

Self-optimizing control: Optimal measurement selection

1 Introduction

Self-optimizing control is when, using a constant set-point feedback policy, acceptable economic operation can be achieved in spite of external disturbances and measurements errors.

- The key in self-optimizing control is to select the feedback controlled variables c .
- The null space method is a systematic method for finding good self-optimizing variables** (Alstad and Skogestad, 2002, 2004).
- Optimal operation (steady-state):

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{u}_0} J_0(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) & \quad - J_0 \text{ is the scalar economic objective.} \\ \text{s.t.} & \quad - \mathbf{x} \text{ the states.} \\ \mathbf{f}(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) = 0 & \quad - \mathbf{u}_0 \text{ the inputs (DOF) and} \\ \mathbf{g}(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) \leq 0 & \quad - \mathbf{d} \text{ the unmeasured external disturbances.} \end{aligned}$$

- Active constraints:** A subset g' of $g(\cdot)$ active for all \mathbf{d} . Control the active constraints:

$$\mathbf{c}_i = \mathbf{g}'(\cdot)$$

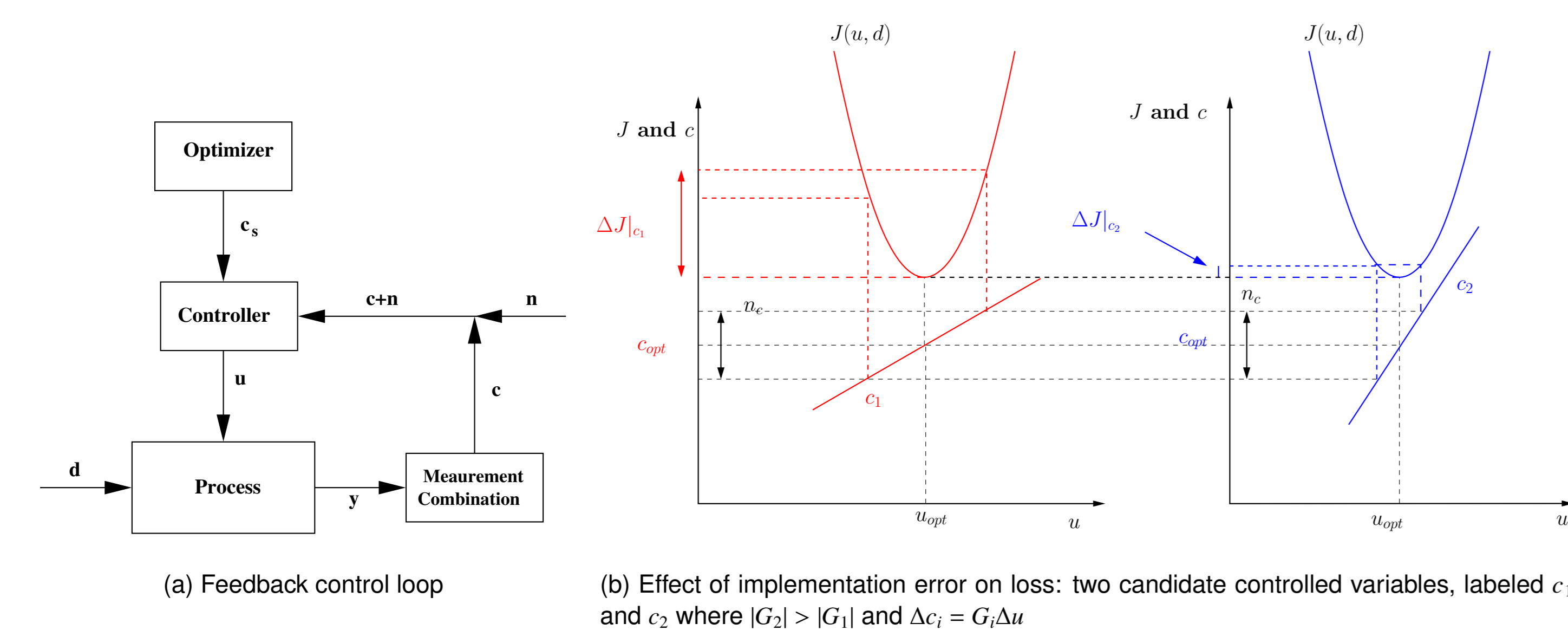
- Resulting unconstrained reduced space optimization problem:

$$\min_{\mathbf{u}} J(\mathbf{u}, \mathbf{d})$$

- Goal: Find feedback controlled variables c of the available measurements y_0 to achieve self-optimizing control.**

1.1 Motivation

- Two sources of uncertainty in operation, see Figure 1(a):
 - External disturbances (\mathbf{d}):** Suppress with feedback.
 - Measurement errors (\mathbf{n}):** Always present, minimize by selecting insensitive feedback variables, see Figure 1(b).



- Two different controlled variables candidates c_1 and c_2 (Figure 1(b)).
- The effect of the implementation error larger for c_1 than c_2 due to lower gain $|G_1| < |G_2|$. Select controlled variables with large gains (Halvorsen et al., 2003).

1.2 Taylor series expansion of the loss function

- A second order accurate expression of the loss function:

$$L = J(\mathbf{c}_s + \mathbf{n}, \mathbf{d}) - J^{opt}(\mathbf{d})$$

where:

- L is a scalar loss function.
- $J(\mathbf{c}_s + \mathbf{n}, \mathbf{d})$ is the actual cost using the constant feedback policy
- $J^{opt}(\mathbf{d})$ is the true optimal value of the objective function.

- Halvorsen et al. (2003) show that the loss is:

$$L = \frac{1}{2} \mathbf{e}_u^T \mathbf{J}_{uu} \mathbf{e}_u = \mathbf{z}^T \mathbf{z} \quad (1)$$

$$\mathbf{z} = \mathbf{J}_{uu}^{1/2} (\mathbf{J}_{uu}^{-1} \mathbf{J}_{ud} - \mathbf{G}^{-1} \mathbf{G}_d) \mathbf{W}_d \mathbf{d}' + \mathbf{J}_{uu}^{1/2} \mathbf{G}^{-1} \mathbf{W}_n \mathbf{n}' \quad (2)$$

$$= \mathbf{M}_d \mathbf{d}' + \mathbf{M}_n \mathbf{n}'$$

$$= [\mathbf{M}_d \quad \mathbf{M}_n] [\mathbf{d}' \quad \mathbf{n}']^T$$

where

$$\mathbf{M}_d = \mathbf{J}_{uu}^{1/2} (\mathbf{J}_{uu}^{-1} \mathbf{J}_{ud} - \mathbf{G}^{-1} \mathbf{G}_d) \mathbf{W}_d$$

$$\mathbf{M}_n = \mathbf{J}_{uu}^{1/2} \mathbf{G}^{-1} \mathbf{W}_n$$

\mathbf{J}_{uu} and \mathbf{J}_{ud} the Hessian matrices

$$\Delta \mathbf{c} = \mathbf{G} \Delta \mathbf{u} + \mathbf{G}_d \Delta \mathbf{d}$$

\mathbf{W}_d and \mathbf{W}_n are scaling matrices

2 The null space method

- The null space method of Alstad and Skogestad (2004, 2002) propose to select controlled variables as functions of a subset of the measurements:

$$\Delta \mathbf{c} = \mathbf{H} \Delta \mathbf{y} \quad \text{where } \Delta \mathbf{y} = \mathbf{G}^y \Delta \mathbf{u} + \mathbf{G}_d^y \Delta \mathbf{d} \quad (3)$$

- The matrix \mathbf{H} is found by selecting the rows \mathbf{h}_i of \mathbf{H} to be the null vectors of the optimal sensitivity matrix \mathbf{F} where

$$\Delta \mathbf{y}^{opt} = \mathbf{F} \Delta \mathbf{d} \quad \text{where } \mathbf{F} = -(\mathbf{G}^y \mathbf{J}_{uu}^{-1} \mathbf{J}_{ud} - \mathbf{G}_d^y) \quad (4)$$

so

$$\mathbf{h}_i^T \in \mathcal{N}(\mathbf{F}^T) \quad (5)$$

such that

$$\mathbf{H} \mathbf{F} = 0$$

- Assumption:

- \mathbf{G}^y and \mathbf{G}_d^y have full column rank.
- The number of controlled variables (n_c) equals the number of input (n_u).
- Implies that the number of measurements are (length of \mathbf{y})

$$n_y = n_u + n_d \quad (6)$$

for the null space of \mathbf{F} to exist.

- Explicit expression for the null space matrix \mathbf{H} is:

$$\mathbf{H} = \mathbf{M}_n^{-1} \mathcal{J}[\tilde{\mathbf{G}}^y]^{-1} \quad \text{where} \quad \begin{aligned} \tilde{\mathbf{G}}^y &= [\mathbf{G}^y \quad \mathbf{G}_d^y] \\ \mathcal{J} &= [\mathbf{J}_{uu}^{1/2} \quad \mathbf{J}_{uu}^{1/2} \mathbf{J}_{uu}^{-1} \mathbf{J}_{ud}] \end{aligned} \quad (7)$$

where \mathbf{M}_n is a parameter matrix and $\tilde{\mathbf{G}}^y$ assumed invertible.

- Selecting \mathbf{H} as given in equation (7) implies that $\mathbf{M}_d = 0$.
- Assume that the total number of measurements $n_{y_0} > n_y$. Issues:

- How to select the best minimum set of measurements in order to reduce the effect of implementation error on the operational objective.
- How to use the null space method when using all available measurements.

3 Selection of the best set of measurements

- Select measurements such that the effect of measurement noise \mathbf{M}_n is minimized, see (1).
- Noise contribution ($\mathbf{M}_d = 0$):

$$\mathbf{z} = \mathbf{M}_n \mathbf{n}_c = \mathbf{M}_n \mathbf{H} \mathbf{n}_y \quad (8)$$

so $\mathbf{M}_n \mathbf{H}$ should be selected as small as possible.

- Now, consider the case of which we have more measurements than the minimum necessary, thus

$$n_{y_0} > n_y = n_u + n_d \quad (9)$$

and we may use these extra measurements to minimize the effect of the measurement error on the loss. This may be achieved in two ways

- Method 1:** Select the best subset of measurements from the full set of measurements.
- Method 2:** Use all measurements and select the best combination.

Best minimum subset of measurements (Method 1)

- Recognizing that from equation (7) we have

$$\mathbf{M}_n \mathbf{H} = \mathcal{J}[\tilde{\mathbf{G}}^y]^{-1} \quad (10)$$

- \mathcal{J} independent of which measurement while $\tilde{\mathbf{G}}^y$ depends on the measurements.
- Selection of the best minimum set of measurements y_i where $i \in \{1, \dots, n_y\}$ from the full set of measurements $y_{0,j}$ for $j = \{1, \dots, n_{y_0}\}$.
- The choice of \mathbf{M}_n does not influence the effect of the measurement noise (right hand side of equation (10) is a constant matrix).
- From equation (10) we get that in order to minimize the loss

$$\max_{\|\mathbf{n}_y\|_2 \leq 1} \frac{1}{2} \mathbf{z}^T \mathbf{z} = \max_{\|\mathbf{n}_y\|_2 \leq 1} \frac{1}{2} \|\mathbf{z}\|_2^2 = \frac{1}{2} \bar{\sigma}(\mathcal{J}[\tilde{\mathbf{G}}^y]^{-1})^2 \leq \frac{1}{2} (\bar{\sigma}(\mathcal{J}) \bar{\sigma}(\tilde{\mathbf{G}}^y)^{-1})^2 = \frac{1}{2} (\bar{\sigma}(\mathcal{J}) \underline{\sigma}(\tilde{\mathbf{G}}^y))^{-2} \quad (11)$$

- Optimal:** Select measurements such that $\bar{\sigma}(\mathcal{J}[\tilde{\mathbf{G}}^y]^{-1})$ is minimized.
- Sub-optimal:** Select measurements y_i such that $\underline{\sigma}(\tilde{\mathbf{G}}^y)$ is maximized.

Best combination of all measurements (Method 2)

Using all measurement we replace the inverse of equation (10) by the pseudo-inverse (Moore-Penrose generalized inverse):

$$\mathbf{H} = \mathbf{M}_n^{-1} \mathcal{J}[\tilde{\mathbf{G}}_0^y]^\dagger \quad (12)$$

where $[\tilde{\mathbf{G}}_0^y]^\dagger$ is the pseudo-left inverse of $\tilde{\mathbf{G}}_0^y$, such that the effect of the measurement error is $\mathbf{M}_n \mathbf{H} = \mathcal{J}[\tilde{\mathbf{G}}_0^y]^\dagger$.

Extensions: Fewer measurements ($n_y < n_u + n_d$)

Methods for reducing the dimension of the problem ($\mathbf{M}_d \neq 0$):

- Lump "similar" disturbances based on SVD of $\mathbf{G}_d^y = \mathbf{U}_d \Sigma_d \mathbf{V}_d^T$.

$$\Delta \mathbf{d} \approx \tilde{\mathbf{V}}_d \Delta \tilde{\mathbf{d}} \quad (13)$$

corresponding to the large singular values $\{\sigma_1, \sigma_2, \dots, \sigma_j\}$ with directions $\tilde{\mathbf{V}}_d = [v_{d,1} \dots v_{d,j}]$.

- Pseudo-right inverse as given by equation (12) above.

4 Toy example

- SISO system with one disturbance and the following objective function

$$J = (u - d)^2 \quad (14)$$

with the nominal disturbance $d^* = 0$.

- Measurements:

$$y_1 = 0.1(u - d) \quad y_2 = 20u \quad y_3 = 10u - 5d \quad y_4 = u$$

- Optimal sensitivity matrix:

$$\Delta \mathbf{y}_0^{opt} = \mathbf{F} \Delta \mathbf{d} = \mathbf{G}^y \Delta u^{opt}(\mathbf{d}) + \mathbf{G}_d^y \Delta \mathbf{d} = [0.1 \ 20 \ 10 \ 1]^T \Delta \mathbf{d} + [-0.1 \ 0 \ -5 \ 0]^T \Delta \mathbf{d} = [0 \ 20 \ 5 \ 1]^T \Delta \mathbf{d} \quad (15)$$

- Null space method:** Minimum number of measurements, see (6), is

$$n_y = n_u + n_d = 1 + 1 = 2$$

- which results in 6 possible candidate sets of measurements to check.
- Sub-optimal rule, see Table 1: Use measurements 2 and 3 (y_2 and y_3).
- Table 2 show the worst case loss for the candidate controlled variables.
- Loss reduced with a factor of 6 using the null space method.
- Using all measurements in equation (12) the loss is marginally smaller compared to $c_{LC,4}$ due to the high implementation error of measurements y_1 and y_4 ($L_{LC}^{all} = 0.04247$).

Table 1: Minimum singular values

$c_{LC}, \#$	$y\#$	$\sigma(\tilde{\mathbf{G}}^y)$
4	2 3	4.4490
6	3 4	0.4458
1	1 2	0.1
3	1 4	0.0995
2	1 3	0.0447
5	2 4	0

Table 2: Worst case loss

Rank	\mathbf{c}	L
1	$c_{LC,4}$	0.0425
2	y_3	0.26
3	y_2	1.0025
4	$c_{LC,6}$	1.04
5	y_4	2
6	y_1	100
7	$c_{LC,5}$	inf

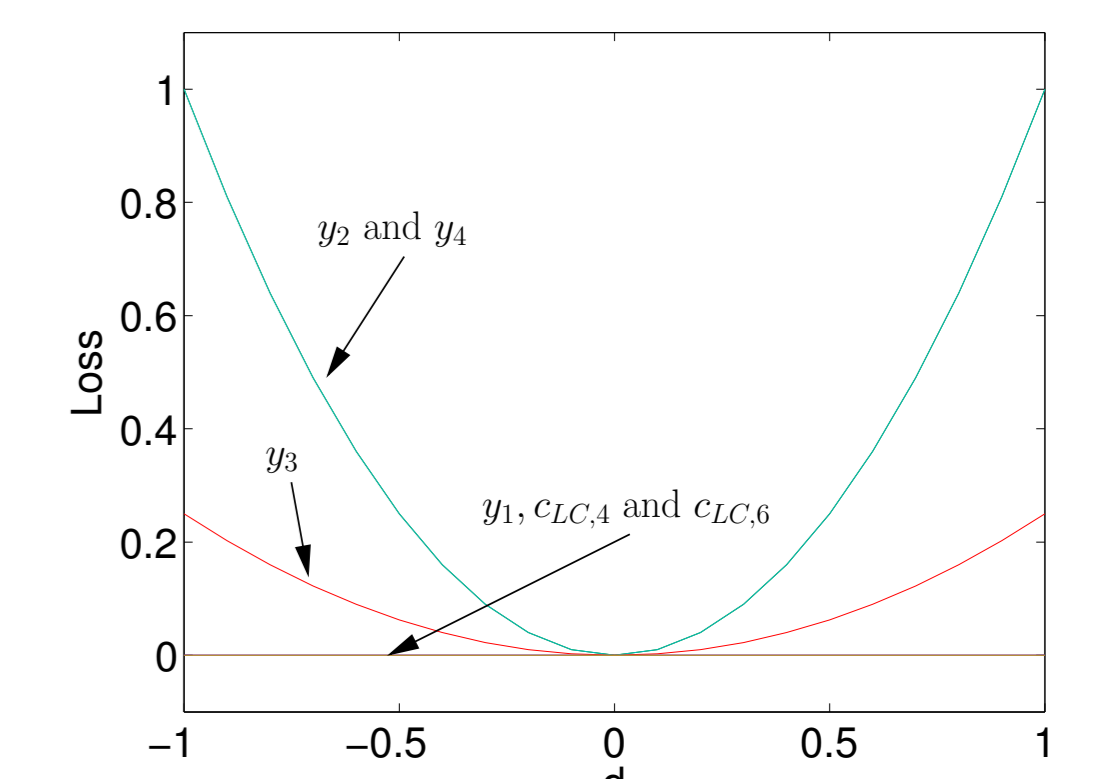


Figure 1: Loss due to disturbance d

References

- Alstad, V. and Skogestad, S. (2002). Robust operation by controlling the right variable combination. *AIChE annual meeting, Indianapolis, USA*.
- Alstad, V. and Skogestad, S. (2004). Combinations of measurements as controlled variables; application to a petlyuk distillation column. *in the IFAC Symposium on Advanced Control of Chemical Processes (ADCHEM) 2003, (Hong Kong)*.
- Halvorsen, I., Skogestad, S., Morud, J., and V. Alstad (2003). Optimal selection of controlled variables. *Ind. Eng. Chem. Res.*, 42(14).

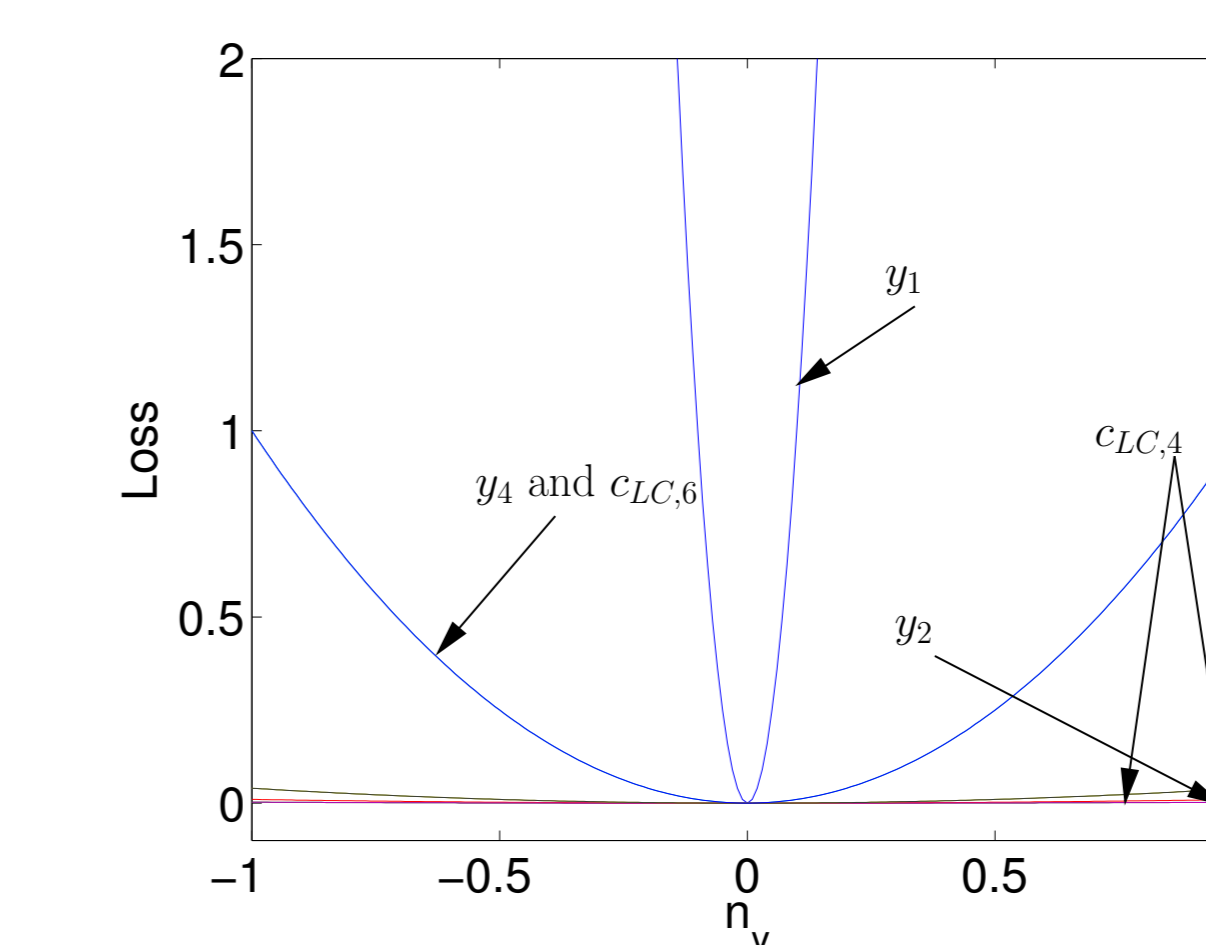


Figure 2: Loss due to measurement error n