order to take into account both the dynamics and space distribution of the main plant's variables. As a case study is considered the Thermal Treatment Process (TTP) of wood materials, which is studied deeply and is characterized with significant heat energy consumption [1, 2]

II. Problems and Methods of DPS Control

In the last five decades an impressive volume of theoretical researches in the area of Distributed Parameter Systems (DPS) control was reported [3, 4, 5, 6, 7, 8]. From author side some results of successful engineering applications of DPS control [9, 10, 11, 12] show that deep domain knowledge is necessary premise to design control systems, which are relevant to the real industry conditions and business requirements.

2.1. Existing results

The engineering approaches in feedback control of DPS described by parabolic PDEs are typically based on finite-dimensional approximation on the initial analytic Mathematical Model (MM) represented usually in continuous time and space variables.

A large variety of methods for optimal control have been developed following that approximation. The most popular and wide studied is Model Predictive Control (MPC) [4, 9, 10] but interesting results have been received in H_∞-synthesis in state space [3, 4, 5] and LQG control as well [3, 4].

Because of different reasons in many cases it is impossible, at least now, to derive initial First Principle Model.

In the last two decades a number of data-driven approaches have been proposed using sensor's or inference state information for control of DPS. The most procedures represent a modification of well established AI-techniques – Neural

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Network (NN) based [6], Learning based [7], dual-control like procedures for MM parameters estimation in data stream [8].

Unfortunately all listed approaches are too sophisticated in algorithmic level and require big computational power [9, 11]. In view of that there exist only a few reported results about application of AI-techniques for control of real plants with distributed parameters (DPS).

2.2. Obstacles and challenges in modeling and control of industrial DPS

a) Design problems:

- Lack of, available of part, expensive or inaccurate sensor data or scarce data for key variables. This make impossible the implementation of AI-based methods, which require a large volume of relevant data;
- Nonlinearities of DPS;
- A number of constrains;
- Necessity for modification of well established methods for control of plants with lumped parameters.

b) Limitation due to business consideration:

- Observation of acceptable relation "price of control system / price of the plant" into the range 2 ÷ 5%;
- Optimization of the relation "gain / losses";
- Ability to seamless incorporation of the new control system into the existing SCADA or DCS;
- Problems with the new control system management – MM maintenance, adaptation, cyber security;
- Acceptance of the new system by the operational personnel which is a prior, critically disposed toward innovations.

2.3. The main focus of the investigation

Fig. 1 shows the possible alternatives of the First Principle Models (FPM) application as a component of the advanced control of TTP:

- Explicit implementation of FPM in MPC;
- A data-based MPC as follows: TTP – Measurements – Sensor data – Data Driven MM – MPC;
- Data oriented control (e.g. Reinforcement Learning (RL), Adaptive Dynamic Programming (ADP), NN-based control);
- Hybrid approach: FPM – Simulation – CBR – DD control.

This investigation considers only the last approach, which is most convenient for DPS control. The main focus of investigations comprises:

- Using FPM as a core of the control system;
- Transformation of the initial FPM via parametrization;

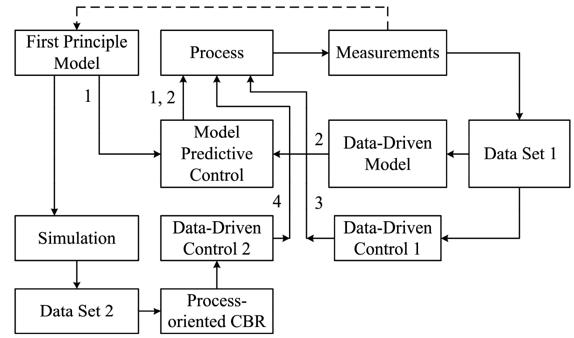

Figure 1. Alternatives of FPM implementation in Advanced Process Control (APC)

- Implementation the Case Based Reasoning as an AI-based technology for transition from model-based toward hybrid model-based / data-driven control (Fig. 2);
- Significant reducing the on-line calculations through preliminary off-line creation of Case Base (CB).

III. PROBLEM DESCRIPTION

Under consideration is control of DPS, which behavior is described with parabolic PDE [2, 3, 8, 13, 14, 15]:

$$c \cdot \rho \frac{\partial t_{\mathrm{w}}(\xi,\tau)}{\partial \tau} = \lambda(\xi) \frac{\partial^2 t_{\mathrm{w}}(\xi,\tau)}{\partial \xi^2} + B(t_{\mathrm{m}},\tau), \tag{1}$$

where $t_{\mathrm{w}}(\xi,\tau)$ is the temperature of the process in the point with coordinates $\xi(x,y,z)$ in a time τ; $B(t_{\mathrm{m}},\tau)$ – control action; λ, ρ, c – thermodynamic parameters; τ – time.

The initial conditions are

$$t_{\mathrm{w}}(\xi,0) = t_{\mathrm{w}}^0 \tag{2}$$

and the boundary conditions are

$$t_{\mathrm{w}}(\upsilon,\tau) = t_{\mathrm{m}}(\tau), \tag{3}$$

The constraints could be a combination of the following relations:

$$\Omega_1 = t_{\mathrm{m}}(\tau) \le t_{\mathrm{m}}^{\max} = \Gamma_1, \tag{4}$$

$$\tau_{\mathrm{f}} = \tau_{\mathrm{f}}^{\mathrm{R}} = \Gamma_2, \tag{5}$$

$$\Omega_2 = \frac{\partial t_{\mathrm{w}}(\xi,\tau)}{\partial n} \le \Gamma_3, \tag{6}$$

$$\Omega_3 = \frac{\partial t_{\mathrm{w}}(\xi,\tau)}{\partial \tau} \le \Gamma_4, \tag{7}$$

$$\Omega_4 = t_{\mathrm{w}}(\upsilon,\tau_{\mathrm{f}}) \le \Gamma_5, \tag{8}$$

$$\Omega_5 = t_{\mathrm{w}}(0,\tau_{\mathrm{f}}) \ge \Gamma_6, \tag{9}$$

where υ represents the surface coordinate; τ_{f} – terminal time; $\tau_{\mathrm{f}}^{\mathrm{R}}$ – reference terminal time; n – direction of the normal; Γ_i – constants; t_{m}, $t_{\mathrm{m}}^{\max}$ – temperature of the heating agent.

The control could be optimized by two objective criteria:

a) J_1 – maximum productivity of the plant:

$$J_1 \leftarrow \tau_f = \tau_f^{min}, \quad (10)$$

subject to constraints (4) ÷ (9);

b) J_2 – minimum heat energy consumption:

$$J_2 \leftarrow Q_a^{min}, \quad (11)$$

subject to constraints (4) ÷ (9).

IV. THE PLANT AND OPERATIONAL CONDITIONS (OC)

4.1. As a case study a Thermal Treatment Process (TTP) is considered (Fig. 2). This is a traditional industrial process, which is studied in multiple aspects [1, 2, 13, 14]. The aim of the TTP is via thermal treatment the wood to become more plasticity and at the same time to obtain another desired characteristics (e.g. change of its natural colour) according to the requirements of the sequential technological stages.

The heating process is non-stationary and space distributed due to the low conductivity of the wood [2, 11, 14]. Most of the thermodynamic characteristics of the wood are directly immeasurable. As the main technological requirements are defined in the terms of internal states of the wood materials, the advanced control of TTP could be successful only by using one or another form of model-based control [12, 15, 16, 17].

4.2. The mathematical model of TTP has been deeply studied both in analytical and computational levels [2, 12, 13, 14] under the following assumptions:

- The behavior of the entire TTP as an aggregation of big number of wood pieces could be presented via dynamics of only one equivalent element;

- The longitudinal heat exchange in autoclaves could be neglected;

- The heat exchange conditions for each of the wood pieces subjected to TTP are identical;

- The constructive parameters of the autoclave are taking into account in additional MM working in parallel with the TTP model.

In acceptance of these assumptions MM of TTP could be represented with high accuracy by the parabolic PDE (1) under the constraints (2) to (9). As analytical solution of eq. (1) under time variable boundary conditions (3), non-linear constraint (6), (7), and right side requirements in (4), (8), and (9) is impossible, only discrete computer-based approximation could be available [2, 13, 14, 15, 16, 17].

4.3. Because of the lack of global feedback the implementation of an observer or Kalmann filter is too sophisticated and costly.

Thus a strategy of suboptimal open loop control is accepted with corrections from batch to batch [2, 12, 15-18]. The stabilization of the temperature t_m of the heating medium is carried out with the help of local PLC-based control system as a part of the SCADA system [15, 16, 17].

In accordance with the Minimum Time Problem (MTP) results concerning the control of PDE [3, 4] and practical experience in many industries (metallurgy, chemistry) we adopted suboptimal "bang-bang" like algorithm with specific terminal part where switching times are optimized [12, 15-17].

4.4. The main operational conditions follow the accepted objective functions:

- Maximum productivity – J_1 (10) (Fig. 3). It corresponds to a minimum terminal time τ_f depending on the temperature of the heating fluid t_m (refer to Fig. 11 below);

- Fixed terminal time τ_f^R (in accordance on the operational scheduling) under the requirement of minimum heat energy consumption – J_2 (11) (Fig. 4).

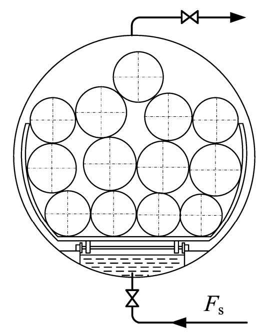

Figure 2. Scheme of TTP realization in an autoclave

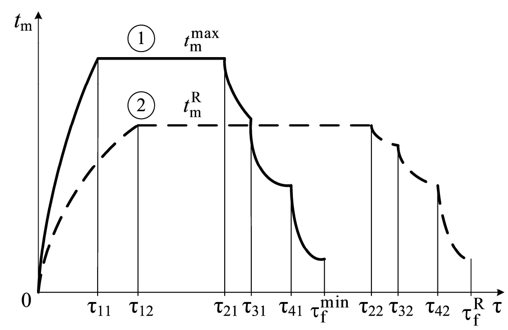

Figure 3. TTP under J_1 realization in dependence on available t_m:
1– $t_m = t_m^{max}$; 2 – $t_m < t_m^{max}$

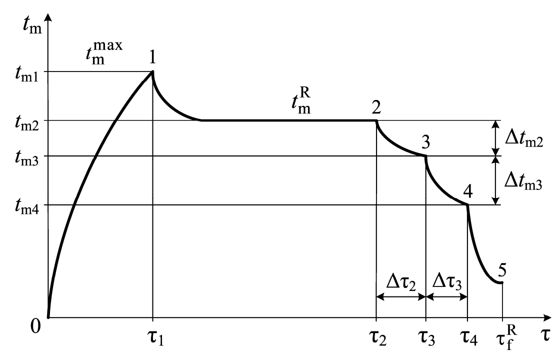

Figure 4. TTP with J_2 realization

The TTP's stage of intensive heating contains two sub-stages: (i) time interval $0 < \tau < \tau_1$ with available $t_{\rm m}^{\max}$; (ii) time interval $\tau_1 \le \tau \le \tau_2$ where $t_{\rm m} = t_{\rm m}^{\rm R}$.

The final three stages on Fig. 4 ($\tau_2 < \tau \le \tau_{\rm f}^{\rm R}$) don't need supplying of the heat energy from external source.

V. Transformation of the Control Problem

The generalized scheme of the proposed approach of using CBR in the suboptimal advanced process control of TTP is presented on Fig. 5. It contains three main functional modules:

- Simulation module, where relevant instances of versions are generated using the developed First Principle Model (eqs. (1) ÷ (9). The computer calculations are fulfilled off-line for corresponding sets of parametrized model parameters (π, a, γ, w, $t_{\rm w}$);

- Parameters' estimation module, where using real time data of the heating fluid $t_{\rm m}(k)$, the key model parameter – batch moisture content $w^{\rm E}$ could be assessed;

- Control module, where a modified Case-Based Reasoning approach in the direction Process Oriented CBR is applied in order to receive suboptimal control of DPS.

5.1. Parametrization of the FPM

For the adopted control strategy (Fig. 5) it turned out that it is advantageous to represent First Principle Model (1) in Virtual Space of virtual situations not in forms of thermodynamic characteristics (λ, ρ, c) but with main batch parameters

$$\mathrm{P_C} = (\pi, a, \gamma, w, t_{\rm m}) \qquad (12)$$

and secondary parameters

$$\mathrm{P_S} = (t_{\rm w}^0, t_{\rm air}), \qquad (13)$$

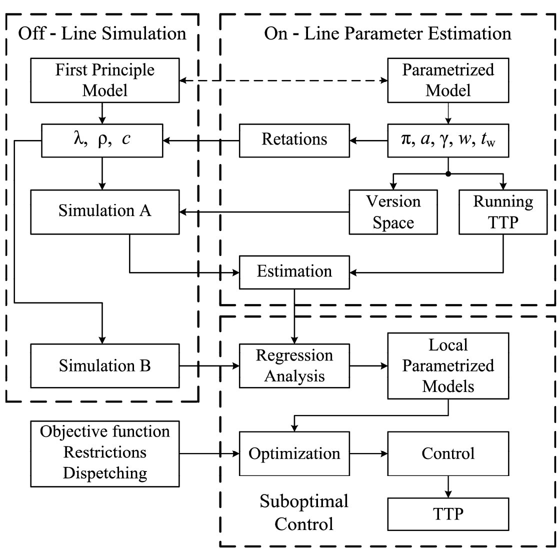

Figure 5. Scheme of the proposed hybrid control system

where π is the wood species; a – representative size of the wood materials; γ – relative degree of batch load; w – wood moisture content; $t_{\rm m}$ – temperature of the heating medium; $t_{\rm w}^0$ - initial wood temperature; $t_{\rm air}$ – ambient air temperature.

The Parametric Model has the following advantages:

- It describes in explicit form the batch conditions (π, a, γ, w), technological abilities ($t_{\rm m}$) and ambient impact factors ($t_{\rm w}^0$, $t_{\rm air}$);
- It uses a domain knowledge of the operational personnel regarding the final part of the batch ($\tau > \tau_2$);

- It corrects the basic assumption about uniformity of the characteristics of separate wood pieces, using average ones;

- It combines the thermodynamic and operational characteristics.

5.2. Version Space as CB

The Version Space (VS) is formed as tree-like structure on the base of the main parametric model features $\mathrm{P_C}$ (12). It is presented on Fig. 6. For each wood species π_i a separate matrix Π_i is formed as follow:

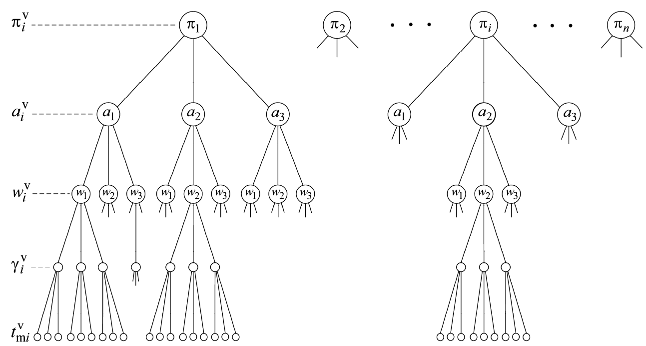

Figure 6. Discrete Version Space structure

$$\Pi_i = \begin{vmatrix} a_1^i & a_s^i & a_3^i & a_4^i \\ \gamma_1^i & \gamma_2^i & \gamma_3^i & \gamma_4^i \\ w_1^i & w_2^i & w_3^i & w_4^i \\ t_{m1}^i & t_{m2}^i & t_{m3}^i & t_{m4}^i \end{vmatrix} \qquad (14)$$

Following Fig. 6 a virtual version sub-space VS_i is formed where each discrete point $\mathrm{P^V}$ contains one element of each row and each column of the matrix Π_i:

$$\mathrm{P^V} = (a_j^i, \gamma_k^i, w_l^i, t_{m_n}^i). \qquad (15)$$

The values of the attributes $a_j^{\rm V}$, $\gamma_k^{\rm V}$, $w_l^{\rm V}$, and $t_{m_n}^{\rm V}$ are chosen in corresponds of specie π_i and span the experimentally known interval of possible changes of each attribute.

As an instance for beech wood materials we accept the next matrix $\Pi_{\rm B}$:

$$\Pi_{\mathrm{B}} = \begin{vmatrix} 0.2 & 0.3 & 0.4 & 0.5 \\ 0.3 & 0.4 & 0.5 & 0.6 \\ 0.4 & 0.5 & 0.6 & 0.7 \\ 130 & 120 & 110 & 100 \end{vmatrix} \begin{vmatrix} \mathrm{m} \\ \%/100 \\ \mathrm{kg \cdot kg^{-1}} \\ {}^{\mathrm{o}}\mathrm{C} \end{vmatrix}. \qquad (16)$$

Each point P^V in the sub-space VS_i contains all necessary data to solve PDE (1) for given operational conditions (16).

In correspondence with (16) each separate sub-space VS_i contains 256 simulated P^V cases. The common Version Space could be presented in the form of union of separate VS_i:

$$\mathrm{VS} = \bigcup_i \mathrm{VS}_i \,. \qquad (17)$$

Version Space VS could be extended in two ways:

a) Adding new k-sub-space containing simulation results of a new wood specie π_k;

b) Adding new case $C^R(P^R, S^R)$ after the sequential real batch in respective sub-space VS_i.

5.3. Transformation of control algorithm

1. Constraints Γ_i (i = 1 ÷ 6) (refer to eqs. (4) ÷ (9)) are calculated during the Simulation B (Fig. 5) for each point of Version Space (VS) and for each critical time τ_2, τ_3, τ_4, τ_f (Fig. 3, Fig. 4). The constraints Γ_1 and Γ_2 are operational and are independent. The constraints Γ_3, Γ_4, and Γ_5 are influenced by Γ_1 and Γ_2 and represent attributes of the given point of VS.

2. Some our previous results for suboptimal switching control of TTP, given in [12, 15, 16, 17], are accepted with in part constant values of $t_m(\tau_i)$.

3. The control structure is open Loop with batch-to-batch adaptive correction (if relevant).

4. Case-Based-Reasoning is admitted as approach to determine the most suitable control actions via retrieval to the most close case in VS.

5. The control quality is gradually increased due to enhancement of the Version Space with new experimental cases.

6. The initial problem of optimal control problem of plants with distributed parameters (DPP) is solved in the presented investigation as two-stage problem:

a) Off-Line optimal or suboptimal solution using simulated plant model described via Partial Differential Equations (PDEs) applying approximate Model Predictive Control [12] and simulation procedures. In this way each case in Version Space contains as attributes corresponding data for each instant situation.

b) On-Line direct suboptimal control using the retrieved switching parameters of the closest of K-nearest neighbors (KNN) by implementation of modified Case-Based Reasoning.

5.4. Functionality of the proposed system

1. Based on the developed First Principle Model [2, 14, 15] a parametrized model is proposed using the derived cross relations between corresponding model parameters [15].

2. After CBR fulfilled retrieval in the Version Space a basic case C^B is determined for the identification stage of the procedure.

3. Using direct measurements of $t_m(\tau)$ in the stage $0 < \tau < \tau_1$ a real moisture content of the wood materials is estimated.

4. On the base of simulated virtual cases C^V local parametrized models are derived. They are used to determine the optimal switching parameters addressed to the running batch – τ_2, t_{m2}, τ_3, t_{m3}, τ_4, t_{m4}, τ_f^R (refer to Fig. 3 and Fig. 4).

5. Batch to batch corrections is applied in order to decrease the level of sub-optimality during the time.

VI. Discussion

Despite of common opinion emerging from the literature for possibility of usage the computational methods for optimal or near to optimal on-line control of plants with distributed parameters [3, 4, 5, 6], such possibility in many cases of practical relevance is too problematic.

Not only from theoretical and computational point of view, but if taking into consideration existing Value Problem, a variety of industry relevant approaches could be of interest.

Recent advances in First Principle modeling of DPP, availability of efficient methods for solving PDE and increasing computational power could be used successfully not only in complex model-based system, which contains a big number of problems – in the essence connected with the uncertainty, lack of measurements, non-stationarity and changeability of the operational conditions.

Therefore we think that synergism between model-based and data-driven approaches could give very promising results.

In our investigation we try to use the strong sides of both approaches – accuracy and availability of broad specter of solutions of PDE in Version Space via off-line computer calculations using virtual (but realistic) combination of operational conditions with easy to be implemented data-driven Case-Based Reasoning in modified form, considering not only static situation but the dynamic episodes too.

This gives advantage to obtain robust solution with better accuracy and close to the theoretically ideal solution which could be only possible with small probability in real operational conditions.

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