Iterative learning control for vacuum heat treatment process

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Abstract

Distributed parameter systems constitute an important class of modern industrial processes. However, in many practical applications the engineers still tend to adapt some classical control techniques developed for lumped systems totally neglecting the spatial dynamics of investigated process. In a view of increasing demands imposed on system accuracy and performance such conventional control algorithms simply become insufficient and there is a great necessity for novel identification and control methods taking into account both the temporal and spatial dynamics. This work reports a dedicated approach to control design for repetitive thermal process consisting of the extension of the existing feedback control scheme with intelligent data-driven component using the iterative learning control technique. Although this is a method which emerged in the context of time-invariant systems, it become adapted to more complex systems due to its flexibility and inherent robustness. The characterization of the resulting control scheme is discussed together with control design and implementation details. In order to compare the quality of the regulation, the approach is illustrated with simulation on the realistic model of wafer heating in industrial vacuum furnace.

1 Introduction

Designing a controller for accurate reference tracking is one of the typical control tasks encountered in industrial applications. Knowledge of the accurate system model is helpful and provide important insight into understanding the process under consideration, if not a ready-to-use inverse model. Closed-form formulas are used as the gold standard of control. On the other hand, most real-world processes have very complicated dynamics (heating processes, fluid dynamics, elastic materials etc.) which evolves not only in time but also in space and cannot be neglected. Such systems are

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known as distributed parameter systems (DPSs) and stimulate the researchers to use of increasingly complex models, such as partial differential equations (PDEs) [3, 6, 7, 10, 11, 22, 26, 30, 34, 35]. Although such sophisticated descriptions usually increase the computational effort, they significantly increase the accuracy of the process modeling. Therefore, the solutions are sought that minimize computational complexity but in the same time are relatively simple to implement in the existing automation systems.

Feedback controllers have been an indispensable control tool throughout their long history. In the literature, there are many types and modifications of the selection of settings for this control method [8, 21, 23, 31, 32]. Despite many advantages, including performance and resistance to uncertainty, unfortunately, it is usually not able to provide the desired performance with nonlinearity, as well as for systems with a very complex structure. Hence, given the complexity of the model, the feedback controller alone cannot achieve the assumed qualitative indicators. Surprisingly, due to the simplicity of implementation, the engineers still are using this approach as a fundamental part of the control system in numerous industrial applications regarding DPSs. Therefore, a hybrid of the feedback regulator and other supporting control algorithms has been observed with many contributions, cf. [17, 25, 33].

One distinct strategy for solving this problem is iterative learning control (ILC) which emerged in the 80s of 20c [4] in the context of machine learning in robotic applications. This method is classified as an intelligent control scheme and become popular due to the simplicity of the concept and robustness to model uncertainty. This control scheme tracks the reference signal at each successive repetition of process, called a trial. For the last 40 years, ILC research focused mainly on time-invariant systems and can be considered as mature and with vast of contributions for different practical situations [1, 2, 4, 9, 13, 14, 24, 25]. However, in the last 10 years some valuable results on the synthesis of this method for distributed parameter systems emerged proving its flexibility. However, these scarce approaches are related to one spatial dimension and are dedicated to a specific class of linear PDEs [12, 15, 16] or steady state [18]. Recently, an approach has been presented that allows for optimal tracking of the reference signal, using the so-called distributed sensing and actuation [20, 27, 28] with applications in elastic materials and heat transfer, provided that the process is inherently repeatable. Here, we extend this approach assuming a strict task-specific constraints: identical initial conditions and finite execution time, yielding e.g. theoretical bounds inapplicable in practice. As the requirement of the industrial application of thermal process the feedback controller is applied as primary but it exhibit the same behavior as the trials go on. To assure a near-perfect tracking, ILC comes to perspective as a promising candidate to allow for nonrepeating disturbance rejection and is incorporated in forward loop. In tandem, possibly noncausal repeating disturbances are rejected via ILC. It is expected that system response is gradually improved providing a tracking error norm convergence.

The main contribution of the research is a development of an effective ILC scheme dedicated for realistic thermal process being the generalization of the approach reported in [28] toward simultaneous feedback and feedforward control. Also, the proper characterization of the design of iterative learning supporting control is discussed for various types of feedback controller. Finally, the proposed approach is verified using a nontrivial simulation benchmark based on the model of industrial vacuum furnace.

2 System description

Consider a thermal spatio-temporal process representing a heat treatment in vacuum furnace whose geometry can be generally represented by bounded domain $\Omega \subset \mathbb{R}^3$ with boundary $\partial\Omega$. Let $T = (0, t_f]$ be a bounded time interval, where $t_f < \infty$ denotes finite process duration. The evolution of the normalized temperature $y(x,t)$ at spatial point $x \in \Omega$ and time $t \in T$ can be described by the following PDE

$$\rho C_p \frac{\partial y(x,t)}{\partial t} + \nabla \cdot \big(-\kappa \nabla y(x,t) \big) = q(x,t) \tag{1}$$

subject to the boundary and initial conditions:

$$\begin{cases} \dfrac{\partial y(x,t)}{\partial n} = \alpha\big(J_0 - \sigma \cdot y^4(x,t)\big), & (x,t) \in \partial\Omega_I \times T, \\ \dfrac{\partial y(x,t)}{\partial n} = h\big(y_{ext} - y(x,t)\big), & (x,t) \in \partial\Omega_E \times T, \\ y(x,0) = y_0, & x \in \Omega \times \{t = 0\}, \end{cases} \tag{2}$$

where $\alpha = \frac{\varepsilon}{1-\varepsilon}$ is a function of surface emissivity ε (dependent on material) and σ is the Stefan–Boltzmann constant. Contact flux with medium of temperature y_{ext} is dictated by convective heat transfer coefficient h. Quantity $J_0 = \rho_d G \varepsilon$ denotes a surface radiosity, ρ_d being surface reflectivity and G the incoming radiative flux. The y_0 is an initial temperature and $\partial y / \partial n$ stands for the partial derivative of y with respect to the outward normal vector $\vec{n}$ to the boundary. Conductive heat transfer is determined by thermal conductivity κ and heat capacity C_p, ρ being the material density. The total heat power rate $q(x,t)$ is described by a scalar function and plays a role of actuation. Boundary $\partial\Omega_E$ denotes the exterior surface of the furnace chassis, while $\partial\Omega_E$ denotes all interior surfaces. The entire system is based on the construction of a vacuum furnace, consisting of three main elements: the chassis (chamber walls and insulation), the actuator - a heater lamp and the heated element, e.g. a wafer (cf. Fig. 1).

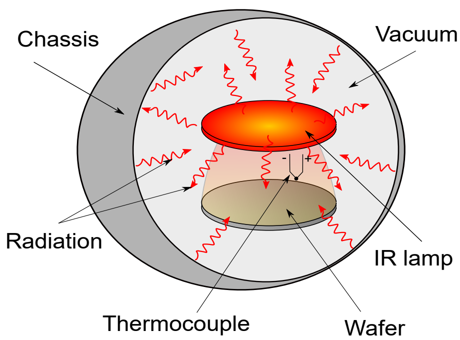


Figure 1: Scheme of vacuum furnace

The constant temperature y_{ext} = const for surrounding environment was assumed. Outline scheme of energy transport, interaction directions and physical laws is included in Fig. 2.

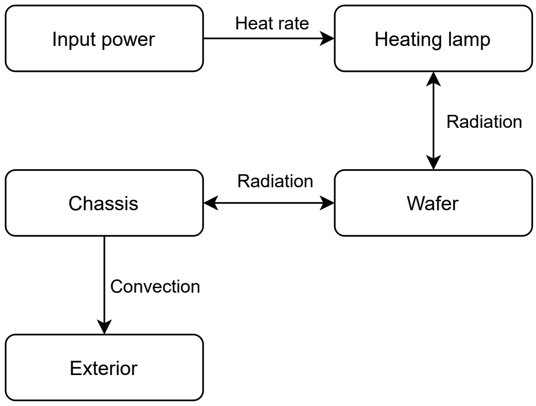


Figure 2: Energy transfer diagram

3 Iterative control scheme

3.1 Baseline controllers

The system is actuated via the source term

$$q(x,t) = \begin{cases} u(t), & x \in \Omega_{\mathrm{a}}, \\ 0, & \text{elsewhere}, \end{cases} \tag{3}$$

where $\Omega_{\mathrm{a}} \subset \Omega$ is a part of spatial domain representing actuator. The control signal $u(t) \in [0, P_{max}]$ is bounded to account for the physical characteristics of available actuators. The step-response of the plant ($u(t) = \text{const} = P_{max}$) has been simulated and it's characteristics computed. With such an information, controller gains were made subject to Cohen-Coon tuning method. Only the proportional part has been increased afterwards, such that the error between the initial condition and steady-state drives the control signal to 100% saturation. In the early stages of heating process, it is expected to drive input as much as possible. Despite the upper limit imposed on the input, the shape of the reference signal is later designed in such a way, that the existence of feasible u is guaranteed. That is, the time constant of y_{ref} was chosen to be smaller than the one of the system.

At the k-th trial, the system response $y_k(x,t)$ is assumed to be observed in a continuous manner over the interval T with the thermocouples, which locations x_{th} in practical setting are arbitrarily chosen as to provide the sufficient information about system dynamics. Here, for simplicity of considerations we reduce our attention to one sensor as the generalization for many sensors can be done without major difficulties. The typical characteristics of thermocouple is that the measurement of temperature is an average on some small spatial region surrounding the probe. Let Ω_{th} be a ball with center at x_{th} and radius r_{th}. Hence, a single observation of the system output at each time instant t, for k-th repetition of the process takes the following form

$$z_k(t) = \int_{\Omega_{\mathrm{th}}} p(x) y_k(x,t) \mathrm{d}x, \ t \in T \tag{4}$$

where $u_k(t)$ is the control input vector at k-th trial and $y_k(x,t) = y(x,t;u_k(t))$. In the following, the measurement made by a single sensor is presented as a uniform spatial distribution $p(x) = p$ defined on the domain Ω_{th} with $\int_{\Omega_{\mathrm{th}}} p(x)\mathrm{d}x = 1$.

3.2 Control update

To achieve the control objective, it is proposed to enhance online feedback control with an ILC calculated offline and stored. The control scheme is presented in Fig. 3. It follows that control signal was a sum of feedback $u_k^{fb}(t)$ and iteratively updated $u_k^{ILC}(t)$:

$$u_k(t) = u_k^{fb}(t) + u_k^{ILC}(t) \tag{5}$$

As mentioned, in order to satisfy practical settings, control signal $u_k(t)$ has been subjected to actuator saturation, i.e. $u_k(t) \in [0, P_{max}]$.

As the feedback controller the PID was used as its a typical solution used in industrial vacuum furnaces. The goal is to adapt the input signal vector $u_k(t)$ (via $u_k^{ILC}(t)$) in each subsequent trial in such a way, as to make the measurement output $z_k(t)$ follows some arbitrarily chosen differentiable trajectory $z_{\text{ref}}(t)$ as accurately as possible. Thus, it is desired to iteratively improve the tracking error norm in the trial domain:

$$\|e_k(t)\| = \|z_{\text{ref}}(t) - z_k(t)\|$$

i.e. to converge uniformly with tracking error approaching zero when $k \to \infty$.

For sake of simplicity, a adopted scheme was feedforward ILC. Where data recorded during the previous trial is used to design a new control input with an update based on the tracking error [4]. In the following, taking into account the relatively high time constant of thermal systems described by dynamics (1)–(2), a noncausal learning rule was derived with some arbitrarily chosen delay time $\delta \geq 0$ [s]:

$$u_{k+1}^{ILC}(t) = u_k^{ILC}(t) + \lambda e_k(t + \delta) \tag{6}$$

where λ is a learning gain coefficient. The conditions for the convergence of the update rule (6) can be obtained as a generalization of the results presented in [28]. The shift parameter $\delta > 0$ give some additional degree of freedom allowing for faster convergence, cf. [19] for a comprehensive substantiation.

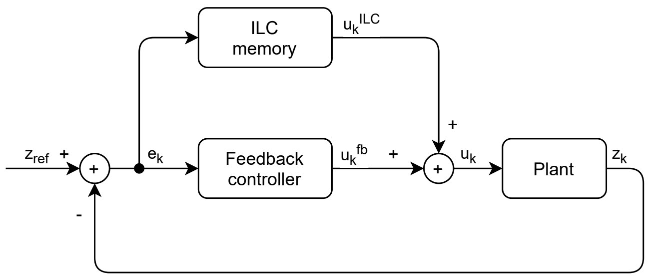


Figure 3: Feedforward ILC scheme

3.3 Implementation

In practical setting the solution of the system (1)–(2) in closed-form is unavailable, therefore it has to be effectively solved numerically. This is achieved by application of the Finite Element Method (FEM). For a detailed treatment of this numerical scheme see [20,27,29]. Finally, the PDEs in such form are especially suited to being directly embedded and effectively solved in numerous efficient

FEM-based solvers. These include the MATLAB PDE Toolbox or the COMSOL environment [5], which in particular were applied here.

One of the key issues which has to be addressed when calculating the control update is determination of appropriate learning gain λ. Aware of the fact, that there is no clear guideline for the qualitative choice, a test simulation has been carried out. Using pure P controller in the feedback channel the root-mean-square (RMS) values of the first order signal derivatives were computed (RMS ratio for other controllers was similar). In order to estimate the magnitude of system input to output, substituting to (6) the upper bound for learning gain has been calculated:

$$\begin{aligned}\lambda_{\max} &\overset{\text{def}}{=} \frac{u_{k+1} - u_k}{e_k} = \frac{\Delta u}{\Delta y} \\ &\approx \frac{\text{rms}(\Delta u)}{\text{rms}(\Delta y)} = 58.8 \approx 60\end{aligned} \tag{7}$$

For the sake of simplicity of the update rule, the optimal gain $\lambda^\star$ was assumed to be time and trial independent. The maximum number of trials was set to $k_{max} = 30$. Then, the $\lambda^\star$ was determined by sampling interval $(0, \lambda_{\max}]$ and choosing:

$$\lambda^\star = \arg\min_{\lambda} \|e_{k_{max}}\| \tag{8}$$

Final gains for feedback controllers of P, PI and PID type were found as $\lambda^\star_P = 8.00$, $\lambda^\star_{PI} = 6.25$, $\lambda^\star_{PID} = 5.00$, respectively.

4 Numerical example

In the COMSOL model of furnace, both heat emitter and heated object (wafer) are disks of identical diameters ($D = 1$[m]) and positioned in parallel with respect to each other inside the furnace chamber, cf. Fig. **??**. Wafer height is $h_w = 0.004$[m], and IR lamp height is $h_{IR} = 0.01$[m]. Chassis is a cylindrical shell with outer and inner radii of $R_o = 1.01$[m] and $R_i = 1$[m], respectively. The height of cylindrical chamber is 1.5[m] and the thickness of its base walls is equal to 0.01[m]. Table 1 summarize values of material parameters in system (1)-(2). It is assumed that each part of furnace is composed of homogenous material.

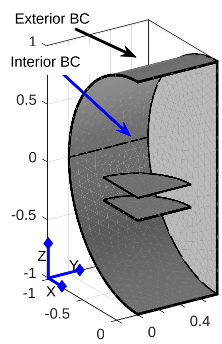


Figure 4: Created system geometry with marked energy transfer BCs

Table 1: Material parameters

Parameter	Chassis	IR lamp	Wafer
ρ [kg/m^3]	20000	8700	1000
C_p [J/(kg·K)]	120	10	300
ε []	0.19	0.99	0.15
κ [W/(m·K)]	75	400	130

Energy is dispersed from the system by convective cooling to outside medium (air) under normal conditions (i.e. $y_{ext} = 293.15$[K] and pressure of 1 atm). Heat transfer coefficient h was set to 1[W/(m^2·K)] accounting for realistic insulation. At each trial of ILC it is assumed that chassis, heater and wafer initial temperature are set to $y_0 = 20$[°C]. Since, measurement domain was composed of one sensor probe located at the center $x_{\text{th}} = [0, 0, h_w/2]$ and $r_{\text{th}} = 0.001[m]$, control process can be considered as a SISO problem. The reference temperature was a smooth step–like shaped function:

$$z_{\text{ref}}(t) = 28 \cdot \tanh((t - 100)/50) + 47, \quad t \in (0, t_f]. \tag{9}$$

With respective initial value of $z(0) = y_0$ and steady-state $z(t_f) = 75$[°C], where $t_f = 600$[s].

The proposed ILC scheme was programmed using Comsol Multiphysics 5.5 and Matlab 2018b. It was run on a PC with the following specification: Intel Core i7 2.20 GHz processor and 24 GB RAM with Windows 10. The finite element method was applied to the spatial mesh consisting of 3480 nodes and 1004 triangular prisms. The implicit family (BDF) solver was used with maximum time step of 6[s].

Tracking error evolution is visualized in Fig. 5, allowing to compare the convergence rate for all feedback controllers. Well defined behavior of norm convergence occurs in the case of proportional feedback only. For the other two types of fusions, the convergence rate is quite slow (but still the value of norm lower compared to P type), what is an direct effect of an assumption of constant $\lambda^\star$.

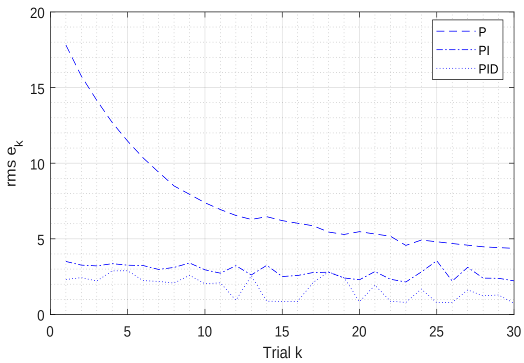


Figure 5: Comparison of error convergence

4.1 P controller

In Fig. 6 it can be seen that proportional controller suffers from steady–state error with distinct lag–time. Just after 10 trials, overshoot occurs and is not compensated even until last iteration.

At final iteration, feedback controller did not contribute significant part to control signal, as shown in figure 7. It would be expected to reach better performance by training for additional iterations.

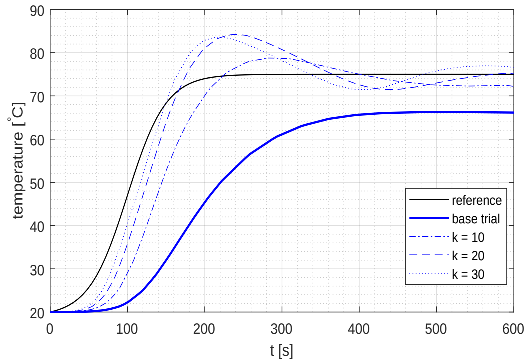


Figure 6: Time responses, P controller

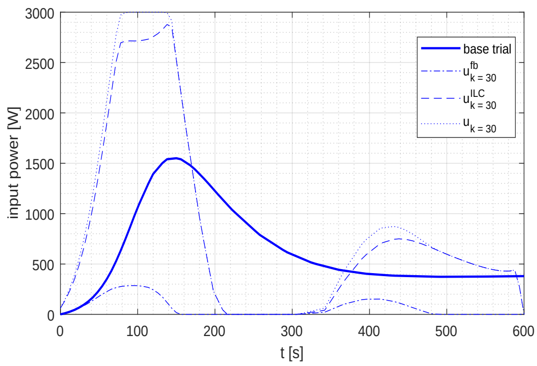


Figure 7: Input signal composition, P controller

4.2 PI controller

Distinguishing feature of PI controllers is, that they respond with quadratic signal, to linearly growing error. Thus as the reference signal reached constant value, the system response reached an characteristic overshoot – figure 8. After a sequence of iterations, control signal was modified in such a way, that aforementioned issue has been noticeably damped. It is important, that u^{ILC} was negative at some interval, showing the effect non–causal action. The accompanying oscillations were shifted in phase, with respect to different trials. Magnitude of one "control peak" has dropped and was shifted back in time by 100[s].

4.3 PID controller

Looking at figure 10 it can be observed that derivative action in the controller did not provide superior tracking. Although initial decrease in overshoot and oscillation magnitude, there was still room for improvement. Just in $k = 20$ iterations, steady–state tracking error was insignificantly small (dashed line). Tracking of the initial rapid growth for $t \leq 100$ was not achieved, for any of

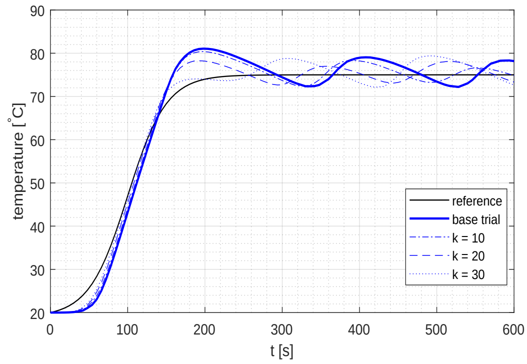


Figure 8: Time responses, PI controller

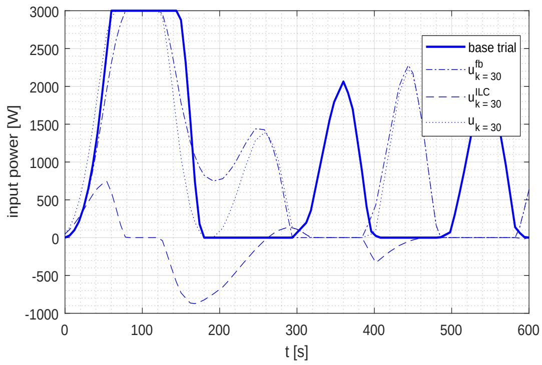


Figure 9: Input signal composition, PI controller

the studied setups, which would suggest modifying learning law for transient changes. Peaks in the u_k signal were shifted ahead in time, with u^{ILC} driving mostly the negative direction. Control signal was linearly (visibly) decreasing at interval $T \in [80, 220]$, just as the reference approached constant value.

5 Concluding remarks

The dedicated approach to fusion control with feedback and iterative learning with the application to the vacuum heat treatment systems is reported. The characterization of control design is provided leading to relatively simple numerical iterative learning scheme. Modeling the dynamics of a real thermal process has been performed to a satisfying degree with closed loop performance improved in each case. There is still room for the important extensions. One is toward an adaptive time and trial dependent learning gain which will constitute the next future research step. Other tangible problem is an optimal location of sensors and actuators providing best system performance.

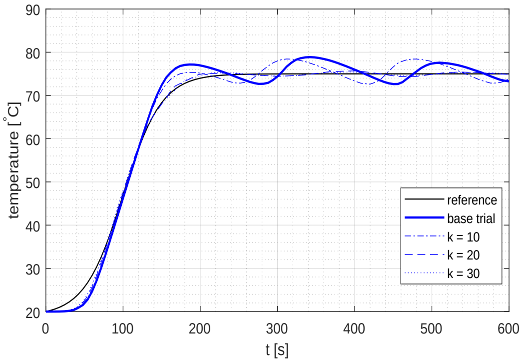


Figure 10: Time responses, PID controller

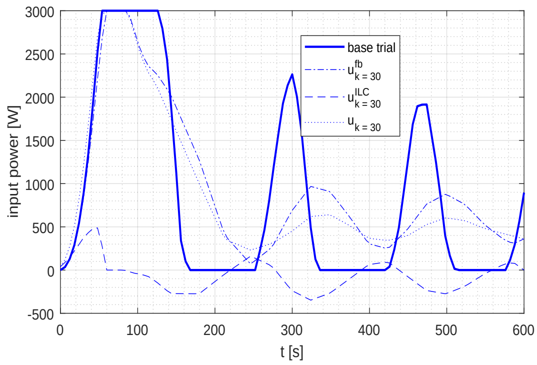


Figure 11: Input signal composition, PID controller

References

[1] Hyo-Sung Ahn, YangQuan Chen, and Kevin L Moore. Iterative learning control: brief survey and categorization. *IEEE Transactions on Systems Man and Cybernetics Part C Applications and Reviews*, 37(6):1099, 2007.

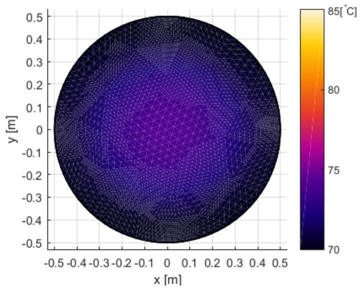
[2] Hyo-Sung Ahn, Kevin L. Moore, and YangQuan Chen. *Iterative Learning Control. Robustness and Monotonic Convergence for Interval Systems*. Communications and Control Engineering. Springer-Verlag, London, 2007.

[3] William F Ames. *Numerical methods for partial differential equations*. Academic press, 2014.

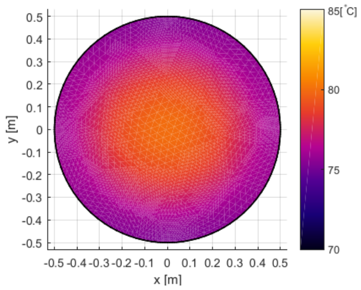
[4] Suguru Arimoto, Sadao Kawamura, and Fumio Miyazaki. Bettering operation of robots by learning. *Journal of Robotic systems*, 1(2):123–140, 1984.

[5] E. Aulisa and D. Gilliam. *A Practical Guide to Geometric Regulation for Distributed Parameter Systems*. Monographs and Research Notes in Mathematics. CRC Press, Taylor & Francis Group, 2015.

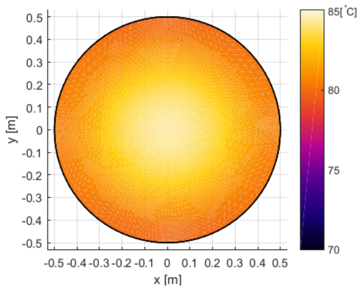
[6] H Thomas Banks and Karl Kunisch. *Estimation techniques for distributed parameter systems*. Springer Science & Business Media, 2012.



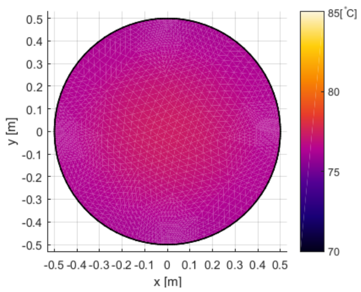
(a) $t = 160s$



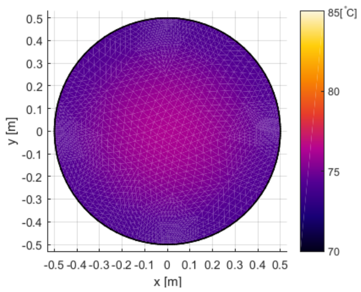
(b) $t = 176s$



(c) $t = 204s$



(d) $t = 320s$



(e) $t = 600s$

Figure 12: Example of temperature evolution on upper wafer surface (P controller).

[7] Alain Bensoussan, Giuseppe Da Prato, Michel C Delfour, and Sanjoy K Mitter. *Representation and control of infinite dimensional systems*, volume 1. Birkhäuser Boston, 1992.

[8] Rakesh P Borase, DK Maghade, SY Sondkar, and SN Pawar. A review of pid control, tuning methods and applications. *International Journal of Dynamics and Control*, 9(2):818–827, 2021.

[9] D. A. Bristow, M. Tharayil, and A. G. Alleyne. A survey of iterative learning control: a learning-based method for high-performance tracking control. *IEEE Control Systems Magazine*, 26(3):96–114, 2006.

[10] Dan Gabriel Cacuci, Ionel Michael Navon, and Mihaela Ionescu-Bujor. *Computational Methods for Data Evaluation and Assimilation*. CRC, Boca Raton, FL, 2014.

[11] Ruth F Curtain and Hans Zwart. *An introduction to infinite-dimensional linear systems theory*, volume 21. Springer Science & Business Media, 2012.

[12] Xi-Sheng Dai, Xing-Yu Zhou, Sen-Ping Tian, and Hong-Tao Ye. Iterative learning control for mimo singular distributed parameter systems. *IEEE Access*, 5:24094–24104, 2017.

[13] C. Freeman, E. Rogers, J.H. Burridge, A.-M. Hughes, and K.L. Meadmore. *Iterative Learning Control for Electrical Stimulation and Stroke Rehabilitation*. SpringerBriefs in Control, Automation and Robotics. Springer-Verlag, London, 2015.

[14] Chris T Freeman, Eric Rogers, A Hughes, Jane H Burridge, and Katie L Meadmore. Iterative learning control in health care: electrical stimulation and robotic-assisted upper-limb stroke rehabilitation. *Control Systems, IEEE*, 32(1):18–43, 2012.

[15] Qin Fu, Panpan Gu, and Jianrong Wu. Iterative learning control for one-dimensional fourth order distributed parameter systems. *Science China Information Sciences*, 60(1):1–13, 2017.

[16] Qin Fu, Wei-Guo Gu, Pan-Pan Gu, and Jian-Rong Wu. Iterative learning control for a class of mixed hyperbolic-parabolic distributed parameter systems. *International Journal of Control, Automation and Systems*, 14(6):1455–1463, 2016.

[17] Brian E Helfrich, Chibum Lee, Douglas A Bristow, XH Xiao, Jingyan Dong, Andrew G Alleyne, Srinivasa M Salapaka, and Placid M Ferreira. Combined hinfty-feedback control and iterative learning control design with application to nanopositioning systems. *IEEE Transactions on Control Systems Technology*, 18(2):336–351, 2009.

[18] Deqing Huang and Jian-Xin Xu. Steady-state iterative learning control for a class of nonlinear pde processes. *Journal of Process Control*, 21(8):1155–1163, 2011.

[19] Deqing Huang, Jian-Xin Xu, Xuefang Li, Chao Xu, and Miao Yu. D-type anticipatory iterative learning control for a class of inhomogeneous heat equations. *Automatica*, 49(8):2397–2408, 2013.

[20] Kamil Klimkowicz, Robert Maniarski, and Maciej Patan. Iterative learning control of deflections in vibrating beam. In *2019 24th International Conference on Methods and Models in Automation and Robotics (MMAR)*, pages 215–220. IEEE, 2019.

[21] Carl Knospe. Pid control. *IEEE Control Systems Magazine*, 26(1):30–31, 2006.

[22] Irena Lasiecka and Roberto Triggiani. *Control theory for partial differential equations: Volume 1, Abstract parabolic systems: Continuous and approximation theories*, volume 1. Cambridge University Press, 2000.

[23] Yun Li, Kiam Heong Ang, and Gregory CY Chong. Patents, software, and hardware for pid control: an overview and analysis of the current art. *IEEE Control Systems Magazine*, 26(1):42–54, 2006.

[24] David H. Owens. *Iterative Learning Control. An Optimization Paradigm.* Advances in Industrial Control. Springer-Verlag, London, 2016.

[25] Krzysztof Patan and Maciej Patan. Neural-network-based iterative learning control of nonlinear systems. *ISA transactions*, 98:445–453, 2020.

[26] Maciej Patan. *Optimal sensor networks scheduling in identification of distributed parameter systems*, volume 425. Springer Science & Business Media, 2012.

[27] Maciej Patan, Kamil Klimkowicz, Robert Maniarski, Krzysztof Patan, and Eric Rogers. Iterative learning control of the displacements of a cantilever beam. Manuscript submitted for publication (CDC 2019).

[28] Maciej Patan, Kamil Klimkowicz, and Krzysztof Patan. Iterative learning control for distributed parameter systems using sensor-actuator network. In *16th International Conference on Control Automation Robotics and Vision, ICARCV 2020*, page 2020, 1200–1205.

[29] Maciej Patan, Krzysztof Patan, Krzysztof Gałkowski, and Eric Rogers. Iterative learning control of repetitive transverse loads in elastic materials. In *57th IEEE Conference on Decision and Control, CDC 2018, Miami, FL, USA, December 17-19, 2018*, pages 5270–5275, 2018.

[30] José M Rodríguez, David Sánchez, Gonzalo S Martínez, Badr Ikken, et al. Techno-economic assessment of thermal energy storage solutions for a 1 mwe csp-orc power plant. *Solar Energy*, 140:206–218, 2016.

[31] Pritesh Shah and Sudhir Agashe. Review of fractional pid controller. *Mechatronics*, 38:29–41, 2016.

[32] Guillermo J Silva, Aniruddha Datta, and Shankar P Bhattacharyya. *PID controllers for time-delay systems*, volume 43. Springer, 2005.

[33] Mei Sun, Lixin Tian, Shumin Jiang, and Jun Xu. Feedback control and adaptive control of the energy resource chaotic system. *Chaos, Solitons & Fractals*, 32(5):1725–1734, 2007.

[34] Ne-Zheng Sun and Alexander Sun. *Model Calibration and Parameter Estimation For Environmental and Water Resource Systems.* Springer, New York, 2015.

[35] Christophe Tricaud and YangQuan Chen. *Optimal Mobile Sensing and Actuation Policies in Cyber-physical Systems.* Springer, London, 2012.