



Attracting Tomorrow



Contactless current sensing with position detection using model-based nonlinear optimization

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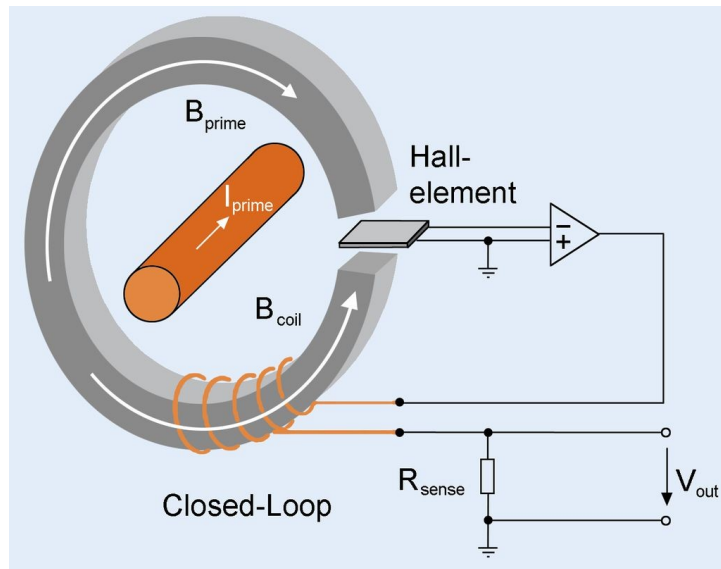
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Magnetic Sensors Business Group • Application Engineering
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State of the art – Contactless current sensing

Enclosure of conductor by a core

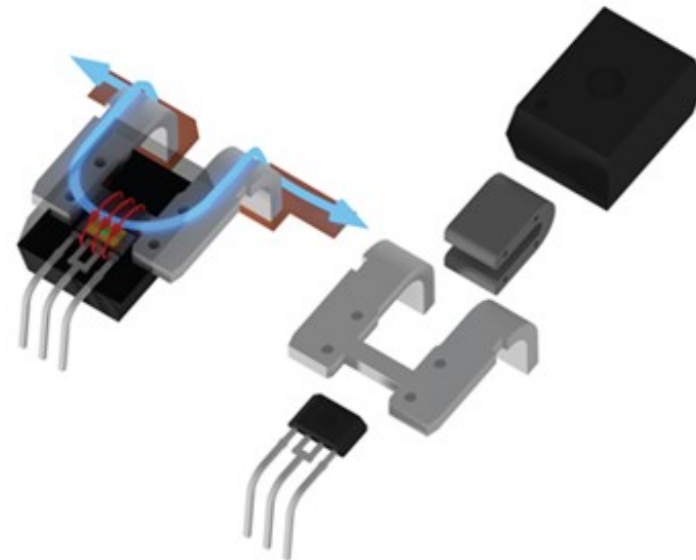
- Big size
- High cost of core
- Bandwidth limitation
- Remanence
- Complicated mounting



www.elektronikpraxis.vogel.de/sensorik/articles/299736/index2.html

Integrated conductor on leadframe

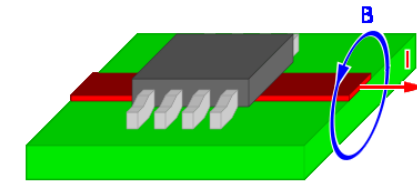
- Dual molding
- High cost of conductor
- Complex assembly process



www.allegromicro.com/en/Products/Current-Sensor-ICs/Fifty-To-Two-Hundred-Amp-Integrated-Conductor-Sensor-ICs.aspx

Coreless placement

- Low stray field immunity
- Precise placement or end of line calibration



de.wikipedia.org/wiki/Stromsensor

An innovative idea

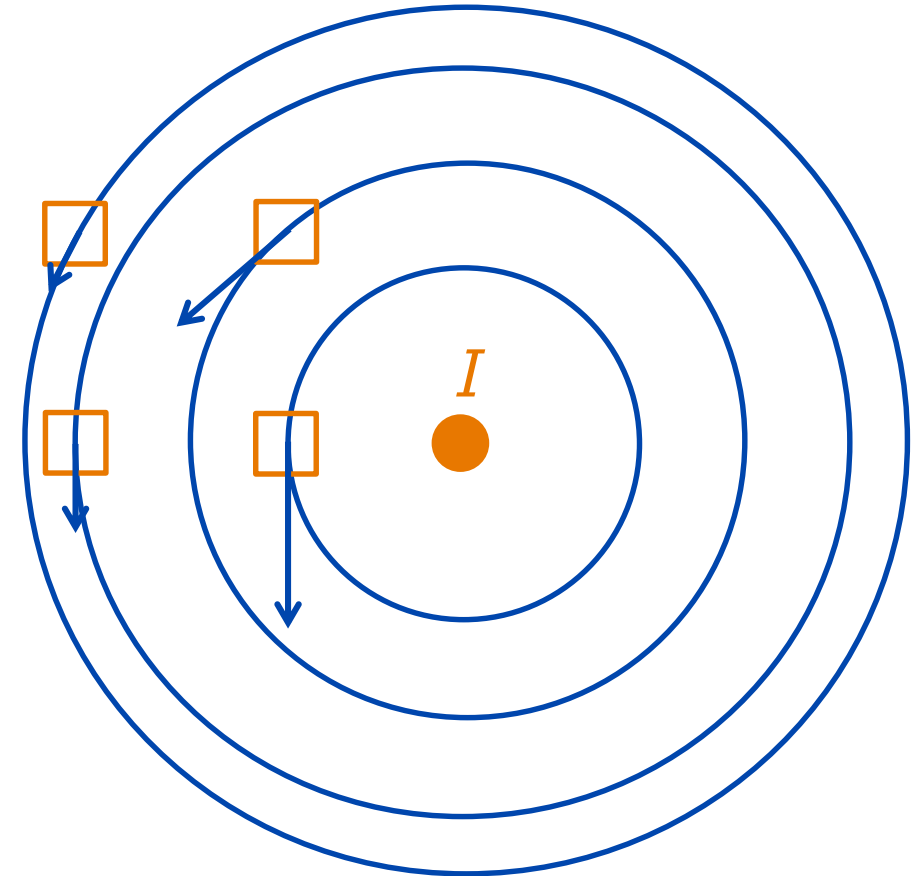
Requirements

- Non-contact sensor → free of potential
- No exact mounting → position tolerant
- No current carrying leadframe → low cost
- No enclosure → easy to mount

Implementation

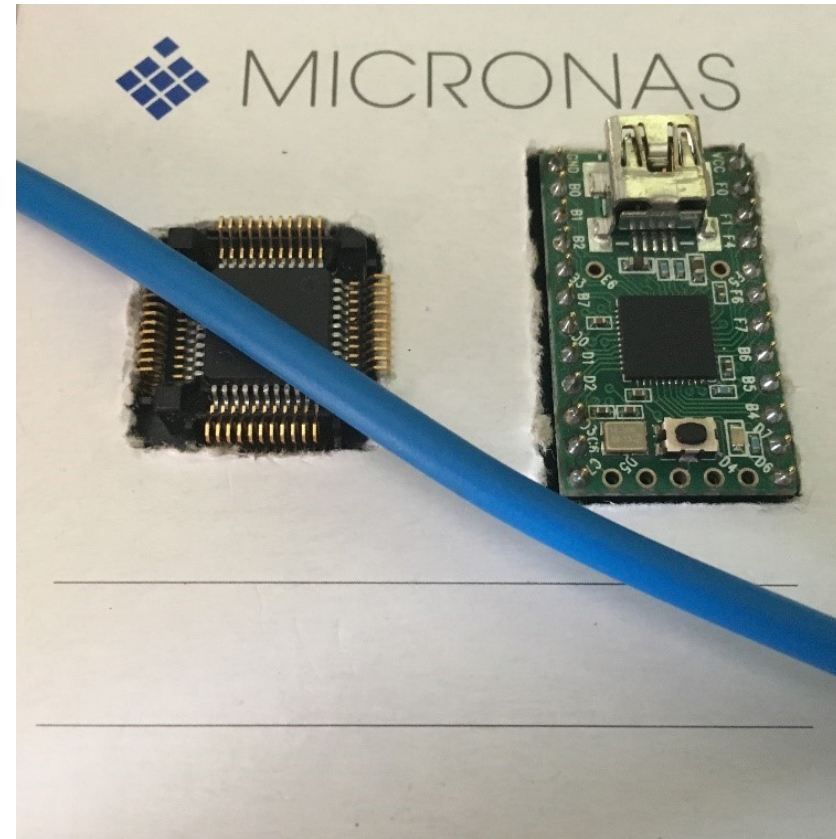
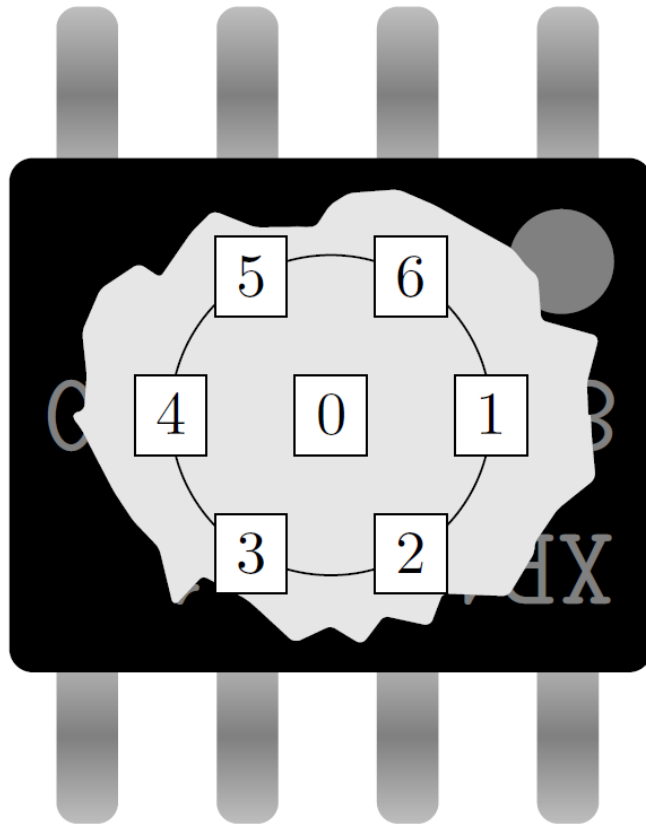
- Measurement of the magnetic field at multiple locations in all three spatial dimensions
- Modelling of the expected magnetic field based on used setup e.g. straight, round conductor, distance between sensors,...
- Estimation of the current by fitting the model to the measurement data using non-linear optimization

$$\underset{\theta}{\text{minimize}} \quad f(\theta) = \frac{1}{2} \|m(\theta) - y\|_2^2$$



The Hardware

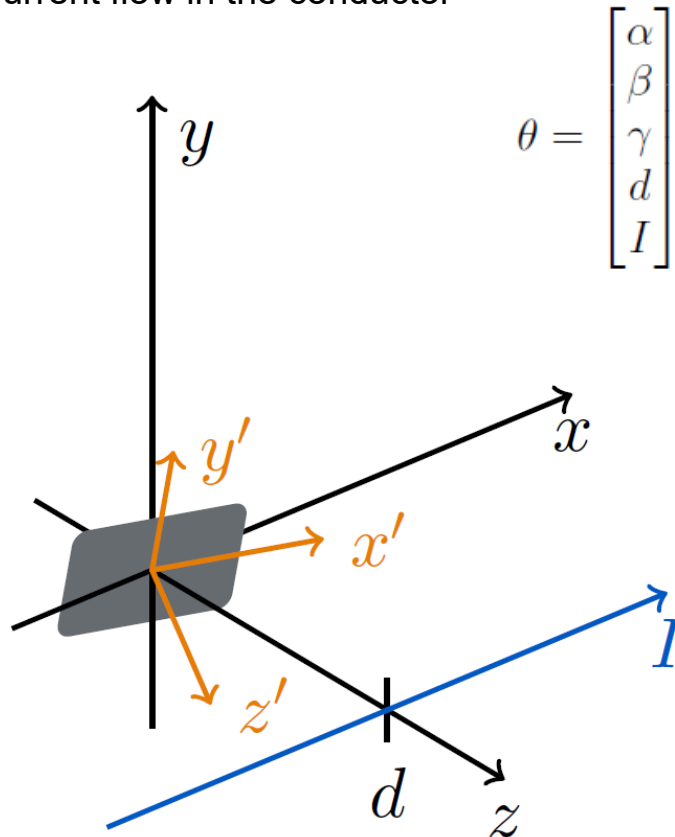
Sensor chip with seven 3D Hall pixel cells → 21 magnetic field values measured at once



The Model

Parameter space consists of 5 variables

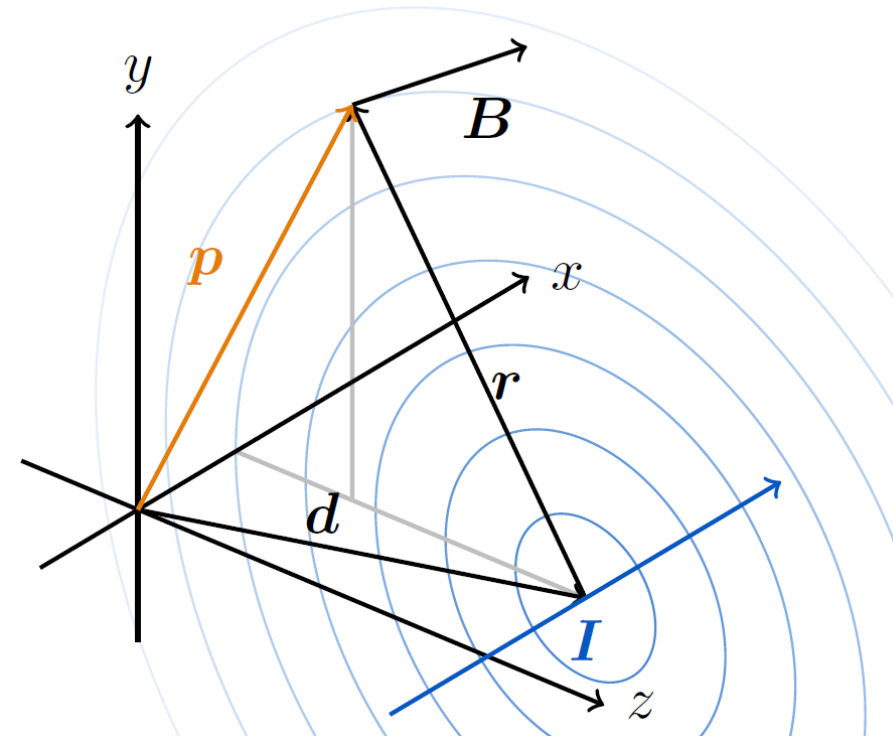
- 4 Spatial degrees of freedom
 - Distance between sensor and conductor – d
 - Rotation of sensor (3 axis) – α , β and γ
- Current flow in the conductor



Magnetic field model according to Biot-Savart:

- Infinitely long
- Straight conductors
- Round cross-section

$$\mathbf{B} = \frac{\mu_0 \mu_r}{2\pi r^2} \mathbf{I} \times \mathbf{r}$$



Model – Equation

Position of i -th sensing elements after rotation:

$$p_{y,i} = \cos(\beta) \sin(\gamma) p_{0,x,i} + \cos(\alpha) \cos(\gamma) p_{0,y,i} + (\sin(\beta) \sin(\gamma) - \sin(\alpha) \cos(\gamma)) p_{0,z,i},$$

$$p_{z,i} = -\sin(\beta) p_{0,x,i} + \sin(\alpha) \cos(\beta) p_{0,y,i} + \cos(\alpha) \cos(\beta) p_{0,z,i},$$

Sensing direction of i -th elements after rotation:

$$e_{y,i} = \cos(\beta) \sin(\gamma) e_{0,x,i} + \cos(\alpha) \cos(\gamma) e_{0,y,i} + (\sin(\beta) \sin(\gamma) - \sin(\alpha) \cos(\gamma)) e_{0,z,i},$$

$$e_{z,i} = -\sin(\beta) e_{0,x,i} + \sin(\alpha) \cos(\beta) e_{0,y,i} + \cos(\alpha) \cos(\beta) e_{0,z,i}.$$

Magnetic flux measured at the i -th sensing element:

$$y_i = m_i(\theta) + \epsilon_i = \frac{\mu_0 I (p_{y,i} e_{z,i} + (d - p_{z,i}) e_{y,i})}{2\pi (p_{y,i}^2 + (d - p_{z,i})^2)} + \epsilon_i$$

Complete system model:

$$m(\theta) = \begin{bmatrix} m_1(\theta) \\ \vdots \\ m_{21}(\theta) \end{bmatrix}$$

Model – Measurement noise

Sensor noise is dependent on the implemented sensing direction:

Direction	σ -noise
X and Y	3.0 μ T
Z	1.2 μ T

The residual is the mismatch between model and measurement scaled by the covariance matrix

$$R(\theta) = \Sigma_{\epsilon}^{-\frac{1}{2}} (m(\theta) - y)$$

Resulting optimization problem:

$$\underset{\theta}{\text{minimize}} \quad f(\theta) = \frac{1}{2} \|R(\theta)\|_2^2$$

Nonlinear parameter estimation – Overview

Optimization problem:

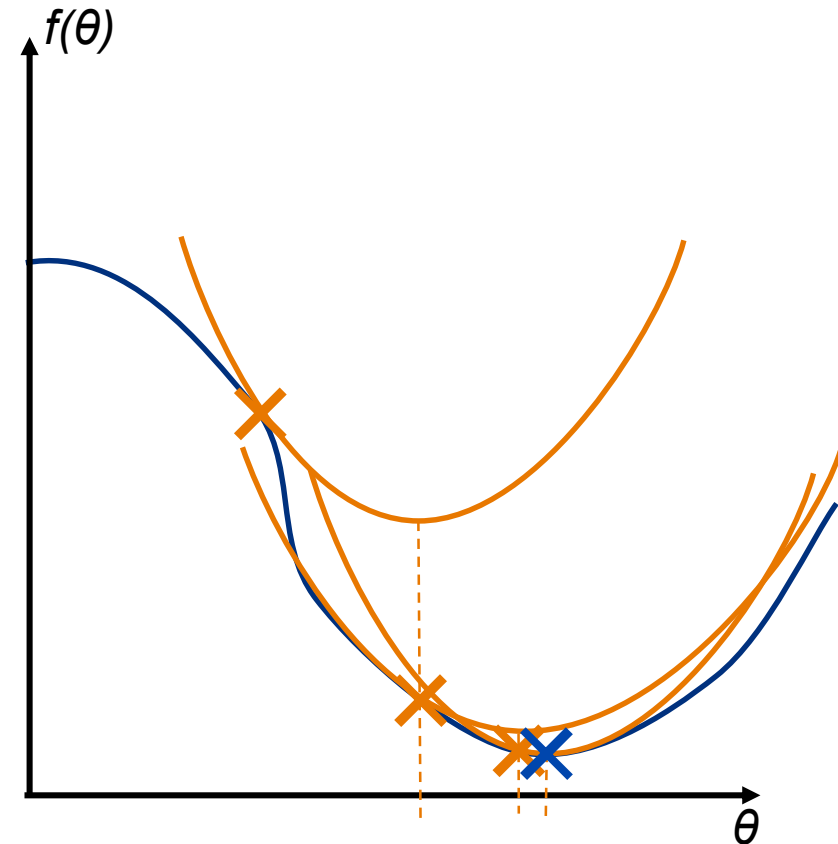
Which parameters fit best to the measured values?

→ Where is the minimum of the sum of squares of the residual?

$$\underset{\theta}{\text{minimize}} \quad f(\theta) = \frac{1}{2} \|R(\theta)\|_2^2$$

Gauss-Newton Algorithm:

1. Start at initial value $\theta_{[0]}$
2. Linearize the residual at the given point
3. Solve the linear optimization problem with the least squares method
4. Repeat from step 2 with solution as new linearization point



Nonlinear parameter estimation – Linearization

First order Taylor series at $\theta_{[k]}$:

$$R_{[k]}(\theta) = R(\theta_{[k]}) + \frac{\partial R}{\partial \theta}(\theta_{[k]})(\theta - \theta_{[k]})$$

Jacobian matrix:

$$J_{[k]} = \frac{\partial R}{\partial \theta}(\theta_{[k]}) \quad J_{[k]} = \left[\frac{\partial R}{\partial \theta_1}(\theta_{[k]}) \quad \dots \quad \frac{\partial R}{\partial \theta_5}(\theta_{[k]}) \right]$$

Imaginary step derivation:

$$\frac{\partial R}{\partial \theta_n}(\theta_{[k]}) = \frac{\text{Im}(R(\theta_{[k]} + i \cdot \varepsilon \cdot e_n))}{\varepsilon}$$

Nonlinear parameter estimation – LLS

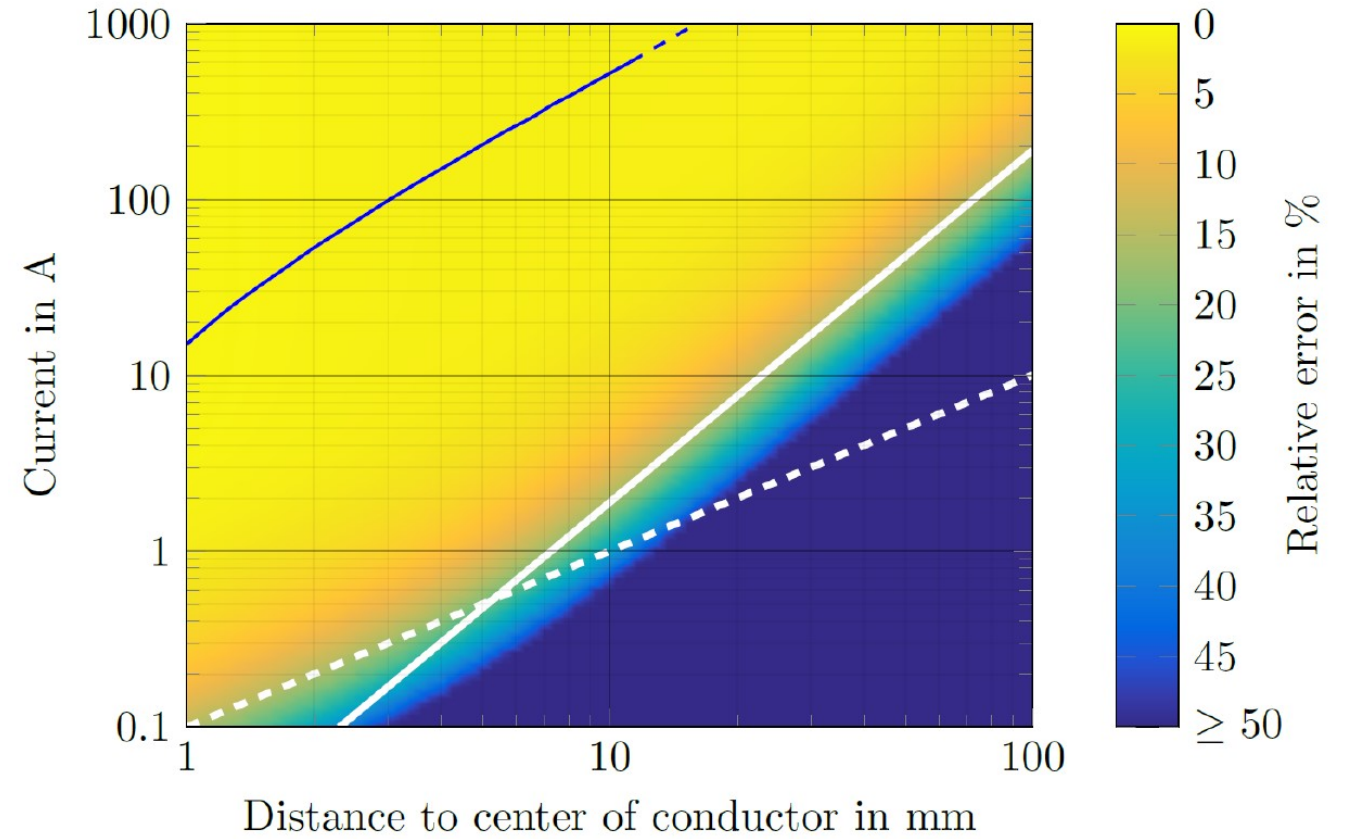
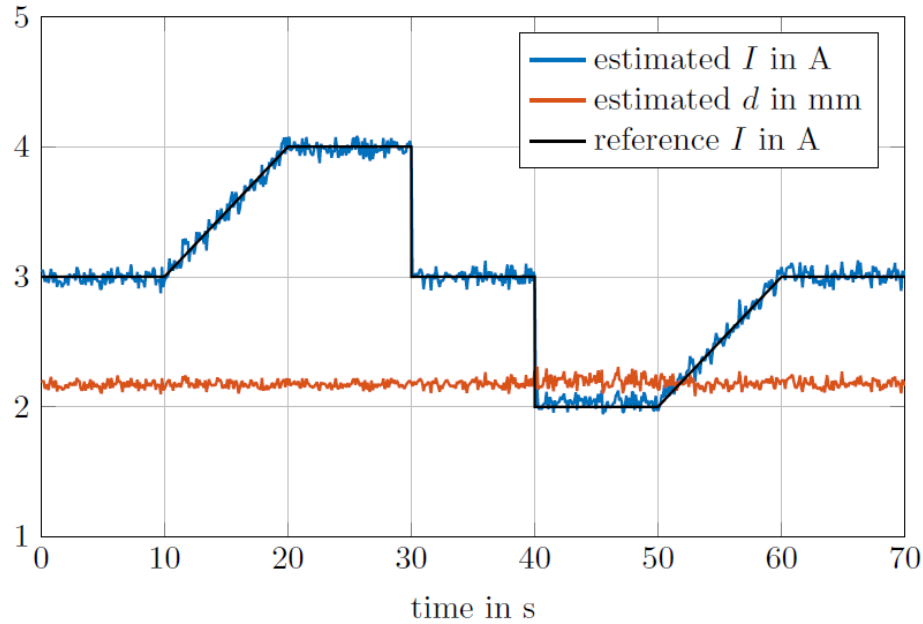
Linear least squares problem:

$$\underset{\theta}{\text{minimize}} \quad f_{[k]}(\theta) = \frac{1}{2} \|R_{[k]}(\theta)\|_2^2$$

Analytical solution with the general Moore-Penrose pseudo-inverse:

$$\theta_{[k+1]} = \theta_{[k]} - J_{[k]}^+ \cdot R(\theta_{[k]})$$

Experimental results





www.micronas.com