DATA-BASED MODELING:

System Identification in practice

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- Introduction
- System identification cycle
- Applications in the automotive industry
- Example

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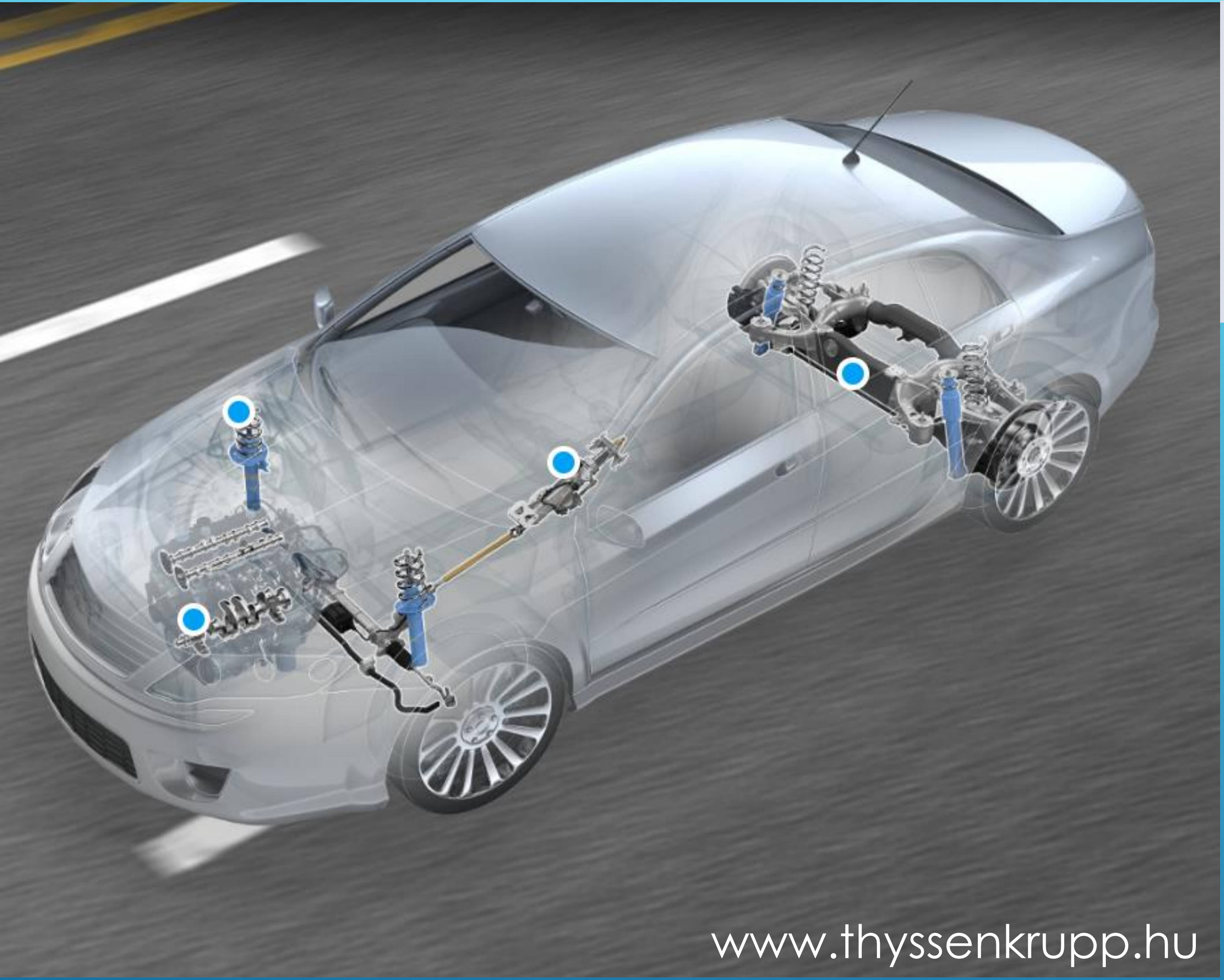
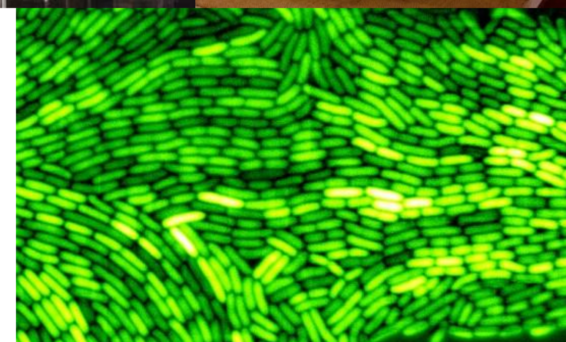


thyssenkrupp

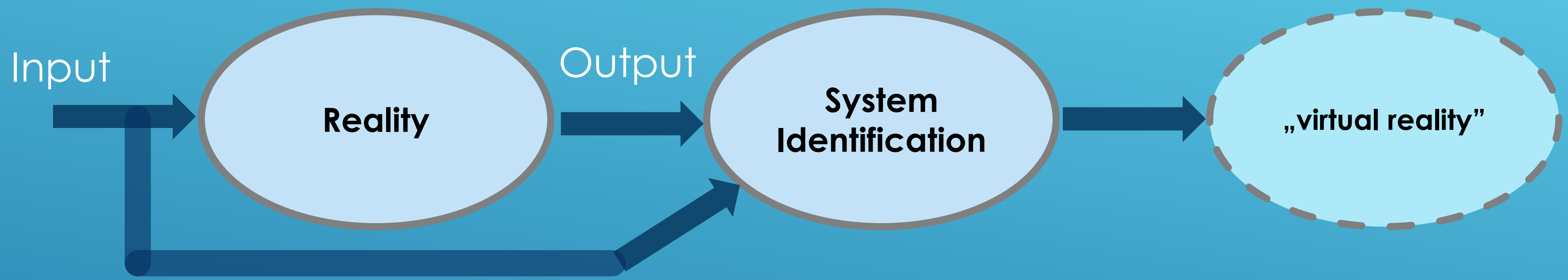
INTRODUCTION



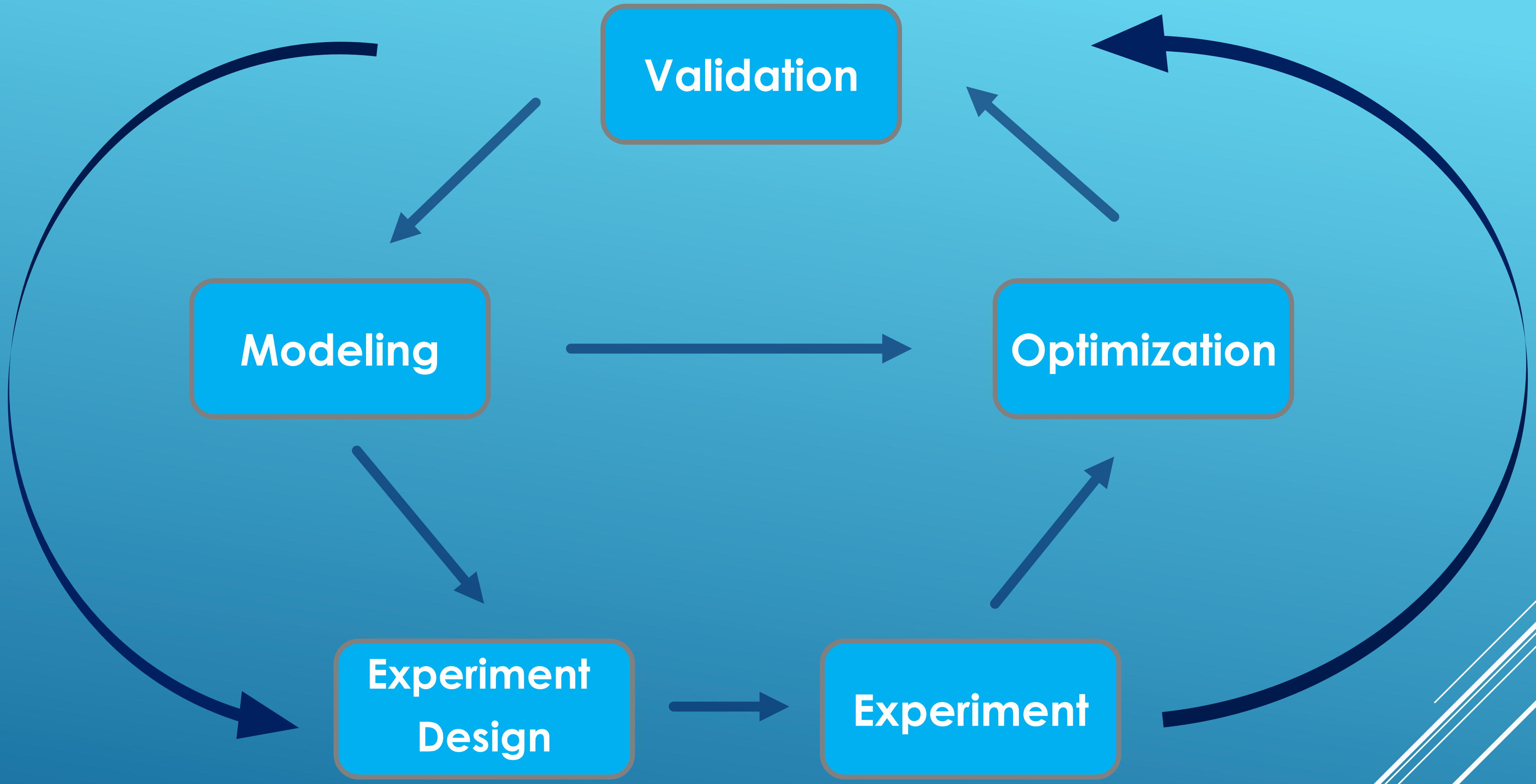
SYSTEM IDENTIFICATION

SYSTEM IDENTIFICATION

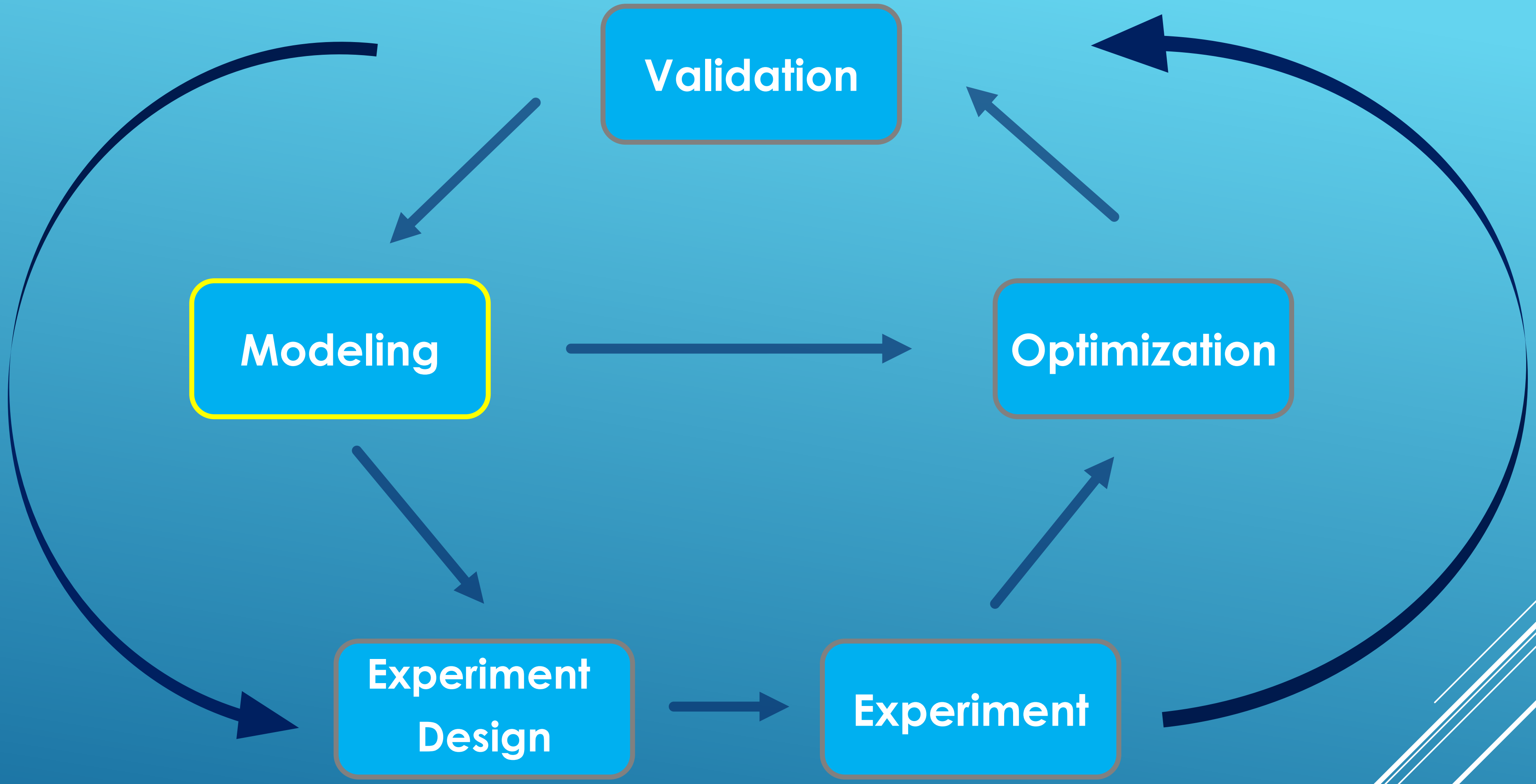
- Basically, how to represent the reality in the virtual space as mathematical model based on measurements:



- Which can be used to predict/simulate the behavior of the reality in a much compact and cheaper way.



SYSTEM IDENTIFICATION



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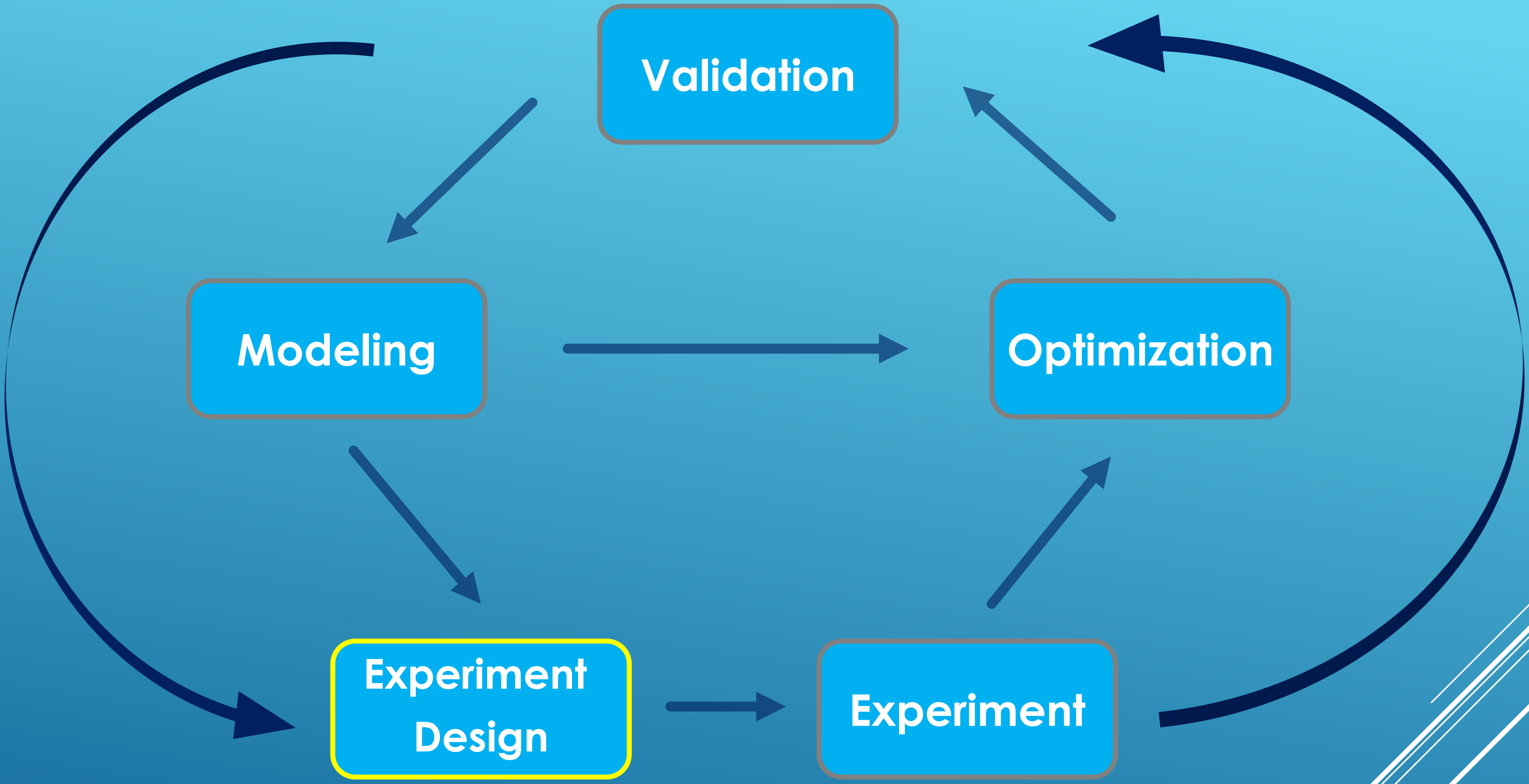

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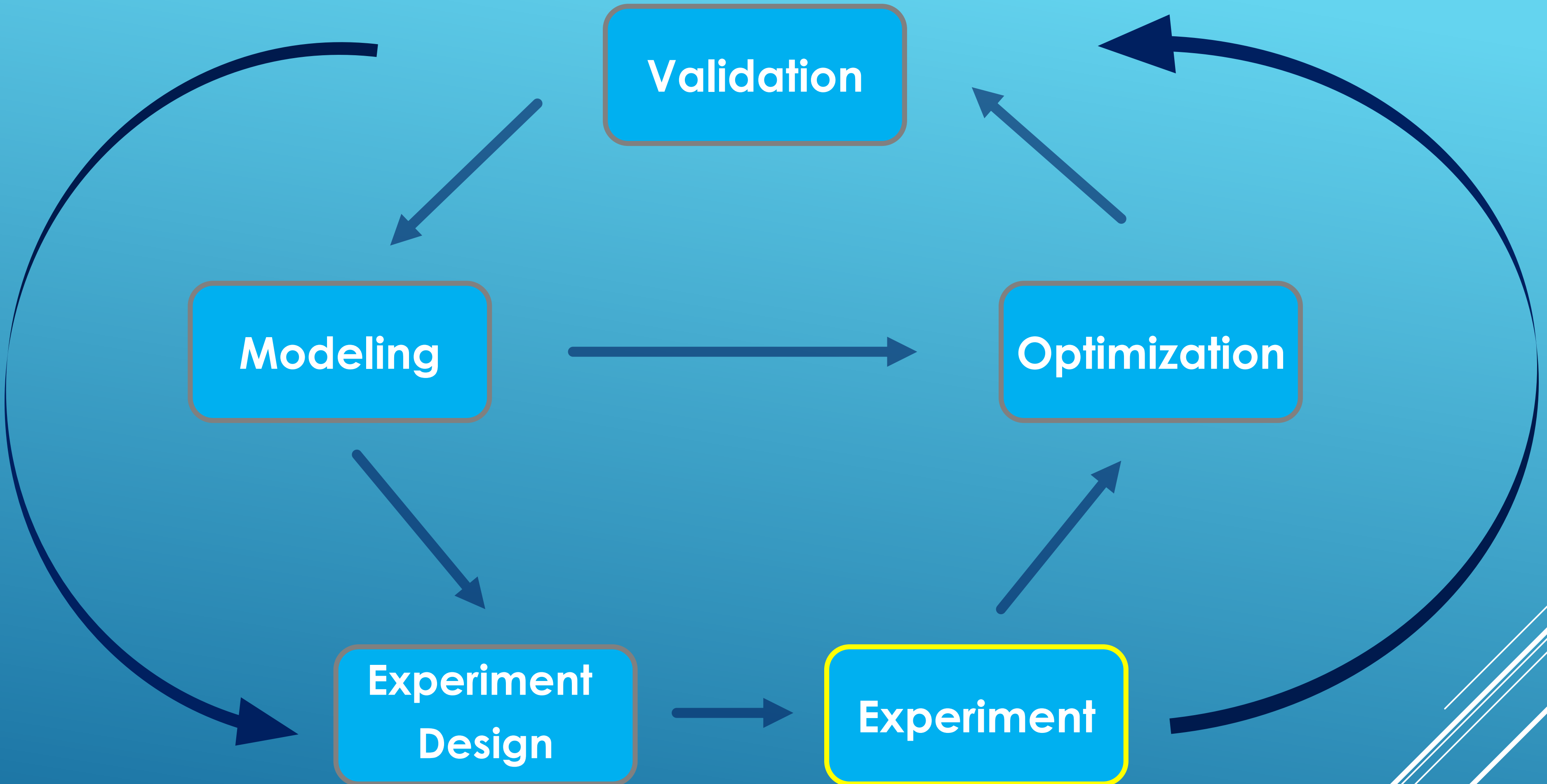

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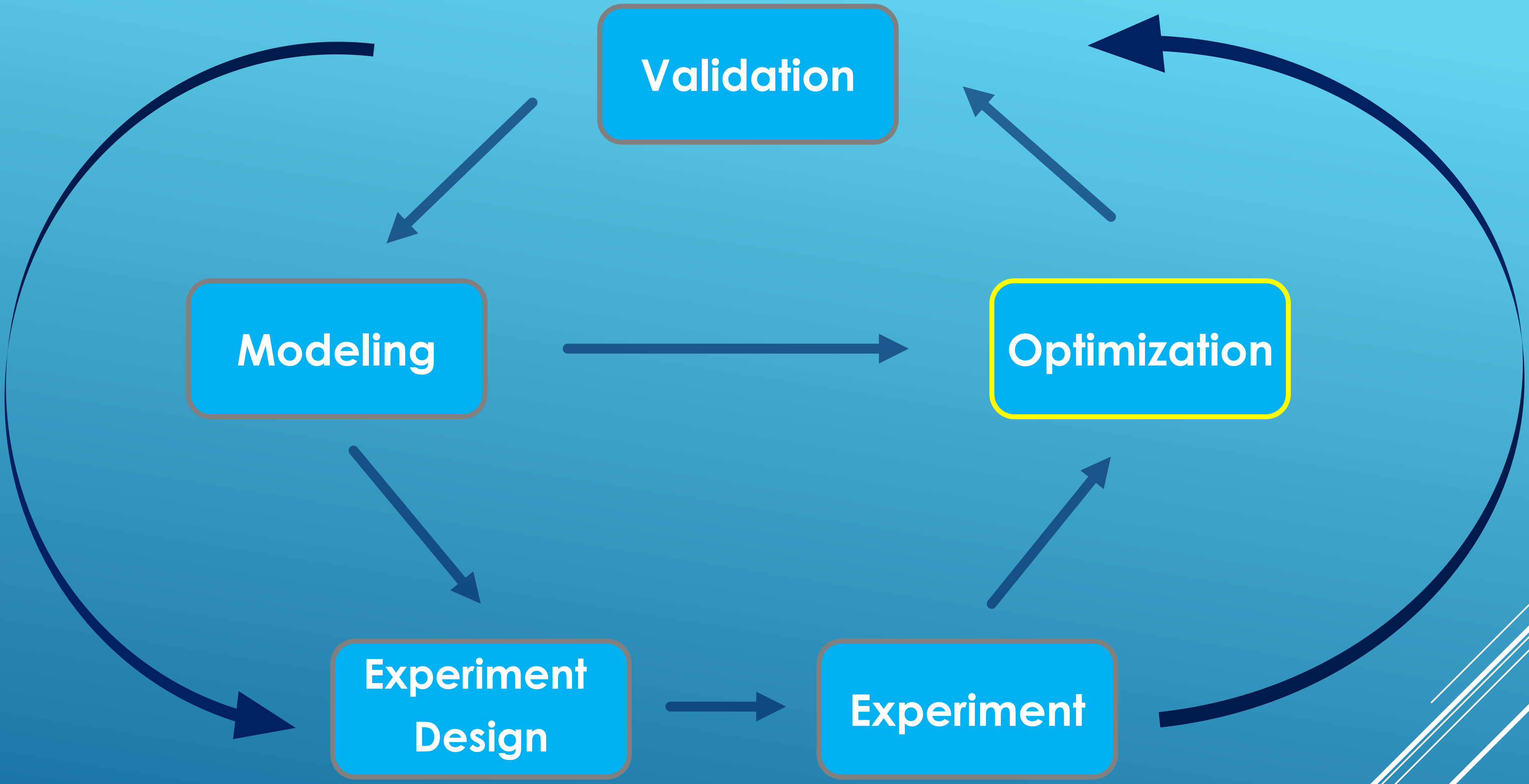

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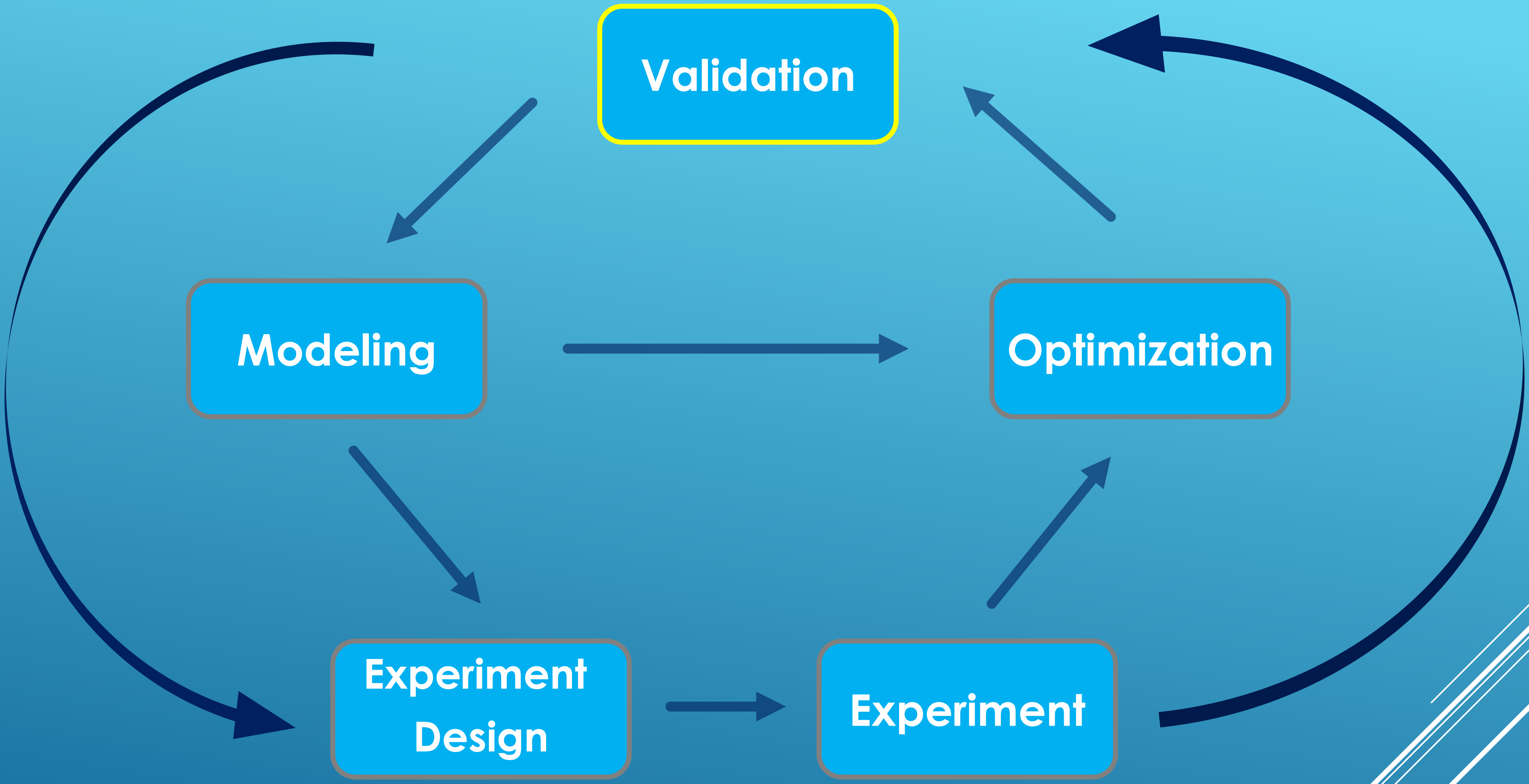

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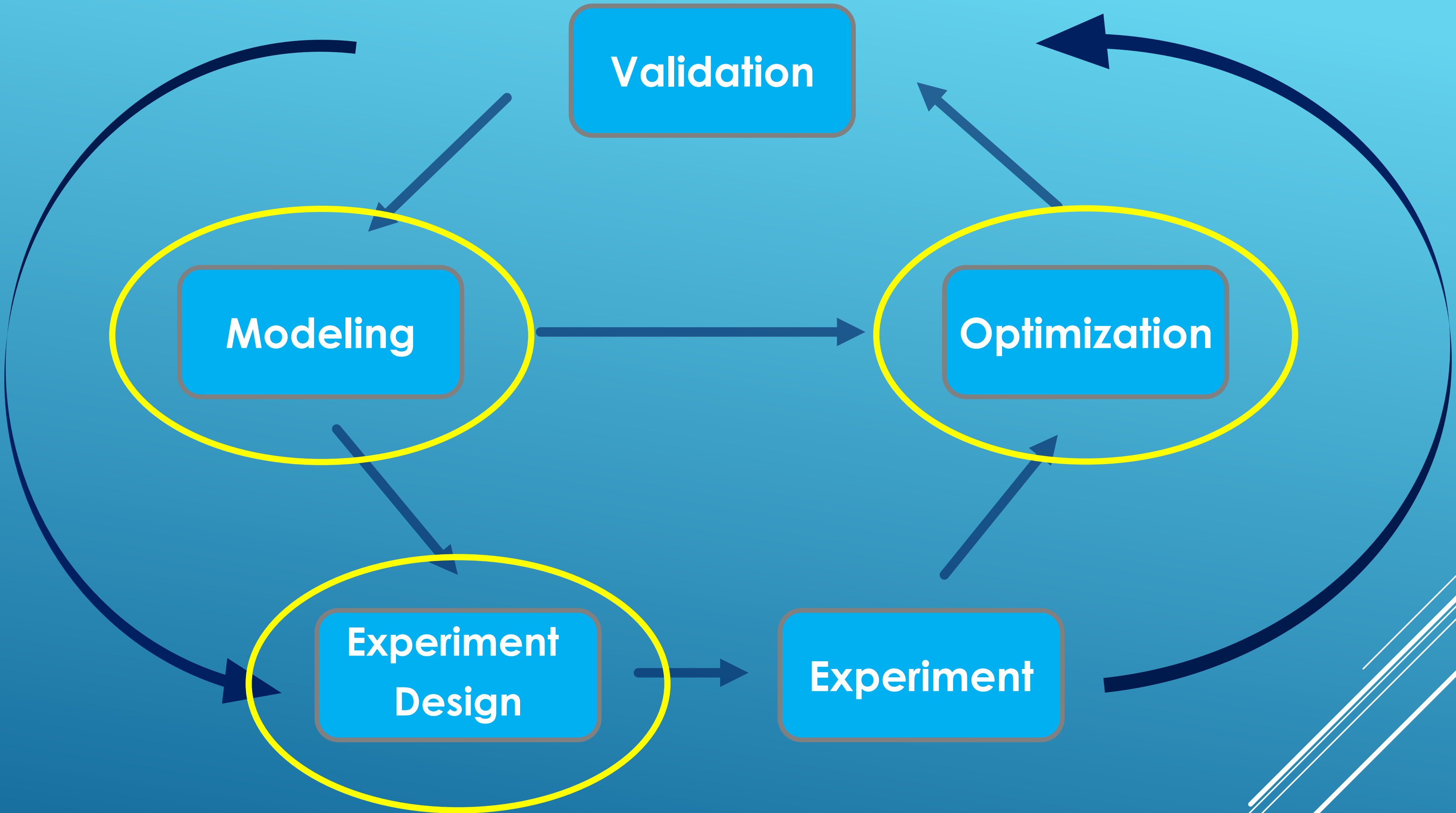
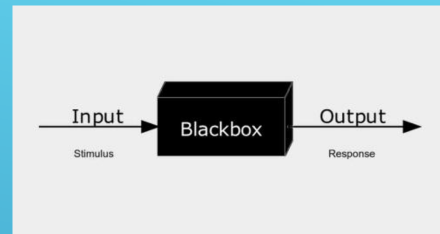


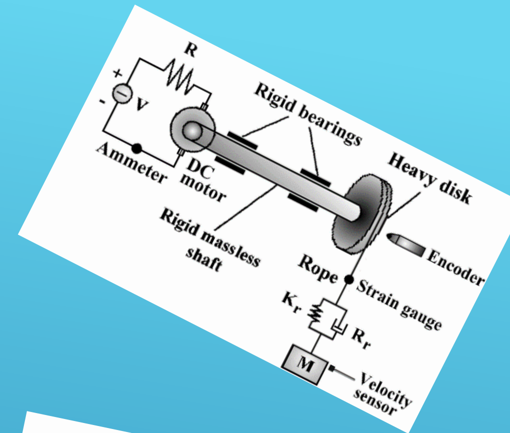
SYSTEM IDENTIFICATION

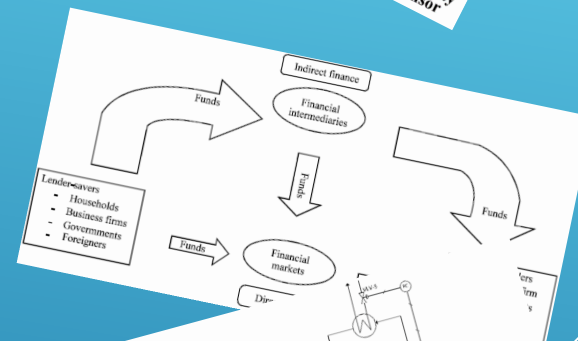
MODELING

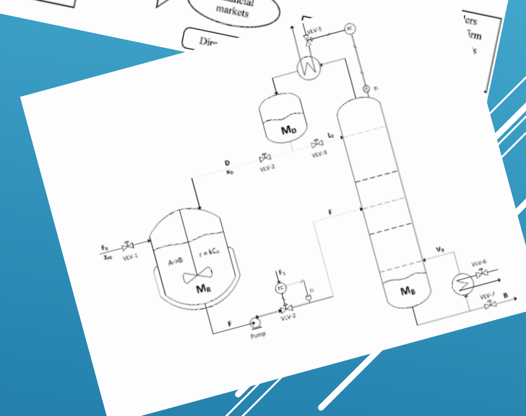
- Black-box
  - Input/output behavior



- White-box
  - Model is created based on the field specific knowledge: differential equations, reaction equations, etc...
- Frequency-domain representation
  - Integral transformed linear differential equation.
  - Discrete-time models are applied usually for computational purposes.
- Identifiability
  - Which makes modeling the most crucial step in indentification.







- How to excite the system in order to get the most information possible?
  - Can contain also optimization.
  - Select the best input signal (magnitude, shape and frequency)

EXPERIMENT DESIGN

EXPERIMENT

- Perform the activity that is needed to gather the data for identification and validation.
  - Highly process dependent task.
    - Physical measurements.
    - Big-data analysis.
    - …

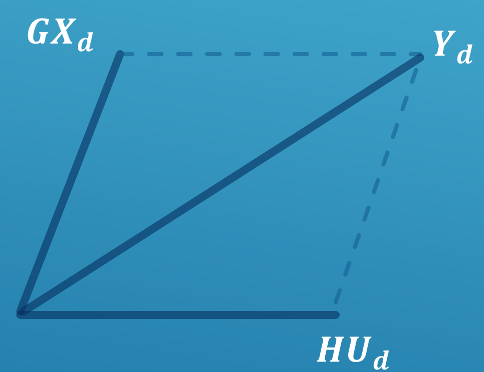
- The frontline application of numerical mathematics
  - Classical parameter estimation using least squares for dynamic systems in time- and frequency domain.

$$J(\boldsymbol{\theta}) = \frac{1}{N}\sum_{k=0}^{N-1} \|y(k) - \hat{y}(k,\boldsymbol{\theta})\|^2$$

    - $\hat{y}(k, \boldsymbol{\theta})$ can be generated using a large set of different models.
  - Modern one-step method using subspace-based techniques.

$$x_{k+1} = Ax_k + Bu_k$$
$$y_k = Cx_k + Du_k$$

$$Y_d = GX_d + HU_d$$



  - Recursive subspace-based techniques.

OPTIMIZATION

VALIDATION

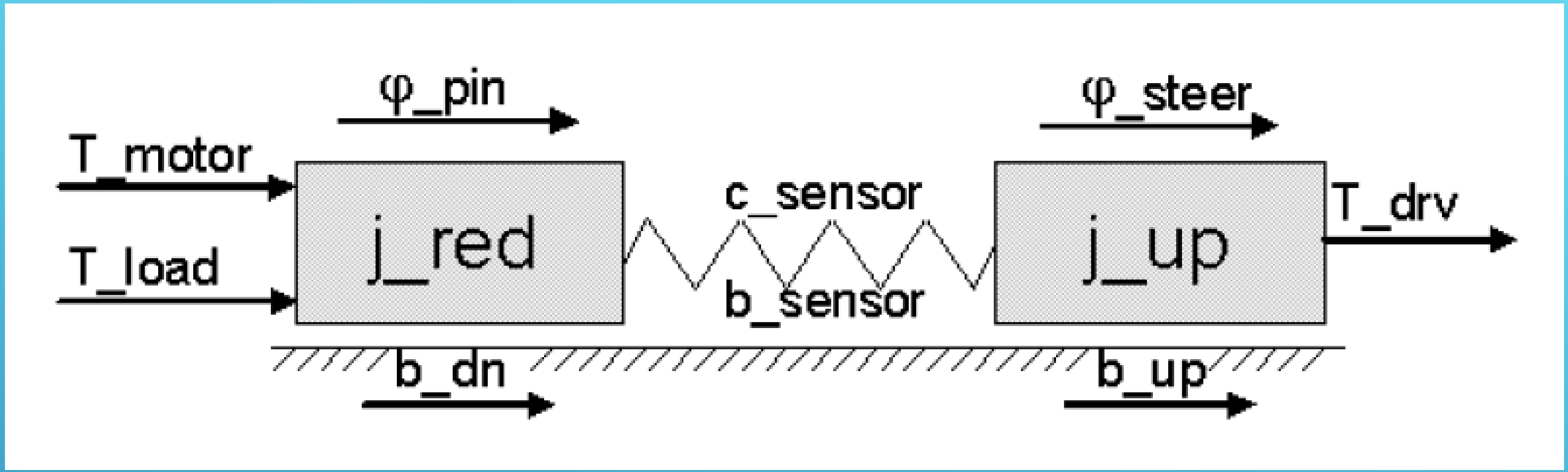
- Check if the model behaves similarly (witihin an error range of accaptance) as the reality does.
  - This step contains simulation of the estimated model based on experimental data gathered on the real system.

- Permanent magnet synchronous motor parameter identification for motor control purposes:

$$\mathbf{f}\left(\begin{bmatrix} i_d \\ i_q \\ \omega \end{bmatrix}\right) = \begin{bmatrix} \frac{-Ri_d + n_p \omega L_q i_q}{L_d} \\ \frac{-Ri_q - n_p \omega L_d i_d - n_p \omega K_g}{L_q} \\ \frac{3n_p}{2j_{mot}}\left(i_q K_g + i_q i_d \left(L_d - L_q\right)\right) - \frac{b_{mot}}{j_{mot}}\omega \end{bmatrix}$$

$$\mathbf{g}\left(\begin{bmatrix} i_d \\ i_q \\ \omega \end{bmatrix}\right) = \begin{bmatrix} \frac{1}{L_d} & 0 & 0 \\ 0 & \frac{1}{L_q} & 0 \\ 0 & 0 & -\frac{1}{j_{mot}} \end{bmatrix}$$

APPLICATION IN TKP



$$\dot{x} = A(\theta)x + B(\theta)u$$
$$y = C(\theta)x + D(\theta)u$$

APPLICATION IN TKP

Dynamic equations:

$$
\begin{aligned}
j_{up}\dot{\omega}_{stw}(t) &= T_{drv}(t) - T_{stc}(t) - T_{damp,up}(t) \\
j_{dn}\dot{\omega}_{pin}(t) &= T_{stc}(t) + i_{gear}T_{mot}(t) + T_{load}(t) - T_{damp,dn}(t) \\
\dot{T}_{mot}(t) &= \frac{1}{\tau}\left(T_{mot,req}(t) - T_{mot}(t)\right)
\end{aligned}
$$

Algebraic equations:

$$
\begin{aligned}
T_{stc}(t) &= c_{sensor}\left(\varphi_{stw}(t) - \varphi_{pin}(t)\right) + b_{sensor}\left(\omega_{stw}(t) - \omega_{pin}(t)\right) \\
T_{damp,up}(t) &= b_{up}\omega_{stw}(t) \\
T_{damp,dn}(t) &= b_{dn}\omega_{pin}(t) \\
T_{TSU} &= c_{sensor}\left(\varphi_{stw}(t) - \varphi_{pin}(t)\right) \\
\omega_{mot} &= i_{gear}\omega_{pin}
\end{aligned}
$$

APPLICATION IN TKP

$$\begin{bmatrix} \dot{\varphi}_{pin} \\ \dot{\omega}_{pin} \\ \dot{\Delta\varphi} \\ \ddot{\Delta\varphi} \\ \dot{T}_{mot} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & -\frac{b_{dn}}{j_{dn}} & \frac{c_{sensor}}{j_{dn}} & \frac{b_{sensor}}{j_{dn}} & \frac{i_{gear}}{j_{dn}} \\ 0 & 0 & 0 & 1 & 0 \\ 0 & -\frac{b_{up}}{j_{up}} + \frac{b_{dn}}{j_{dn}} & -\frac{c_{sensor}}{j_{up}} - \frac{c_{sensor}}{j_{dn}} & -\frac{b_{up}+b_{sensor}}{j_{up}} - \frac{b_{sensor}}{j_{dn}} & -\frac{i_{gear}}{j_{dn}} \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} \varphi_{pin} \\ \omega_{pin} \\ \Delta\varphi \\ \dot{\Delta\varphi} \\ T_{mot} \end{bmatrix} + $$

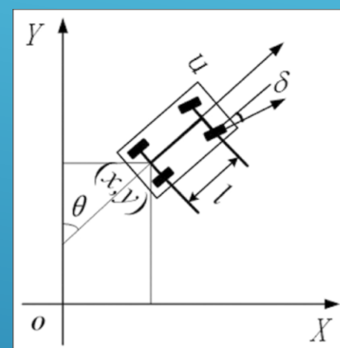
$$+ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & \frac{1}{j_{dn}} \\ 0 & 0 & 0 \\ 0 & \frac{1}{j_{up}} & -\frac{1}{j_{dn}} \\ \frac{1}{\tau} & 0 & 0 \end{bmatrix} \begin{bmatrix} T_{mot,req} \\ T_{drv} \\ T_{load} \end{bmatrix}$$

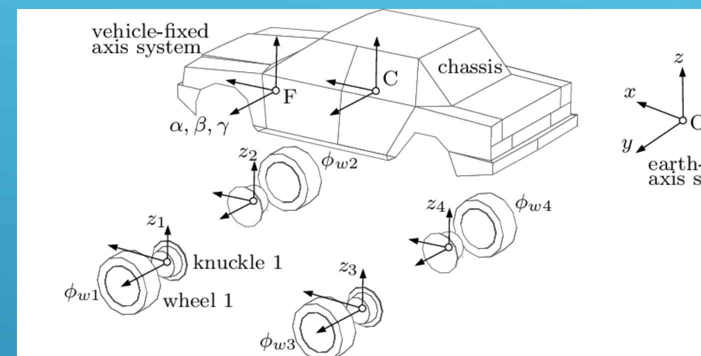
$$\begin{bmatrix} \omega_{mot} \\ T_{TSU} \\ T_{mot} \end{bmatrix} = \begin{bmatrix} 0 & i_{gear} & 0 & 0 & 0 \\ 0 & 0 & c_{sensor} & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varphi_{pin} \\ \omega_{pin} \\ \Delta\varphi \\ \dot{\Delta\varphi} \\ T_{mot} \end{bmatrix}$$

APPLICATION IN TKP

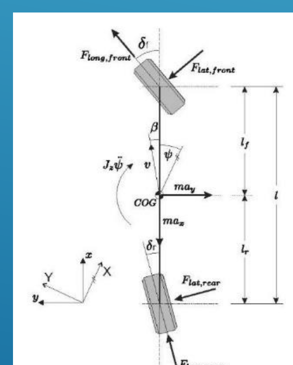
APPLICATION IN TKP

- White-box vehicle model identification
  - Linear and nonlinear vehicle model in state-space form. These models are used to simulate dangerous vehicle movements.
  - Autonomous Driving Controllers and algorithms developement use these vehicle models.



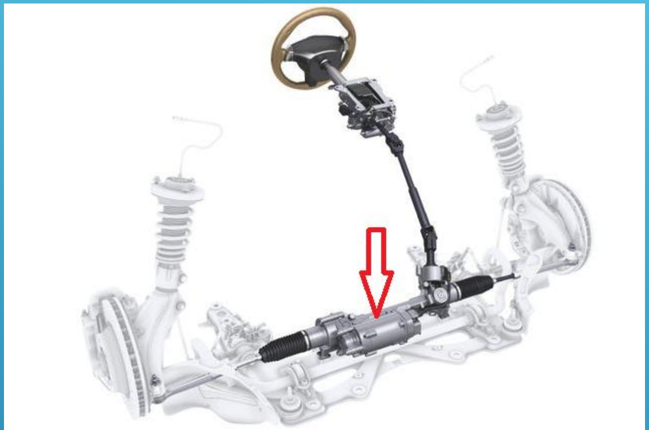


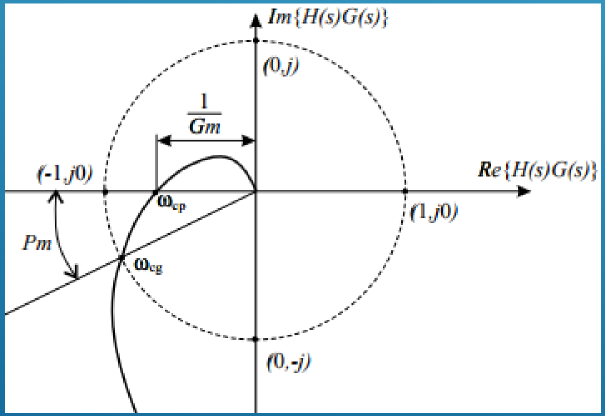
$$\dot{x} = A(\theta)x + B(\theta)u$$
$$y = C(\theta)x + D(\theta)u$$



APPLICATION IN TKP

- Black-box vehicle model identification
  - Models used for stability analysis in a complete software in the loop environment.
  - Nyquist stability criterion is used to proove the vehicle level sytability.

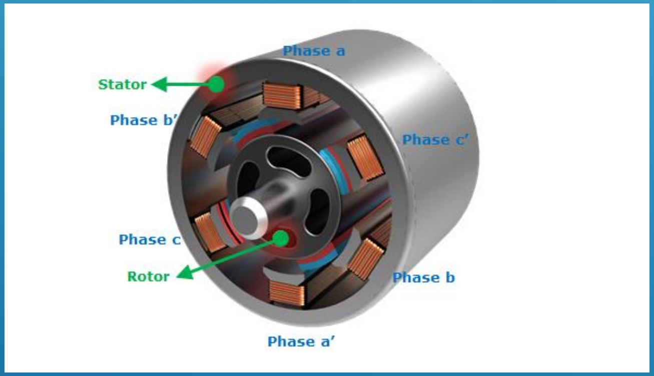




$$\dot{x} = Ax + Bu$$
$$y = Cx + Du$$

APPLICATION IN TKP

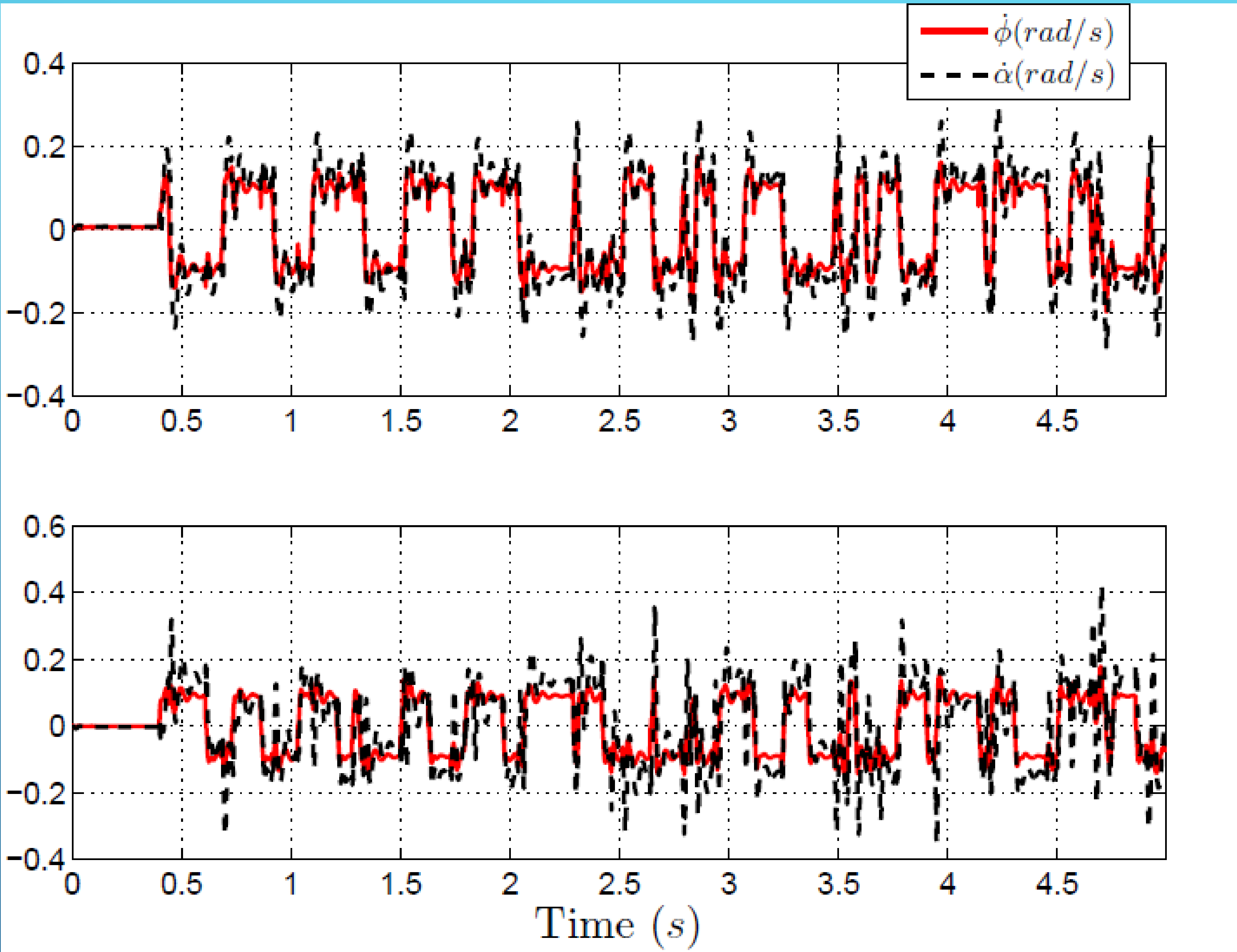
- Permanent magnet synchronous motor parameter identification for motor control purposes:
- Electro-mechanical steering system model identification.
  - White-box linear and nonlinear
- White-box vehicle model identification
- Black-box vehicle model identification



- Development and maintenance of the numerical optimization tools (bypassing matlab toolboxes)
- Performing identification, controller design and optimization.
- Processing the obtained simulation results.
- Analyitycal investigation of every aspects of the system:
  - Feasibility studies for controller and function design.
  - Mechanical change effect on the system behavior.
- Seeking for better optimization tools and methods.
- Model-based controller design for the steering system, autonomous driving.

WHERE A MATEMATICIAN CAN ENTER INTO THIS PICTURE

THANKS FOR YOUR ATTENTION!


$\dot{\phi}(rad/s)$
$\dot{\alpha}(rad/s)$
0.4
0.2
0
−0.2
−0.4
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
0.6
0.4
0.2
0
−0.2
−0.4
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
Time (s)

LPV MODELING

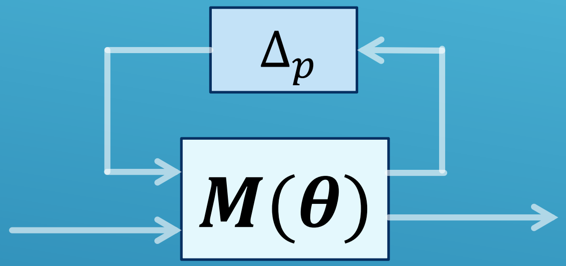
Equations of the nonlinear system

$$\dot{\boldsymbol{x}} = f(\boldsymbol{x}, \boldsymbol{u})$$
$$\boldsymbol{y} = g(\boldsymbol{x}, \boldsymbol{u})$$

LPV model

$$\dot{\boldsymbol{x}} = \boldsymbol{A}_{LPV}(\boldsymbol{p})\boldsymbol{x} + \boldsymbol{B}_{LPV}(\boldsymbol{p})\boldsymbol{u}$$
$$\boldsymbol{y} = \boldsymbol{C}_{LPV}(\boldsymbol{p})\boldsymbol{x} + \boldsymbol{D}_{LPV}(\boldsymbol{p})\boldsymbol{u}$$

Rational LPV model (LPV/LFR)



$$\boldsymbol{M}(\boldsymbol{\theta}) = \begin{bmatrix} \boldsymbol{D}_{zw} & \boldsymbol{C}_{z} & \boldsymbol{D}_{zu} \\ \boldsymbol{B}_{w} & \boldsymbol{A}_{0} & \boldsymbol{B}_{0} \\ \boldsymbol{D}_{yw} & \boldsymbol{C}_{0} & \boldsymbol{D}_{0} \end{bmatrix}$$

$$\Delta_p = diag\left(p_1 I_{r_1}, \dots, p_{n_p} I_{r_{n_p}}\right)$$

$$\begin{bmatrix} \boldsymbol{A}_{LPV}(\boldsymbol{p}) & \boldsymbol{B}_{LPV}(\boldsymbol{p}) \\ \boldsymbol{C}_{LPV}(\boldsymbol{p}) & \boldsymbol{D}_{LPV}(\boldsymbol{p}) \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}_0 & \boldsymbol{B}_0 \\ \boldsymbol{C}_0 & \boldsymbol{D}_0 \end{bmatrix} + \begin{bmatrix} \boldsymbol{B}_w \\ \boldsymbol{D}_{yw} \end{bmatrix} \Delta_p \left(\boldsymbol{I} - \boldsymbol{D}_{zw}\Delta_p\right)^{-1} \begin{bmatrix} \boldsymbol{C}_z & \boldsymbol{D}_{zu} \end{bmatrix}$$

LOCAL MODEL ESTIMATION

- 11 operating points are selected: $\left[\frac{\pi}{8}:\frac{\pi}{16}:\frac{6\pi}{8}\right]$;
- 4x2 MIMO black-box local LTI models are estimated by using a subspace-based technique;
- The estimated models are validated locally (BFT %);
- A white-box 2x2 MIMO LPV model is estimated by using a frequency-domain interpolation method based on the 1,3,5,7,9,11th working points;

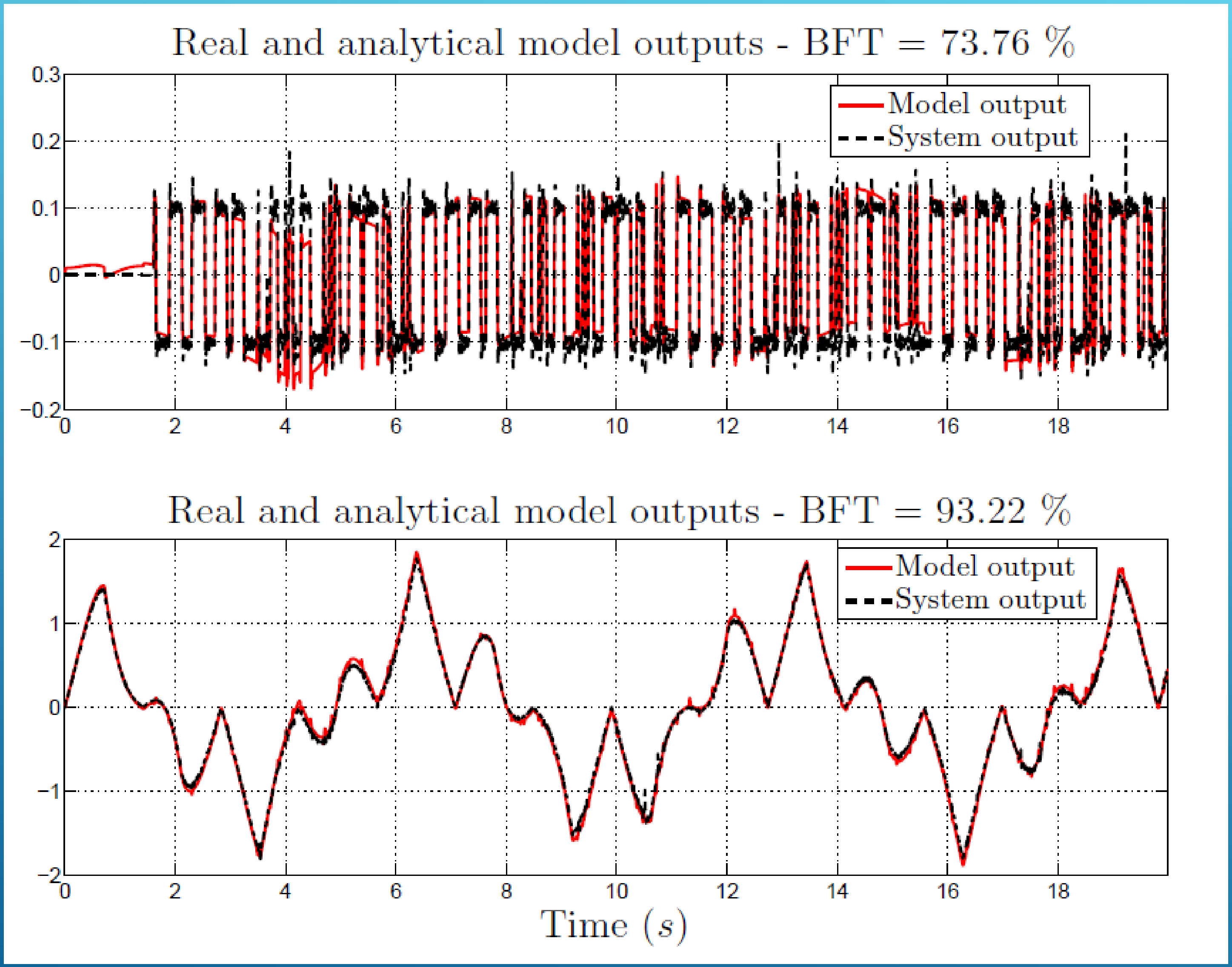
LPV MODEL IDENTIFICATION

Concatenation of the black-box LTI models.

Forzen LPV model.

$$\min_{\theta} \sum_{i=1}^{N} \| \boldsymbol{G}^{i}{}_{BB}(j\omega) - \boldsymbol{G}_{LPV}(j\omega, \boldsymbol{p}_i, \theta) \|_{\infty}{}^{2}$$

GLOBAL VALIDATION



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- P. Van Overschee, B. de Moor: Subspace identification for linear systems
- R. Tóth: Identification and Modeling of Linear Parameter-Varying Systems
- D. Luenberger: Optimization by vector space methods
- D. Vizer: Application of the H_∞-norm for the identification of linear time-invariant and linear parameter-varying models, Ph.D thesis.
- K. Pelckmans: Lecture Notes for a course on system identification.
- R. Pintelon, J. Shoukens: System identification: A frequency domain approach

FURTHER READING

THANKS FOR YOUR ATTENTION!