Theory to Practice:
Grid-connected, data-driven inverter control

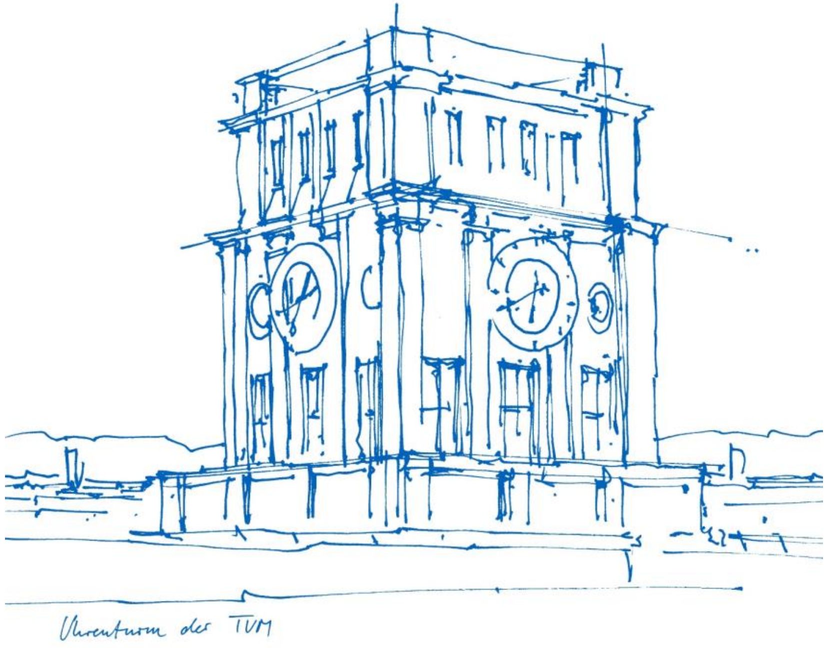
EMT Colloquium

Anurag Mohapatra

Center for Combined Smart Energy Systems,

TUM

11.12.2024



Modeling a dynamical system for online control

How do we define a dynamical system?

- Linear Time Invariant systems to be precise

1. State space model
2. Transfer function
3. Neural network

Modeling a dynamical system for online control

How do we define a dynamical system?
- Linear Time Invariant systems to be precise

1. State space model
2. Transfer function
3. Neural network

4. Non-parametric model definition

Available online at www.sciencedirect.com
SCIENCE DIRECT®
Systems & Control Letters 54 (2005) 325–329
SYSTEMS & CONTROL LETTERS
www.elsevier.com/locate/sysconle

A note on persistency of excitation

Jan C. Willems[a], Paolo Rapisarda[b], Ivan Markovsky[a,*], Bart L.M. De Moor[a]
[a]ESAT, SCD/SISTA, K.U. Leuven, Kasteelpark Arenberg 10, B 3001 Leuven, Heverlee, Belgium
[b]Department of Mathematics, University of Maastricht, 6200 MD Maastricht, The Netherlands

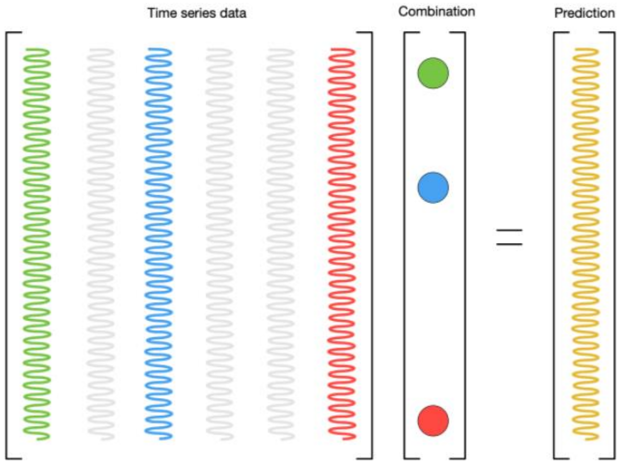
Received 3 June 2004; accepted 7 September 2004
Available online 30 November 2004

[1] Willems, J., et al. "A note on persistency of excitation," in *Systems & Control Letters*, vol. 54, no. 4, pp. 325–329, 2005.

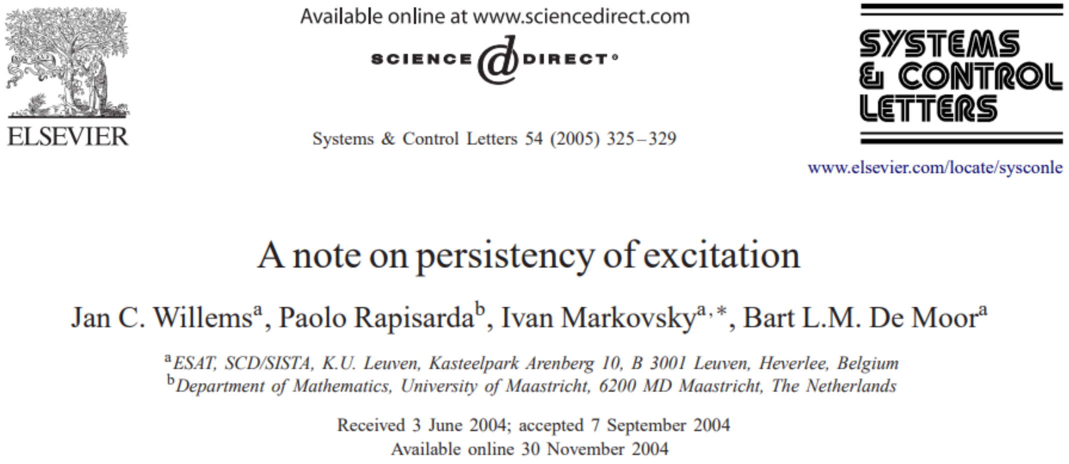
Non-parametric model definition

A system is described by its behaviour, which is the set of all possible trajectories it can generate.

AND, a <u>sufficiently exciting input</u> signal allows us to <u>completely determine the system</u>'s behaviour from a <u>finite number of input-output</u> data points.



https://control.ee.ethz.ch/research/theory/data-enabled-predictive-control.html


ELSEVIER
Available online at www.sciencedirect.com
SCIENCE DIRECT
Systems & Control Letters 54 (2005) 325–329
SYSTEMS & CONTROL LETTERS
www.elsevier.com/locate/sysconle

A note on persistency of excitation

Jan C. Willems[a], Paolo Rapisarda[b], Ivan Markovsky[a,*], Bart L.M. De Moor[a]

[a] *ESAT, SCD/SISTA, K.U. Leuven, Kasteelpark Arenberg 10, B 3001 Leuven, Heverlee, Belgium*
[b] *Department of Mathematics, University of Maastricht, 6200 MD Maastricht, The Netherlands*

Received 3 June 2004; accepted 7 September 2004
Available online 30 November 2004

[1] Willems, J., et al. "A note on persistency of excitation," in *Systems & Control Letters*, vol. 54, no. 4, pp. 325–329, 2005.

Continuing the work.

- Willem paper became standard literature in data-driven control
- Closed loop representations were developed.
- Stable state-feedback controller design was developed.

IEEE CSS IEEE TRANSACTIONS ON AUTOMATIC CONTROL, VOL. 65, NO. 3, MARCH 2020 909

Formulas for Data-Driven Control: Stabilization, Optimality, and Robustness

Claudio De Persis and Pietro Tesi

B. Data-Based Closed-Loop Representation

We now exploit Lemma 2 to derive a parametrization of system (1a) in closed loop with a state-feedback law $u = Kx$. We give here a proof of this result since the arguments we use will often recur in the next sections.

Theorem 2: Let condition (6) hold. Then, system (1a) in closed loop with a state feedback $u = Kx$ has the following equivalent representation:

$$x(k+1) = X_{1,T} G_K x(k) \qquad (11)$$

where G_K is a $T \times n$ matrix satisfying

$$\begin{bmatrix} K \\ I_n \end{bmatrix} = \begin{bmatrix} U_{0,1,T} \\ \hline X_{0,T} \end{bmatrix} G_K. \qquad (12)$$

In particular

$$u(k) = U_{0,1,T} G_K x(k). \qquad (13)$$

A. State Feedback Design and Data-Based Parametrization of All Stabilizing Controllers

By Theorem 2, the closed-loop system under state-feedback $u = Kx$ is such that

$$A + BK = X_{1,T} G_K$$

where G_K satisfies (12). One can, therefore, search for a matrix G_K such that $X_{1,T} G_K$ satisfies the classic Lyapunov stability condition. As the next result shows, it turns out that this problem can be actually cast in terms of a simple LMI.

Theorem 3: Let condition (6) hold. Then any matrix Q satisfying

$$\begin{bmatrix} X_{0,T}\, Q & X_{1,T} Q \\ Q^\top X_{1,T}^\top & X_{0,T}\, Q \end{bmatrix} \succ 0 \qquad (15)$$

is such that

$$K = U_{0,1,T} Q (X_{0,T} Q)^{-1} \qquad (16)$$

stabilizes system (1a). Conversely, if K is a stabilizing state-feedback gain for system (1a), then it can be written as in (16), with Q solution of (15).

[2] C. De Persis, P. Tesi. "Formulas for Data-Driven Control: Stabilization, Optimality, and Robustness," in *IEEE Transactions on Automatic Control*, vol. 65, no. 3, pp. 909–924, 2020.

Genesis of data-driven predictive control

- Formulated as a counter to standard MPC
- Constrained optimization to calculate stabilizing feedback
- Ensures guaranteed behaviour
  - Similar to H_inf
  - Safety Filter literature

Data-Enabled Predictive Control: In the Shallows of the DeePC

Jeremy Coulson John Lygeros Florian Dörfler

Abstract— We consider the problem of optimal trajectory cking for unknown systems. A novel data-enabled predictive itrol (DeePC) algorithm is presented that computes optimal

In the context of unknown black-box systems, the no approach which solves the optimal trajectory tra problem subject to constraints and partial (output) obs

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t), \end{cases}$$

Plant (only available as data)

Feedback controller determined by a constrained optimisation

$$\begin{array}{ll} \underset{g,u,y}{\text{minimize}} & \sum_{k=0}^{N-1} \left(\|y_k - r_{t+k}\|_Q^2 + \|u_k\|_R^2 \right) \\ \text{subject to} & \begin{pmatrix} U_\mathrm{p} \\ Y_\mathrm{p} \\ U_\mathrm{f} \\ Y_\mathrm{f} \end{pmatrix} g = \begin{pmatrix} u_\mathrm{ini} \\ y_\mathrm{ini} \\ u \\ y \end{pmatrix}, \\ & u_k \in \mathcal{U},\ \forall k \in \{0,\dots,N-1\}, \\ & y_k \in \mathcal{Y},\ \forall k \in \{0,\dots,N-1\}. \end{array}$$

[3] J. Coulson, J. Lygeros, F. Dörfler, "Data-Enabled Predictive Control: In the Shallows of the DeePC," in 2019 18th European Control Conference (ECC), 2019, pp. 307–312.

Genesis of data-driven predictive control

- Formulated as a counter to standard MPC
- Constrained optimization to calculate stabilizing feedback
- Ensures guaranteed behaviour
  - Similar to H_inf
  - Safety Filter literature
- Extended to Non-linear systems, to handle noise and scalable optimisation

Data-Enabled Predictive Control: In the Shallows of the DeePC

Jeremy Coulson John Lygeros Florian Dörfler

Abstract—We consider the problem of optimal trajectory tracking for unknown systems. A novel data-enabled predictive control (DeePC) algorithm is presented that computes optimal

In the context of unknown black-box systems, the no approach which solves the optimal trajectory tra problem subject to constraints and partial (output) obs

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t), \end{cases}$$

Plant (only available as data)

Feedback controller determined by a constrained optimisation

$$\begin{aligned} \underset{g,u,y}{\text{minimize}} \quad & \sum_{k=0}^{N-1} \left(\|y_k - r_{t+k}\|_Q^2 + \|u_k\|_R^2 \right) \\ \text{subject to} \quad & \begin{pmatrix} U_\mathrm{p} \\ Y_\mathrm{p} \\ U_\mathrm{f} \\ Y_\mathrm{f} \end{pmatrix} g = \begin{pmatrix} u_\mathrm{ini} \\ y_\mathrm{ini} \\ u \\ y \end{pmatrix}, \\ & u_k \in \mathcal{U}, \ \forall k \in \{0, \dots, N-1\}, \\ & y_k \in \mathcal{Y}, \ \forall k \in \{0, \dots, N-1\}. \end{aligned}$$

Regularized and Distributionally Robust Data-Enabled Predictive Control

Jeremy Coulson John Lygeros Florian Dörfler

Abstract—In this paper, we study a data-enabled predictive

Hence, none of the approaches above are suitable for real-

[4] J. Coulson, J. Lygeros, F. Dörfler, "Regularized and Distributionally Robust Data-Enabled Predictive Control," in 2019 IEEE 58th Conference on Decision and Control (CDC), 2019, pp. 2696–2701

[3] J. Coulson, J. Lygeros, F. Dörfler, "Data-Enabled Predictive Control: In the Shallows of the DeePC," in 2019 18th European Control Conference (ECC), 2019, pp. 307–312.

Application in power system?

- Grid agnostic inverter control

- Computationally intensive
  - Hankel matrices are huge
  - Cannot work online

Data-Enabled Predictive Control for Grid-Connected Power Converters

Linbin Huang, Jeremy Coulson, John Lygeros and Florian Dörfler

***Abstract*— We apply a novel data-enabled predictive control (DeePC) algorithm in grid-connected power converters to perform safe and optimal control. Rather than a model, the DeePC algorithm solely needs input/output data measured from the unknown system to predict future trajectories. We show that the DeePC can eliminate undesired oscillations in**

loop, can become unstable when the power converter connected to a weak grid with high grid impedance equivalently, low short-circuit ratio) [6]–[8].

Even though offline design and analysis (based on a no nal model) can be conducted to determine an optimal con

[5] Huang, L., et al, "Data-Enabled Predictive Control for Grid-Connected Power Converters," in 2019 IEEE 58th Conference on Decision and Control (CDC), 2019, pp. 8130–8135.

Application in power system?

- Grid agnostic inverter control

- Computationally intensive
  - Hankel matrices are huge
  - Cannot work online

- Introduced Page Matrix instead of Hankel Matrix
  - Better noise cancellation by SVD filtering
  - But longer matrix

- Introduced decentral solution to optimisation
  - Will scale better
  - Might work online??

Data-Enabled Predictive Control for Grid-Connected Power Converters

Linbin Huang, Jeremy Coulson, John Lygeros and Florian Dörfler

***Abstract*— We apply a novel data-enabled predictive control (DeePC) algorithm in grid-connected power converters to perform safe and optimal control. Rather than a model, the DeePC algorithm solely needs input/output data measured from the unknown system to predict future trajectories. We show that the DeePC can eliminate undesired oscillations in**

loop, can become unstable when the power converter connected to a weak grid with high grid impedance equivalently, low short-circuit ratio) [6]–[8].

Even though offline design and analysis (based on a no nal model) can be conducted to determine an optimal con

Decentralized Data-Enabled Predictive Control for Power System Oscillation Damping

Linbin Huang, Jeremy Coulson, John Lygeros, and Florian Dörfler

***Abstract*—We employ a novel data-enabled predictive control (DeePC) algorithm in voltage source converter (VSC) based high-voltage DC (HVDC) stations to perform safe and optimal wide-**

stations by employing model predictive control (MPC) or linear quadratic Gaussian (LQG) control to stabilize the system [14]–[16]. In fact, the application of WAMS greatly facilitates

[5] Huang, L., et al, "Data-Enabled Predictive Control for Grid-Connected Power Converters," in 2019 IEEE 58th Conference on Decision and Control (CDC), 2019, pp. 8130–8135.
[6] Huang, L., et al. "Decentralized Data-Enabled Predictive Control for Power System Oscillation Damping," in IEEE Transactions on Control Systems Technology, vol. 30, no. 3, pp. 1065–1077, 2022.

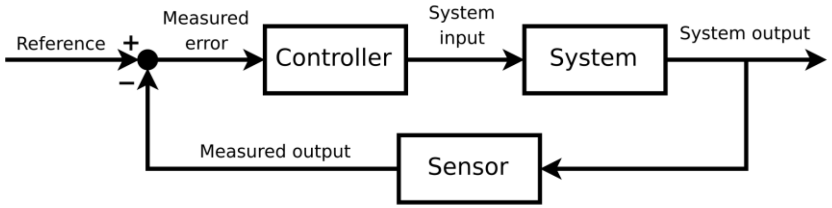
Controller biasing the identification?

In classical control theory,

- Observer design is *time-scale separated* from controller design

Similarly we must separate,

- Estimating a predictive model from data and quantifying its uncertainty
- Optimising the controller based on the estimated model and its uncertainty



https://en.wikipedia.org/wiki/Control_loop#/media/File:Feedback_loop_with_descriptions.svg

Theorem 1 (Separation Principle) *Let* $L_t(u_f)$ *be defined as in* (21)*, the Final Control Error in* (11) *is given by*

$$FCE(u_f) = \mathbb{E}[L_t(u_f)|\mathcal{D}] \doteq J(u_f) + r(u_f), \qquad (26a)$$

where

$$J(u_f) := \|\bar{\delta}_W(u_f)\|_Q^2 + \|u_r - u_f\|_R^2, \qquad (26b)$$

$$r(u_f) := \mathrm{Tr}\left[Q\mathrm{Var}[\delta_W(u_f)|\mathcal{D}]\right], \qquad (26c)$$

Error cost assuming perfect knowledge of system dynamics

Error cost from uncertainty in predictions

Harnessing Uncertainty for a Separation Principle in Direct Data-Driven Predictive Control ⋆

Alessandro Chiuso [a], Marco Fabris [a], Valentina Breschi [b], Simone Formentin [c]

[a] *Department of Information Engineering, University of Padova, Via Gradenigo 6/b, 35131 Padova, Italy.*

[b] *Department of Electrical Engineering, Eindhoven University of Technology, 5600 MB Eindhoven, The Netherlands.*

[c] *Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, P.za L. Da Vinci, 32, 20133 Milano, Italy.*

[7] Chiuso, A., et al, "Harnessing Uncertainty for a Separation Principle in Direct Data-Driven Predictive Control," 2023, arXiv preprint.

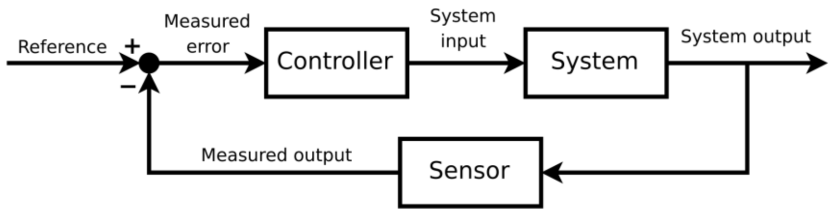
Controller biasing the identification?

In classical control theory,

- Observer design is *time-scale separated* from controller design

Similarly we must separate,

- Estimating a predictive model from data and quantifying its uncertainty
- Optimising the controller based on the estimated model and its uncertainty



https://en.wikipedia.org/wiki/Control_loop#/media/File:Feedback_loop_with_descriptions.svg

In other words,

- Plant dynamics and controller dynamics can be separated.
- With only input-output data.

Harnessing Uncertainty for a Separation Principle in Direct Data-Driven Predictive Control ⋆

Alessandro Chiuso [a], Marco Fabris [a], Valentina Breschi [b], Simone Formentin [c]

[a] Department of Information Engineering, University of Padova, Via Gradenigo 6/b, 35131 Padova, Italy.

[b] Department of Electrical Engineering, Eindhoven University of Technology, 5600 MB Eindhoven, The Netherlands.

[c] Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, P.za L. Da Vinci, 32, 20133 Milano, Italy.

[7] Chiuso, A., et al, "Harnessing Uncertainty for a Separation Principle in Direct Data-Driven Predictive Control," 2023, arXiv preprint.

New ideas?

So far,

- Identifying complete system with only data
- Closed for stabilizing controller design
- Robust to signal noise by regularisation
- Guaranteed behaviour through constrained optimisation
- Decentral solution of optimisation to scale
- Separation principle to remove controller biasing in data collection

- Contribution by Moffat et.al - Optimal predictor for finite amount of available data *(manuscript under preparation)*

- Better performance in low-data
  - Better for real world.
- Low computation burden
  - Might just run online!

New ideas?

So far,

- Identifying complete system with only data
- Closed for stabilizing controller design
- Robust to signal noise by regularisation
- Guaranteed behaviour through constrained optimisation
- Decentral solution of optimisation to scale
- Separation principle to remove controller biasing in data collection

- Contribution by Moffat et.al - Optimal predictor for finite amount of available data

- Better performance in low-data
  - Better for real world.
- Low computation burden
  - Might just run online!

Is this finally useful for power system applications??

Inverter control ideas

Lets put on our power systems engineer hats!

- Seminal inverter control paper.
  - How to design control loops for grid forming, grid following inverters

34 IEEE TRANSACTIONS ON POWER ELECTRONICS, VOL. 27, NO. 11, NOVEMBER 2012

Control of Power Converters in AC Microgrids

Joan Rocabert, *Member, IEEE*, Alvaro Luna, *Member, IEEE*, Frede Blaabjerg, *Fellow, IEEE*, and Pedro Rodríguez, *Senior Member, IEEE*

(Invited Paper)

[8] Rocabert, J., et al. "Control of Power Converters in AC Microgrids," in IEEE Transactions on Power Electronics, vol. 27, no. 11, pp. 4734–4749, 2012.

Inverter control ideas

Lets put on our power systems engineer hats!

- Seminal inverter control paper.
  - How to design control loops for grid forming, grid following inverters

- Concepts of emulating Synchronous machines can be added to inverters

However!!!!!!
- Require grid knowledge
- R/X ratio

34 IEEE TRANSACTIONS ON POWER ELECTRONICS, VOL. 27, NO. 11, NOVEMBER 2012

Control of Power Converters in AC Microgrids

Joan Rocabert, *Member, IEEE*, Alvaro Luna, *Member, IEEE*, Frede Blaabjerg, *Fellow, IEEE*, and Pedro Rodríguez, *Senior Member, IEEE*

(Invited Paper)

Virtual Synchronous Machine

Prof. Dr.-Ing. Hans-Peter Beck
Clausthal University of Technology
Institute of Electric Power Technology (IEE)
Clausthal-Zellerfeld, Germany
info@iee.tu-clausthal.de

Dipl.-Ing. Ralf Hesse
Clausthal University of Technology
Institute of Electric Power Technology (IEE
Clausthal-Zellerfeld, Germany
ralf.hesse@tu-clausthal.de

IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, VOL. 58, NO. 4, APRIL 2011 1259

Synchronverters: Inverters That Mimic Synchronous Generators

Qing-Chang Zhong, *Senior Member, IEEE*, and George Weiss

[8] Rocabert, J., et al. "Control of Power Converters in AC Microgrids," in IEEE Transactions on Power Electronics, vol. 27, no. 11, pp. 4734–4749, 2012.
[9] H. Beck, R. Hesse, "Virtual synchronous machine," in 2007 9th International Conference on Electrical Power Quality and Utilisation, 2007, pp. 1–6.
[10] Q. Zhong, G. Weiss. "Synchronverters: Inverters That Mimic Synchronous Generators," in IEEE Transactions on Industrial Electronics, vol. 58, no. 4, pp. 1259–1267, 2011.

Inverter control ideas – grid agnostic

- State estimation based control / Probing based control
  - Perturb the system and estimate eigen modes
  - Online and offline versions

2462 IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 36, NO. 3, MAY 2021

Roles of Dynamic State Estimation in Power System Modeling, Monitoring and Operation

IEEE Task Force on Power System Dynamic State and Parameter Estimation

Junbo Zhao (TF Chair), *Senior Member, IEEE*, Marcos Netto, *Member, IEEE*, Zhenyu Huang, *Fellow, IEEE*, Samson Shenglong Yu, *Member, IEEE*, Antonio Gómez-Expósito, *Fellow, IEEE*, Shaobu Wang, *Senior Member, IEEE*, Innocent Kamwa, *Fellow, IEEE*, Shahrokh Akhlaghi, *Senior Member, IEEE*, Lamine Mili, *Life Fellow, IEEE*, Vladimir Terzija, *Fellow, IEEE*,

Data-Driven Modeling of Grid-Forming Inverter Dynamics Using Power Hardware-in-the-Loop Experimentation

NISCHAL GURUWACHARYA[1,2], (Student Member, IEEE), SOHAM CHAKRABORTY[3], (Member, IEEE), GOVIND SARASWAT[4], (Senior Member, IEEE), RICHARD BRYCE[2], (Senior Member, IEEE), TIMOTHY M. HANSEN[1], (Senior Member, IEEE), AND REINALDO TONKOSKI[5], (Senior Member, IEEE)

[1] Department of Electrical Engineering and Computer Science, South Dakota State University, Brookings, SD 57007, USA
[2] National Renewable Energy Laboratory, Golden, CO 80401, USA
[3] Department of Electrical and Computer Engineering, University of Minnesota, Minnesota, MN 55455, USA
[4] Enphase Energy, Austin, TX 78758, USA
[5] Department of Electric Power Transmission and Distribution, Technical University of Munich, 80333 Munich, Germany

[11] Zhao, J., et al. "Roles of Dynamic State Estimation in Power System Modeling, Monitoring and Operation," in IEEE Transactions on Power Systems, vol. 36, no. 3, pp. 2462–2472, 2021.
[12] Guruwacharya, N., et al. "Data-Driven Modeling of Grid-Forming Inverter Dynamics Using Power Hardware-in-the-Loop Experimentation," in IEEE Access, vol. 12, pp. 52267–52281, 2024.

Inverter control ideas – grid agnostic

- State estimation based control / Probing based control
  - Perturb the system and estimate eigen modes
  - Online and offline versions

- Sensitivity paramter based control
  - Change in P, Q correlated to change in V,I
  - Calculated from Load Flow Jacobian
  - Mature literature on efficient computation and robustness

Sensitivity in Power Systems

JOHN PESCHON, MEMBER, IEEE, DEAN S. PIERCY, WILLIAM F. TINNEY, SENIOR MEMBER, IEEE, AND ODD J. TVEIT, MEMBER, IEEE

Transactions on Power Systems, Vol. 7, No. 1, February 1992

CONTROL OF VOLTAGE STABILITY USING SENSITIVITY ANALYSIS

Miroslav M. Begović, Member IEEE
School of Electrical Engineering
Georgia Institute of Technology
Atlanta GA 30332–0250

Arun G. Phadke, Fellow IEEE
Dept. of Electrical Engineering
Virginia Polytechnic Institute & State Univ.
Blacksburg VA 24061–0111

IEEE TRANSACTIONS ON SMART GRID, VOL. 4, NO. 2, JUNE 2013 741

Efficient Computation of Sensitivity Coefficients of Node Voltages and Line Currents in Unbalanced Radial Electrical Distribution Networks

Konstantina Christakou, *Member, IEEE*, Jean-Yves LeBoudec, *Fellow, IEEE*, Mario Paolone, *Senior Member, IEEE*, and Dan-Cristian Tomozei, *Member, IEEE*

[13] Peschon, J., et al. "Sensitivity in Power Systems," in IEEE Transactions on Power Apparatus and Systems, vol. PAS-87, no. 8, pp. 1687–1696, 1968.
[14] M. Begovic, A. Phadke. "Control of voltage stability using sensitivity analysis," in IEEE Transactions on Power Systems, vol. 7, no. 1, pp. 114–123, 1992.
[15] Christakou, K., et al. "Efficient Computation of Sensitivity Coefficients of Node Voltages and Line Currents in Unbalanced Radial Electrical Distribution Networks," in IEEE Transactions on Smart Grid, vol. 4, no. 2; 2013.
[16] R. Gupta and M. Paolone, "Experimental Validation of Model-less Robust Voltage Control using Measurement-based Estimated Voltage Sensitivity Coefficients," 2023 IEEE Belgrade PowerTech, Belgrade, Serbia, 2023

Inverter control ideas – grid agnostic

- State estimation based control / Probing based control
  - Perturb the system and estimate eigen modes
  - Online and offline versions

- Sensitivity paramter based control
  - Change in P, Q correlated to change in V,I
  - Calculated from Load Flow Jacobian
  - Mature literature on efficient computation and robustness

The nodal voltage magnitude of i−th node at time t_k (i.e., $|v_{i,t_k}|$) can be approximated by

$$|v_{i,t_k}| \approx |v_{i,t_{k-1}}| + \Delta \mathbf{p}_{t_k} \mathbf{K}^p_{i,t_{k-1}} + \Delta \mathbf{q}_{t_k} \mathbf{K}^q_{i,t_{k-1}} \quad \forall i \in \mathcal{N}_b \quad (1)$$

To account for the uncertainty on the estimates, the coefficients are represented by following intervals with $\Delta \mathbf{K}^p_{i,t_k}, \Delta \mathbf{K}^q_{i,t_k}$ being the estimated uncertainty

$$\mathbf{K}^p_{i,t_k} \in [\widehat{\mathbf{K}}^p_{i,t_k} - \Delta \mathbf{K}^p_{i,t_k},\ \widehat{\mathbf{K}}^p_{i,t_k} + \Delta \mathbf{K}^p_{i,t_k}] \quad \forall i \in \mathcal{N}_b \quad (2a)$$

$$\mathbf{K}^q_{i,t_k} \in [\widehat{\mathbf{K}}^q_{i,t_k} - \Delta \mathbf{K}^q_{i,t_k},\ \widehat{\mathbf{K}}^q_{i,t_k} + \Delta \mathbf{K}^q_{i,t_k}] \quad \forall i \in \mathcal{N}_b. \quad (2b)$$

Sensitivity in Power Systems

JOHN PESCHON, MEMBER, IEEE, DEAN S. PIERCY, WILLIAM F. TINNEY, SENIOR MEMBER, IEEE, AND ODD J. TVEIT, MEMBER, IEEE

Transactions on Power Systems, Vol. 7, No. 1, February 1992

CONTROL OF VOLTAGE STABILITY USING SENSITIVITY ANALYSIS

Miroslav M. Begović, Member IEEE
School of Electrical Engineering
Georgia Institute of Technology
Atlanta GA 30332–0250

Arun G. Phadke, Fellow IEEE
Dept. of Electrical Engineering
Virginia Polytechnic Institute & State Univ.
Blacksburg VA 24061–0111

IEEE TRANSACTIONS ON SMART GRID, VOL. 4, NO. 2, JUNE 2013 741

Efficient Computation of Sensitivity Coefficients of Node Voltages and Line Currents in Unbalanced Radial Electrical Distribution Networks

Konstantina Christakou, *Member, IEEE*, Jean-Yves LeBoudec, *Fellow, IEEE*, Mario Paolone, *Senior Member, IEEE*, and Dan-Cristian Tomozei, *Member, IEEE*

[13] Peschon, J., et al. "Sensitivity in Power Systems," in IEEE Transactions on Power Apparatus and Systems, vol. PAS-87, no. 8, pp. 1687–1696, 1968.
[14] M. Begovic, A. Phadke. "Control of voltage stability using sensitivity analysis," in IEEE Transactions on Power Systems, vol. 7, no. 1, pp. 114–123, 1992.
[15] Christakou, K., et al. "Efficient Computation of Sensitivity Coefficients of Node Voltages and Line Currents in Unbalanced Radial Electrical Distribution Networks," in IEEE Transactions on Smart Grid, vol. 4, no. 2; 2013.
[16] R. Gupta and M. Paolone, "Experimental Validation of Model-less Robust Voltage Control using Measurement-based Estimated Voltage Sensitivity Coefficients," 2023 IEEE Belgrade PowerTech, Belgrade, Serbia, 2023

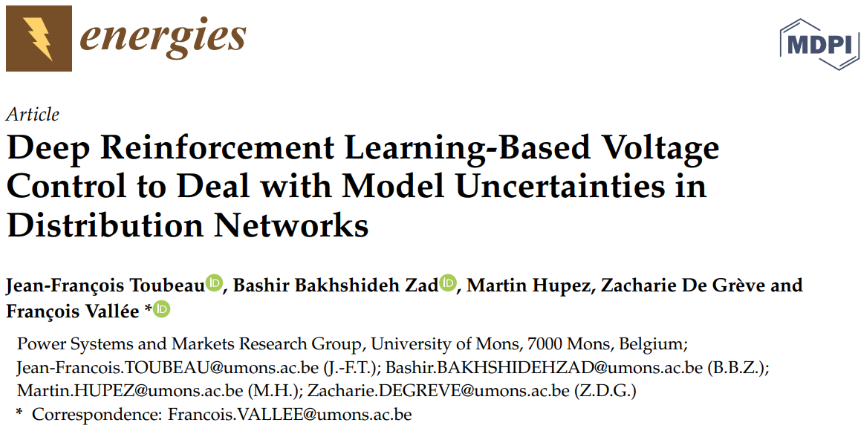
Inverter control ideas – grid agnostic

- State estimation based control / Probing based control
  - Perturb the system and estimate eigen modes
  - Online and offline versions

- Sensitivity paramter based control
  - Change in P, Q correlated to change in V,I
  - Calculated from Load Flow Jacobian
  - Mature literature on efficient computation and robustness

- Machine learning models ??
  - Mostly an alternative way to do #1 or #2

- The Holy Grail – Plug and play inverter with real time control!


energies MDPI

Article

Deep Reinforcement Learning-Based Voltage Control to Deal with Model Uncertainties in Distribution Networks

Jean-François Toubeau, Bashir Bakhshideh Zad, Martin Hupez, Zacharie De Grève and François Vallée *

Power Systems and Markets Research Group, University of Mons, 7000 Mons, Belgium; Jean-Francois.TOUBEAU@umons.ac.be (J.-F.T.); Bashir.BAKHSHIDEHZAD@umons.ac.be (B.B.Z.); Martin.HUPEZ@umons.ac.be (M.H.); Zacharie.DEGREVE@umons.ac.be (Z.D.G.)

* Correspondence: Francois.VALLEE@umons.ac.be

[17] Toubeau, J. et.al , “Deep Reinforcement Learning-Based Voltage Control to Deal with Model Uncertainties in Distribution Networks”. Energies 2020, 13, 3928.

Lets combine the two worlds

Inverter control world need controllers which are:

- Model free and yet mathematically rigorous
- Acceptable for Online/Real-time computation
- Can adapt to different control policies
- Robust with low setup requirement

Data driven control theory gives us a controller that has,

- Closed form non-parametric (model free) represenation of system
- Guaranteed behaviour, can handle noise, can scale
- Separates controller dynamics from plant dynamics
- Low computation burden and needs less measurement
- Will solve as an online policy

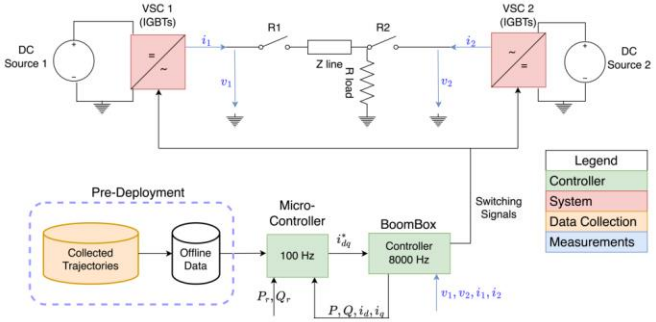
Lets combine the two worlds

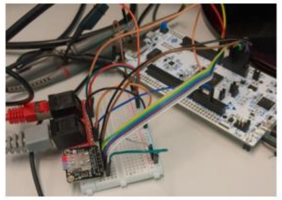
Inverter control world need controllers which are:

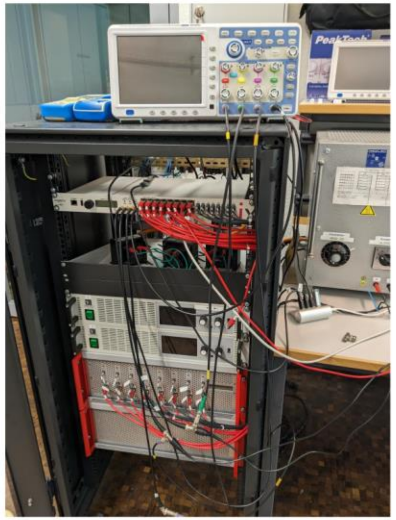
- Model free and yet mathematically rigorous
- Acceptable for Online/Real-time computation
- Can adapt to different control policies
- Robust with low setup requirement

Data driven control theory gives us a controller that has,

- Closed form non-parametric (model free) represenation of system
- Guaranteed behaviour, can handle noise, can scale
- Separates controller dynamics from plant dynamics
- Low computation burden and needs less measurement
- Will solve as an online policy







Test setup at ETH Zürich

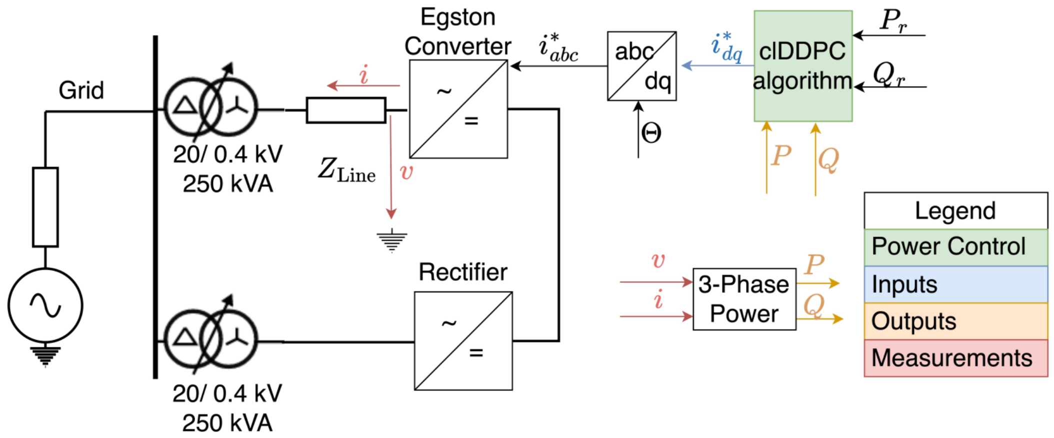
1. *Controller deployed on STM Microcontoller*
2. *Inverter emulated by Imperix system*

Tests in CoSES

Grid connected mode and controlling a 25kW Grid following inverter

- Inverter current control loop @5kHz, RT
- Predictive controller feeding into inverter @100Hz

- Toolchain
  - NI VeriStand RT engine.
  - Simulink for Inverter current controller and PLL
  - MATLAB for offline training
  - Compiled C routine for online optimisation
  - Python script to interface with CoSES

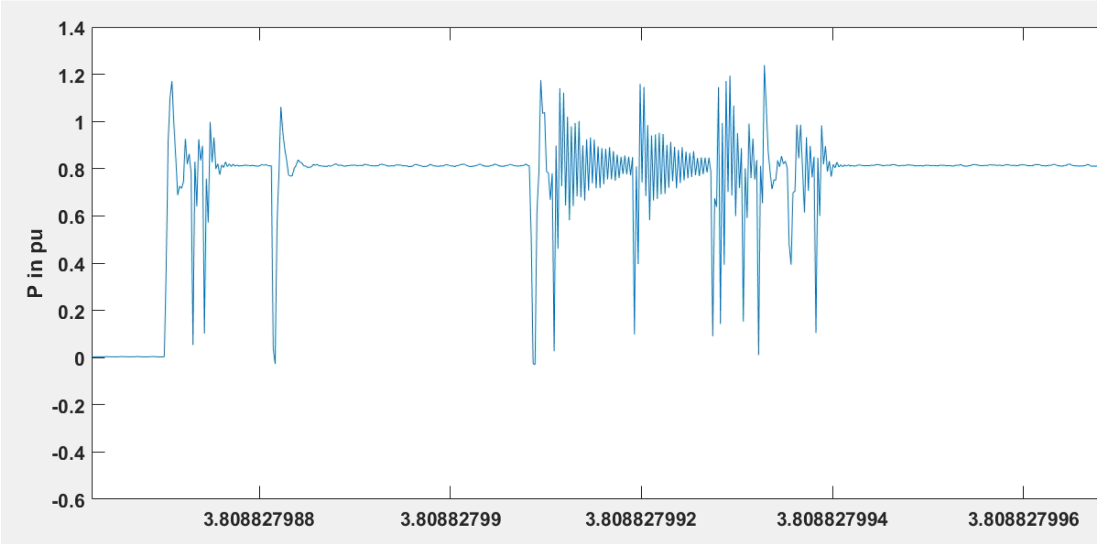


Controller

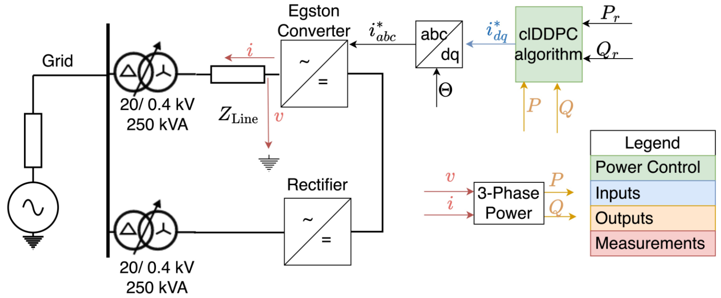
- Reference – P_{set}, Q_{set}
- Feedback – P_{real}, Q_{real}
- Output – $I_{d,set}$, $I_{q,set}$ reference for inverter

- Data pipeline
  - 500 data points for training @50Hz → One-time Offline tuning → Deployed Live

Early results



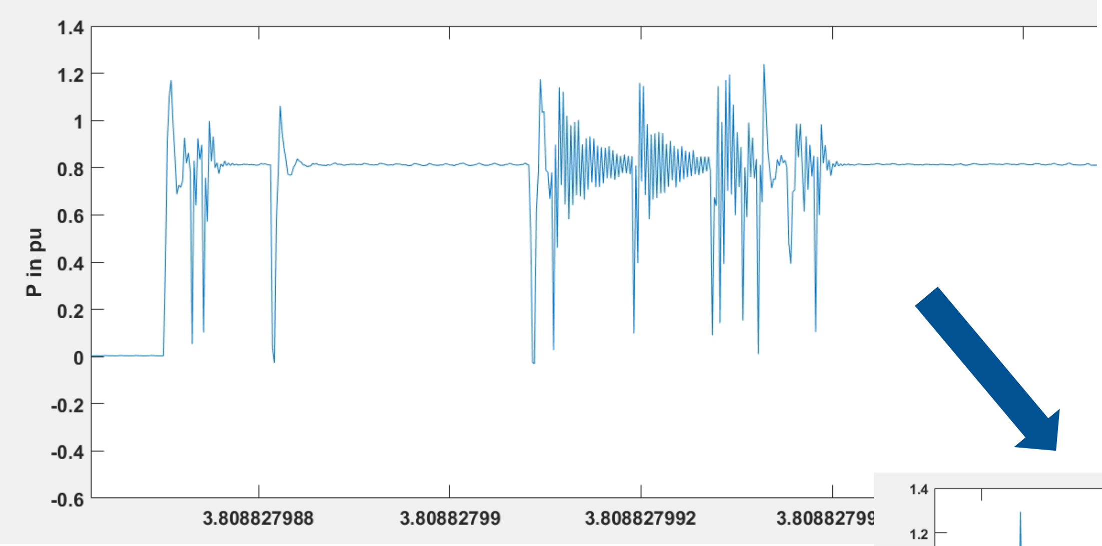
- Decent tracking
- Severe overshoots
  - Cost function should be updated
- Dropouts
  - C-solver has bugs



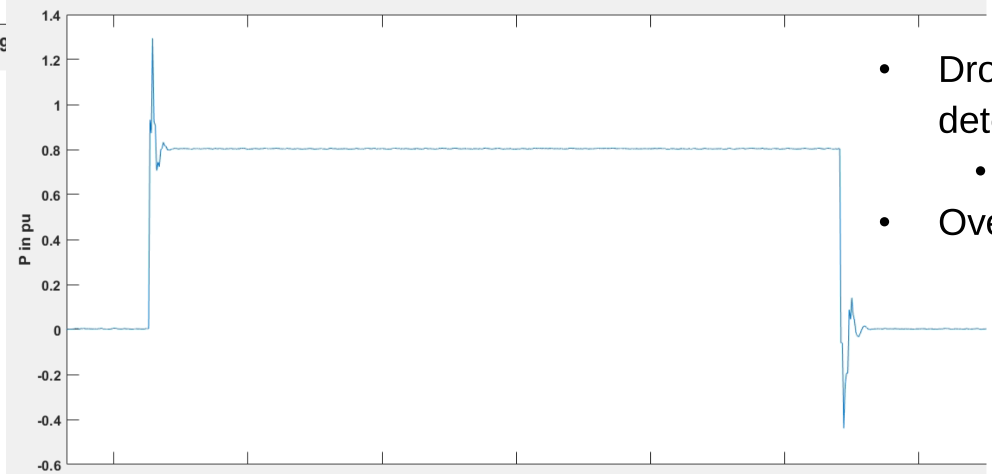
Controller

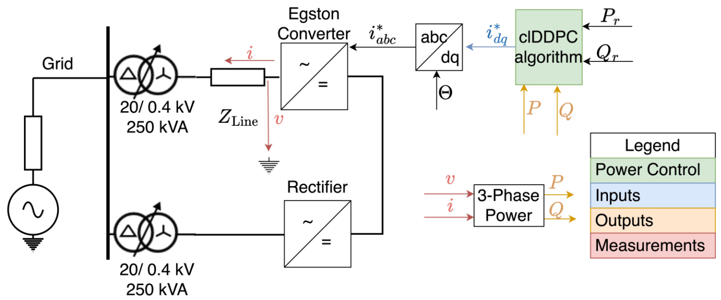
- Reference – P_{set}, Q_{set}
- Feedback – P_{real}, Q_{real}
- Output – $I_{d,set}$, $I_{q,set}$ reference for inverter

Early results



- Decent tracking
- Severe overshoots
  - Cost function should be updated
- Dropouts
  - C-solver has bugs



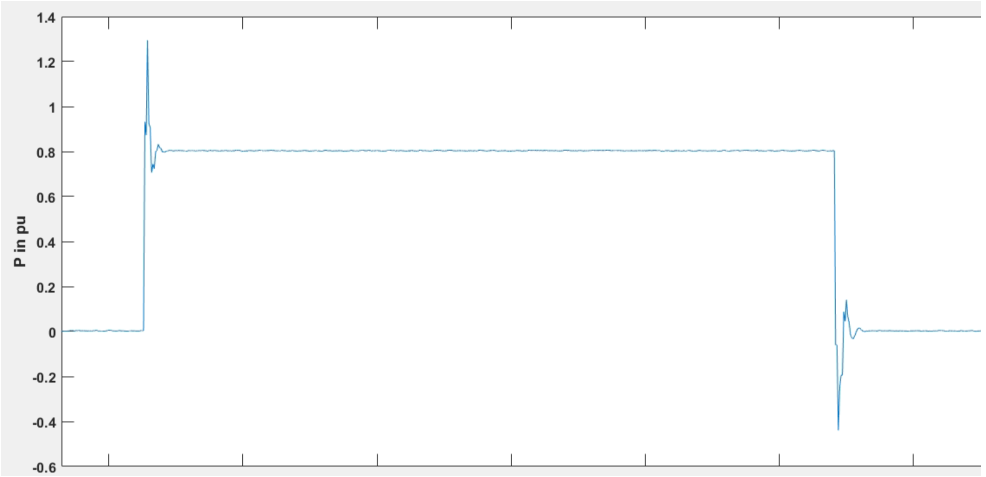


Controller

- Reference – P_{set}, Q_{set}
- Feedback – P_{real}, Q_{real}
- Output – $I_{d,set}$, $I_{q,set}$ reference for inverter

- Dropouts fixed by anomaly detection
  - If error, take previous value
- Overshoot remains an issue

Removing overshoot



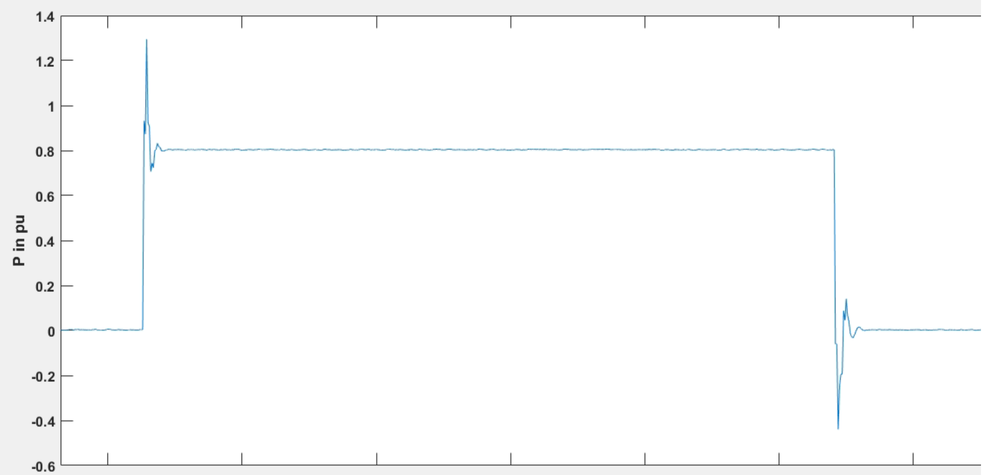
How to remove overshoot without Integral control?

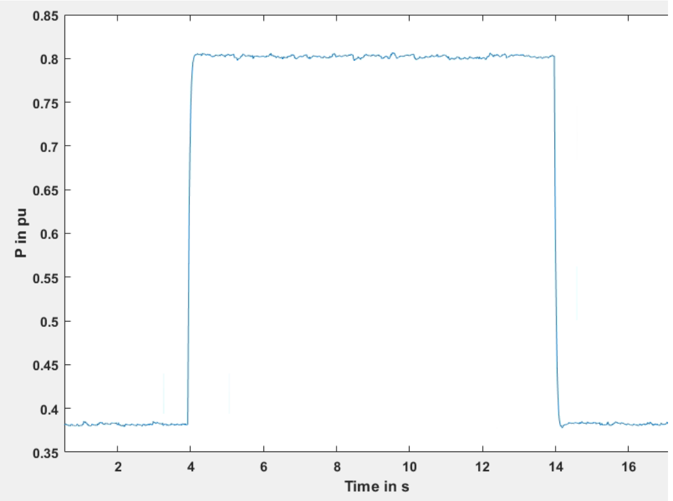
- Penalise the rate of change of input.

In other words,

- For the same final control action, steady rise is cheaper than oscillations.

Removing overshoot





How to remove overshoot without Integral control?

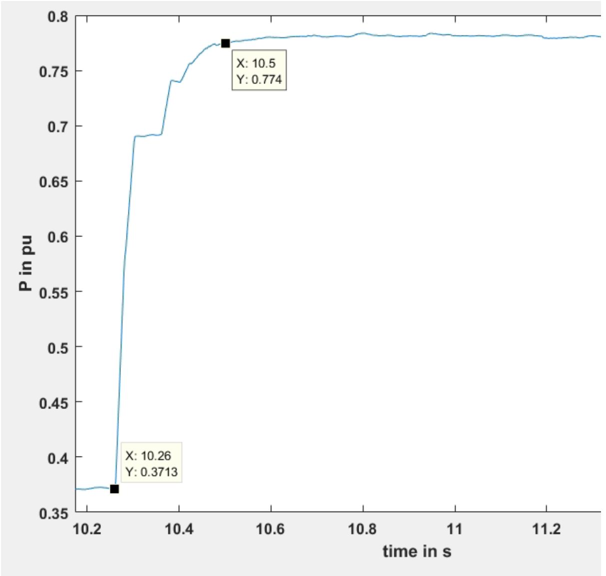
- Penalise the rate of change of input.

In other words,

- For the same final control action, steady rise is cheaper than oscillations.

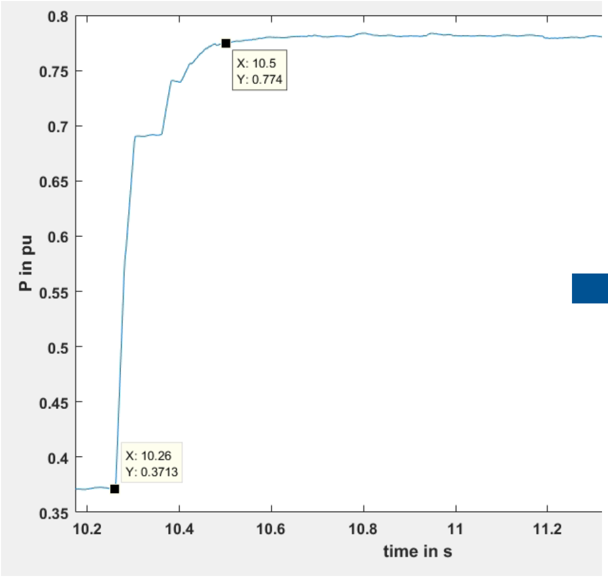
- Overshoot all but eliminated.
- Steady state error can be improved

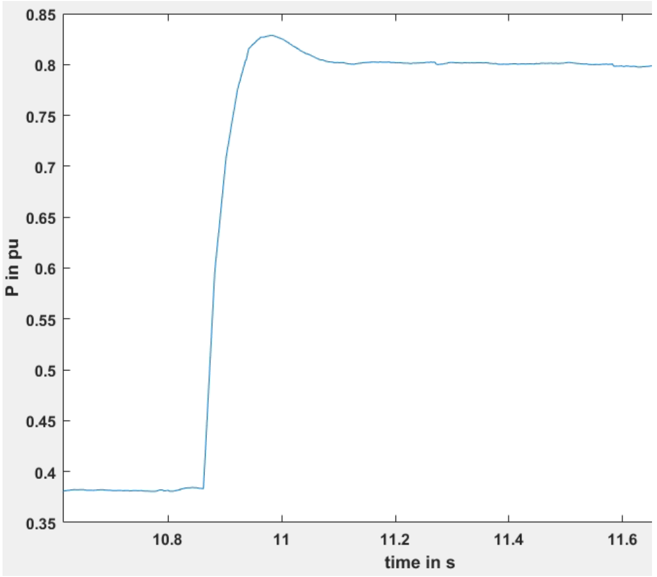
Evolution of results



- Anomaly detection is acting like a Low pass filter.
- Must change solver!!

Evolution of results

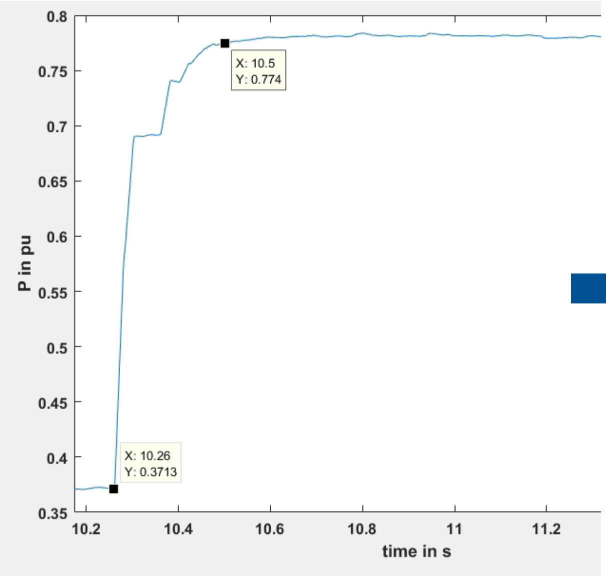


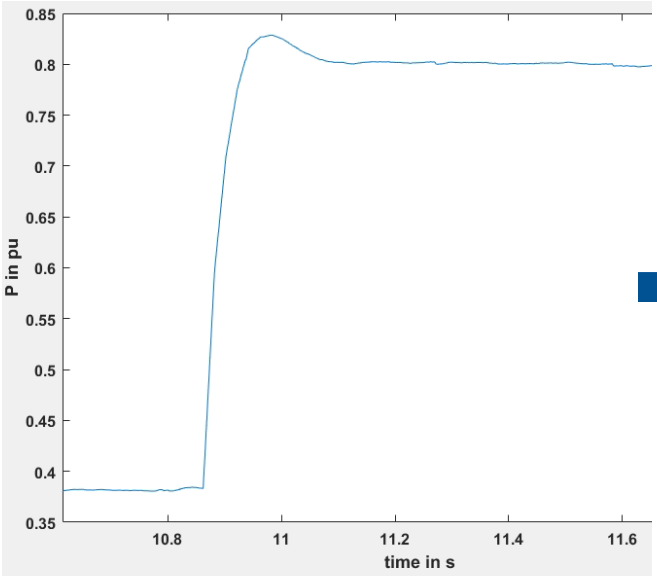


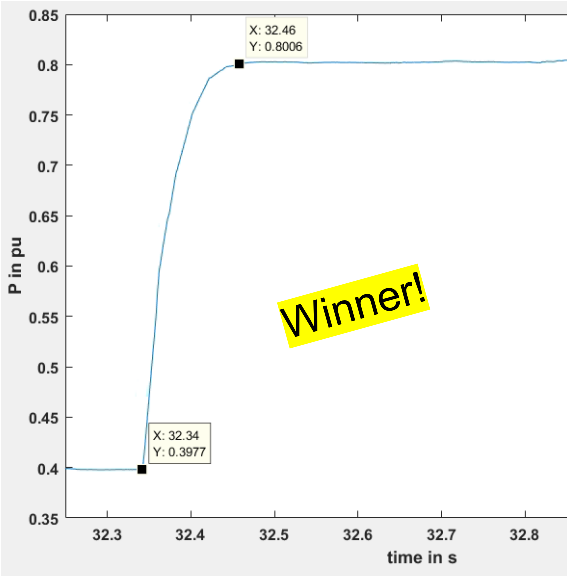
- Anomaly detection is acting like a Low pass filter.
- Must change solver!!

- Switched to MOSEK and CVXPY
- Stable behaviour without anomaly filter
- A bit more overshoot
- Get more data

Evolution of results





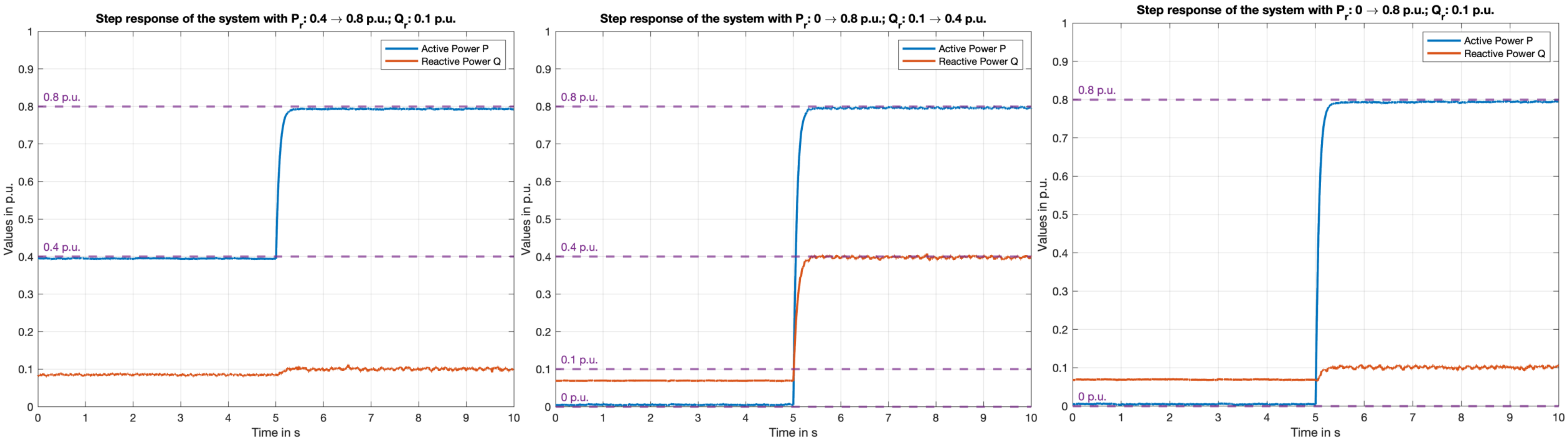


- Anomaly detection is acting like a Low pass filter.
- Must change solver!!

- Switched to MOSEK and CVXPY
- Stable behaviour without anomaly filter
- A bit more overshoot
- Get more data

- Increased data from 500 to 5000 points
- Adjusted the cost weights
- Near zero tracking error
- No overshoot
- Best rise time

Final results



Learnings during experiment

- The grid is linear – this is a valid assumption!
  - Training at one loading and controlling at another loading is possible

- Grid drifts in hours or days.
  - Must repeat training periodically.
  - Good thing it takes less than 30s and can be done online.

- Increasing excitation power of training signal has bigger impact than increasing data collection window.

- Safety filters like anomaly detection causes slow response.

- A variety of control functions can be served by the predictive controller
  - Integral-like part to remove overshoot

- Inverter can be operated in Grid following or Grid forming mode.
  - Trialed a Virtual synchronous machine as well

Conclusion

It works!

You can control,

- a grid following or grid forming inverter,
- to achieve zero steady state error and no overshoot,
- with zero knowledge of the grid,
- using only 500 training points,
- in a mathematically verifiable data-driven model,
- while rejecting controller bias,
- being robust to noise, and
- being computationally tractable for online operation, with
- guaranteed system behaviour.

References

[1] Willems, J., et al. "A note on persistency of excitation," in Systems & Control Letters, vol. 54, no. 4, pp. 325–329, 2005.

[2] C. De Persis, P. Tesi. "Formulas for Data-Driven Control: Stabilization, Optimality, and Robustness," in IEEE Transactions on Automatic Control, vol. 65, no. 3, pp. 909–924, 2020.

[3] J. Coulson, J. Lygeros, F. Dörfler, "Data-Enabled Predictive Control: In the Shallows of the DeePC," in 2019 18th European Control Conference (ECC), 2019, pp. 307–312.

[4] J. Coulson, J. Lygeros, F. Dörfler, "Regularized and Distributionally Robust Data-Enabled Predictive Control," in 2019 IEEE 58th Conference on Decision and Control (CDC), 2019, pp. 2696–2701

[5] Huang, L., et al, "Data-Enabled Predictive Control for Grid-Connected Power Converters," in 2019 IEEE 58th Conference on Decision and Control (CDC), 2019, pp. 8130–8135.

[6] Huang, L., et al. "Decentralized Data-Enabled Predictive Control for Power System Oscillation Damping," in IEEE Transactions on Control Systems Technology, vol. 30, no. 3, pp. 1065–1077, 2022.

[7] Chiuso, A., et al, "Harnessing Uncertainty for a Separation Principle in Direct Data-Driven Predictive Control," 2023, arXiv preprint.

[8] Rocabert, J., et al. "Control of Power Converters in AC Microgrids," in IEEE Transactions on Power Electronics, vol. 27, no. 11, pp. 4734–4749, 2012.

[9] H. Beck, R. Hesse, "Virtual synchronous machine," in 2007 9th International Conference on Electrical Power Quality and Utilisation, 2007, pp. 1–6.

[10] Q. Zhong, G. Weiss. "Synchronverters: Inverters That Mimic Synchronous Generators," in IEEE Transactions on Industrial Electronics, vol. 58, no. 4, pp. 1259–1267, 2011.

[11] Zhao, J., et al. "Roles of Dynamic State Estimation in Power System Modeling, Monitoring and Operation," in IEEE Transactions on Power Systems, vol. 36, no. 3, pp. 2462–2472, 2021.

[12] Guruwacharya, N., et al. "Data-Driven Modeling of Grid-Forming Inverter Dynamics Using Power Hardware-in-the-Loop Experimentation," in IEEE Access, vol. 12, pp. 52267–52281, 2024.

[13] Peschon, J., et al. "Sensitivity in Power Systems," in IEEE Transactions on Power Apparatus and Systems, vol. PAS-87, no. 8, pp. 1687–1696, 1968.

[14] M. Begovic, A. Phadke. "Control of voltage stability using sensitivity analysis," in IEEE Transactions on Power Systems, vol. 7, no. 1, pp. 114–123, 1992.

[15] Christakou, K., et al. "Efficient Computation of Sensitivity Coefficients of Node Voltages and Line Currents in Unbalanced Radial Electrical Distribution Networks," in IEEE Transactions on Smart Grid, vol. 4, no. 2; 2013.

[16] R. Gupta and M. Paolone, "Experimental Validation of Model-less Robust Voltage Control using Measurement-based Estimated Voltage Sensitivity Coefficients," 2023 IEEE Belgrade PowerTech, Belgrade, Serbia, 2023

[17] Toubeau, J. et.al , “Deep Reinforcement Learning-Based Voltage Control to Deal with Model Uncertainties in Distribution Networks”. Energies 2020, 13, 3928.