Hochschule Harz
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Parameter Identification for Process Models Based on a Combination of Systems Theory and Deep Learning†

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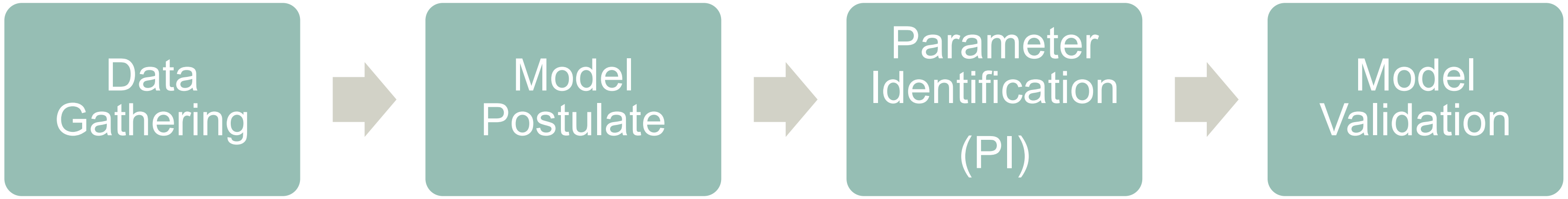
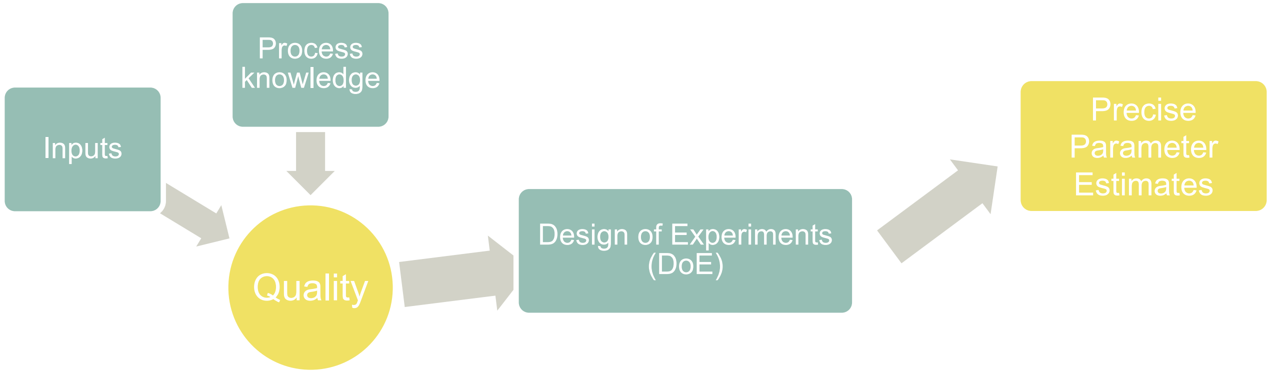
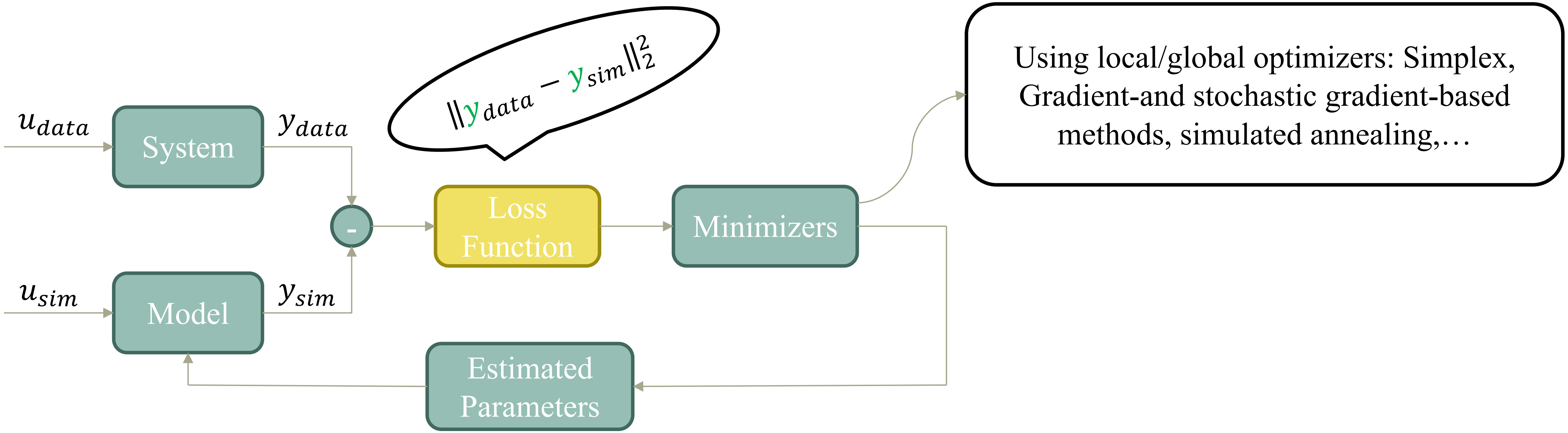
Motivation

System Identification – can be applied to any industrial process where the inputs and outputs can be measured to build its mathematical model.

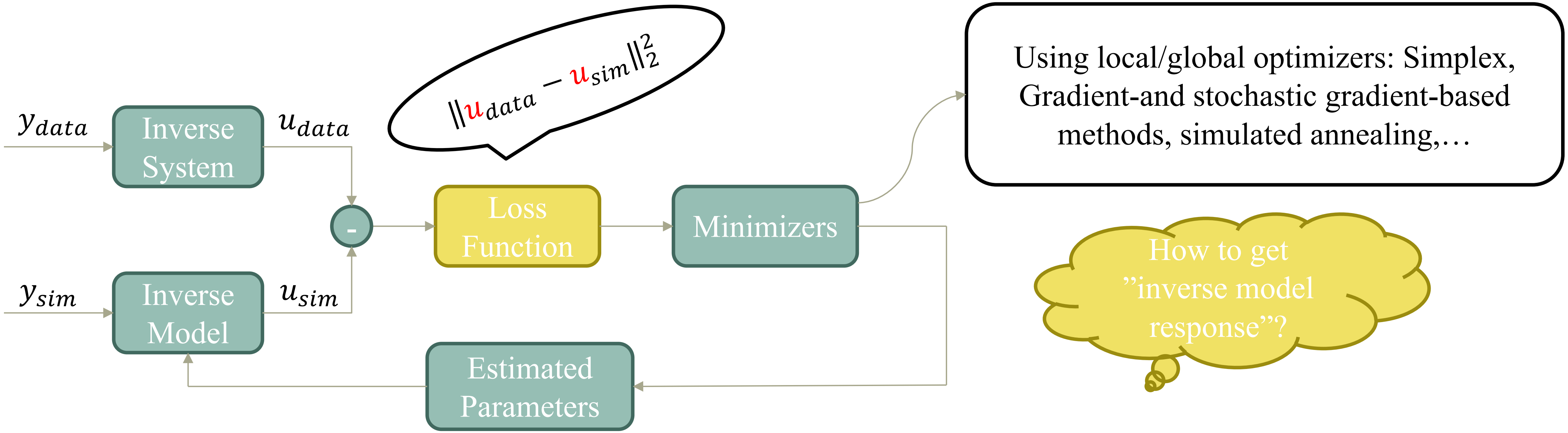




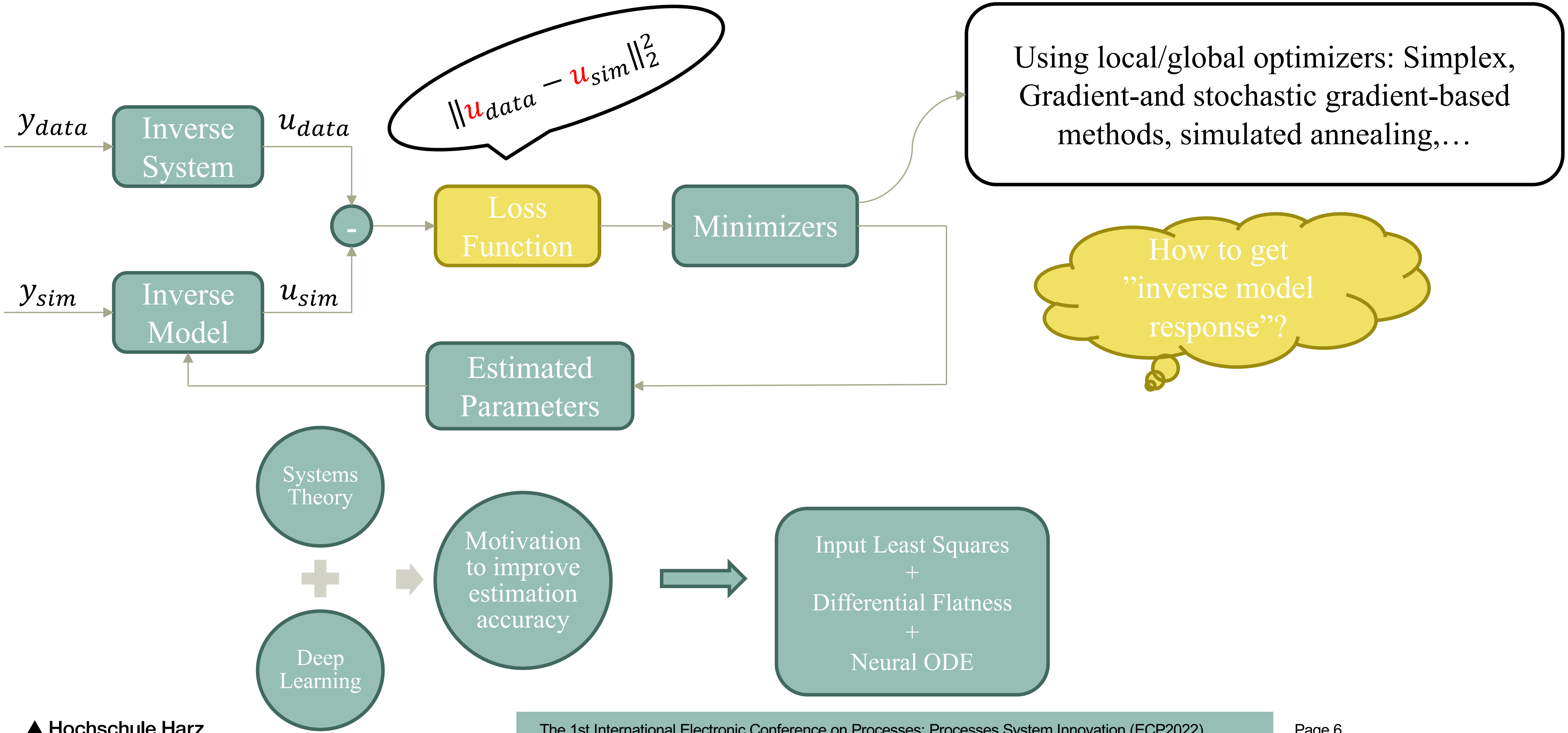
Standard Parameter Identification Framework



Input-based Parameter Identification Framework



Input-based Parameter Identification Implementation Aspects



Differential Flatness for Distributed-Parameter Problems

Identification of Parametric Models: from Experimental Data; Eric Walter, and Luc Pronzato
Springer; Auflage: 1997.

Conditions for a system to be differentially flat:

- Existence of a flat output

$$y^{flat} = h^{flat}(x, u, \dot{u}, \dots, u^{s}, p)$$

- Fulfilling the following conditions:

$$x = \Psi_x\left(y^{flat}, \dot{y}^{flat}, \dots, y^{flat^{\alpha}}, p\right)$$

$$u = \Psi_u\left(y^{flat}, \dot{y}^{flat}, \dots, y^{flat^{\alpha+1}}, p\right)$$

$$\dim y^{flat} = \dim u$$

Case Study: Diffusion-type Problem

Considering a parabolic PDE:

$$\frac{\partial \Phi}{\partial t} = p\frac{\partial^2 \Phi}{\partial x^2} + u(x,t)$$

with $\mathrm{p} = 0.1$ and $u_0 = \sin(2\pi x)$.

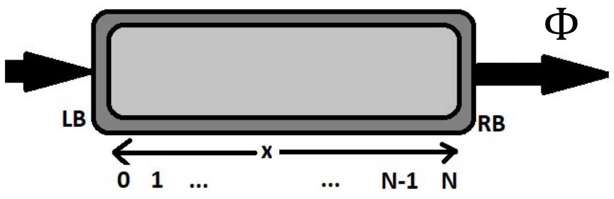


Fig. 1:A simple diffusion system.

- The system is differentially flat with a flat output defined as the vector:

$$y^{flat} = [y_{t_k,1}, y_{t_k,2}, \dots, y_{t_k,N}]$$

where y corresponds to the measured output of Φ.

Case Study: Diffusion-type Problem + Neural ODEs

Considering a parabolic PDE:

$$\frac{\partial \Phi}{\partial t} = p\frac{\partial^2 \Phi}{\partial x^2} + u(x,t)$$

with $\mathrm{p} = 0.1$ and $u_0 = \sin(2\pi x)$.

No model,
Only measurements

An alternative approach…

$$\mathrm{NNL}_0(x) = x \in \mathrm{R}^{\mathrm{d}_0},$$

$$\mathrm{NNL}_\mathrm{j}(x) = \sigma\left(\mathrm{W}^\mathrm{j}\mathrm{NNL}_{\mathrm{j}-1}(\mathrm{x}) + \mathrm{b}_\mathrm{j}\right) \in \mathrm{R}^{\mathrm{d}_\mathrm{j}}$$

$$\forall 1 \leq j \leq I-1$$

$$\mathrm{NNL}_\mathrm{I}(x) = \mathrm{W}^\mathrm{I}\mathrm{NNL}_{\mathrm{I}-1}(x) + \mathrm{b}_\mathrm{I} \in \mathrm{R}^{\mathrm{d}_\mathrm{I}}.$$

- Uses neural ODEs to get the data-driven model of the process under study, generally represented as:

$$\begin{cases} \dot{x}(t) = NN(x(t), u(t), p); \\ x(t_0) = x_0 \end{cases}$$

- This acts as a surrogate model – the output functions and their derivatives are derived.

✓ Discovers and creates numerical solutions
✓ Including time derivatives
✓ Might be combined with process knowledge (i.e., physics informed neural networks)

Control Input by Model Inversion

- Control input (at a particular point in dimension) in time domain is calculated using the formula:

$$u(y_{t_k,1}) = \dot{y}_{1,1} - \frac{p}{\Delta x^2}\phi_{t_k,N+1} + \frac{2p}{\Delta x^2}\, y_{t_k,N} - \frac{p}{\Delta x} y_{t_k,N-1}$$

- Extending this throughout the dimensional space – new control u_{data} fed back to get an effective control of diffusion.

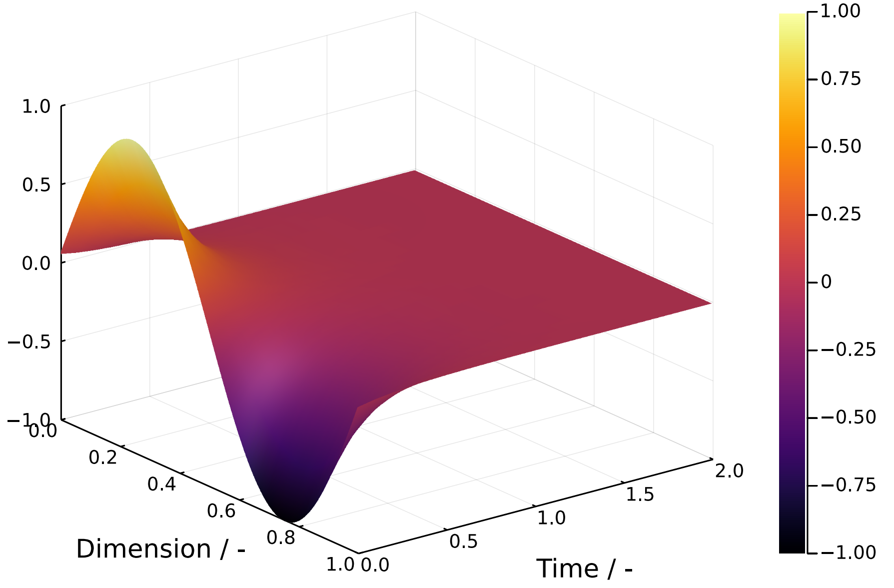


Fig. 2a: A conventional diffusion profile for the chosen diffusion coefficient $p = 0.1$.

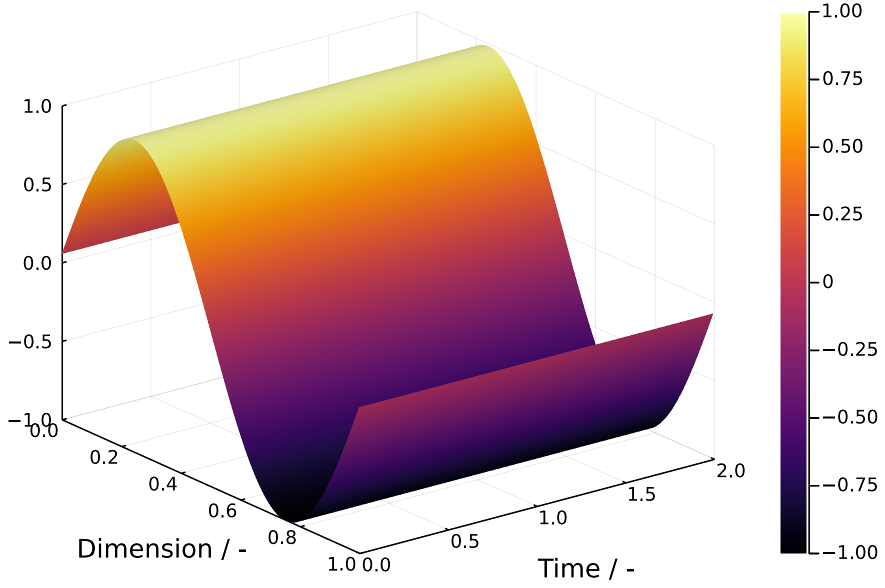
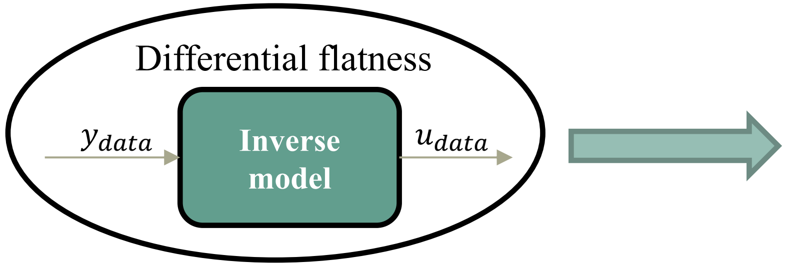


Fig. 2b: Compensated diffusion profile by closing the loop with u_{data} from the inverse model.

Parameter Sensitivity Analyses



1. $\frac{\partial y}{\partial p}$:= parameter sensitivities based on output profiles
2. $\frac{\partial u}{\partial p}$:= parameter sensitivities based on input profiles

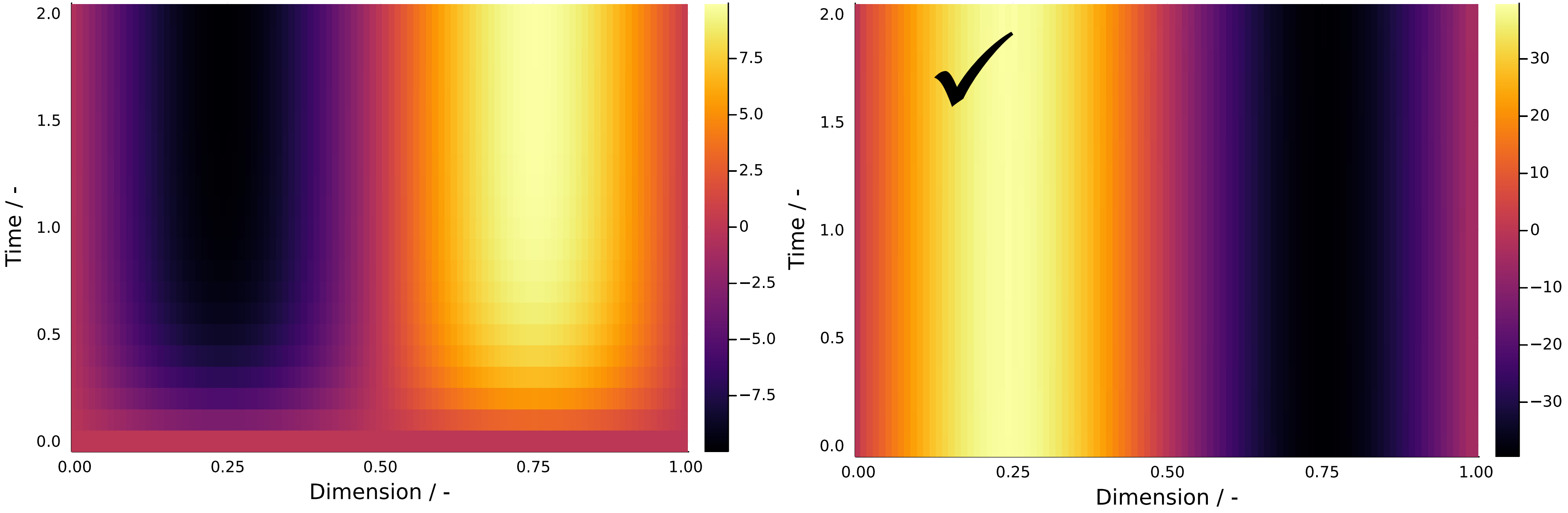
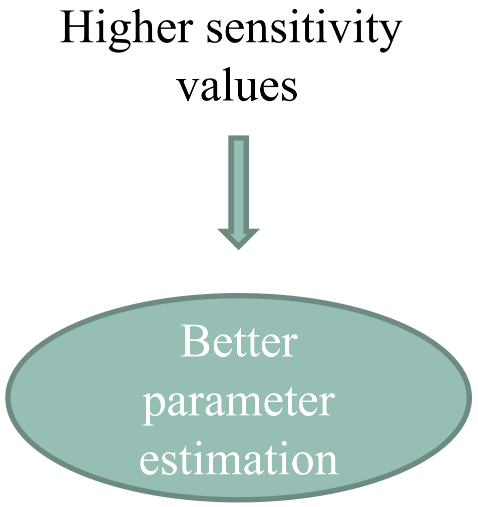


Fig. 3: Sensitivities to the diffusion parameter variation: (a) based on the measured output: (b) based on the re-constructed input.



Conclusions

- Standard framework for parameter identification which gets its loss function based on the output data is given an advancement – introducing an input-based framework.
- Differential flatness concept – to calculate the control input.
- The surrogate model involving neural ODEs – to get the output functions and their derivatives.
- Sensitivity analyses – based on the output data and the control input.
- Input-based analysis – higher sensitivity value, so better probability to identify the parameter.
- But the calculated input u_{data} depends on the quality of model inversion and the neural ODE surrogate model – could be improved using more optimization design tools.

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