Multi-Rate Moving Horizon Estimation for an Electric Arc Furnace Steelmaking Process

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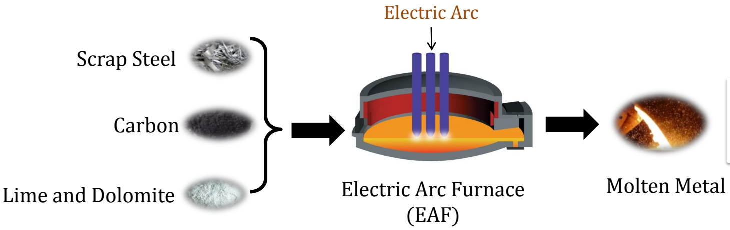
Outline

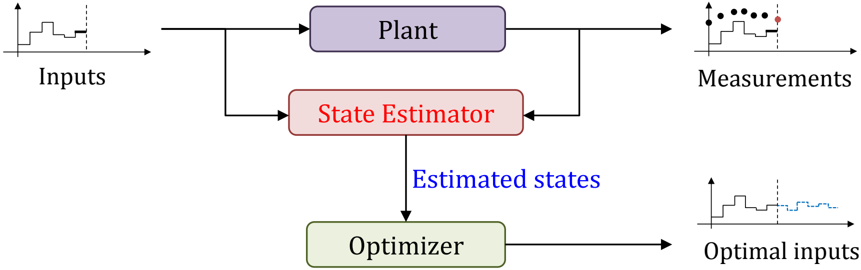
Introduction



EAF: 40 % steel production in North America

High energy intensive batch process, Low level of automation

Objective: Develop estimation and control strategies for EAF



Nonlinear State Estimation Methods

Nonlinear State Estimation

Moving Horizon Estimation (MHE)[1]
since 1990s

Dynamic Optimization

Nonlinear Model

- Handles constraints directly
- Uses state-of-the-art solvers

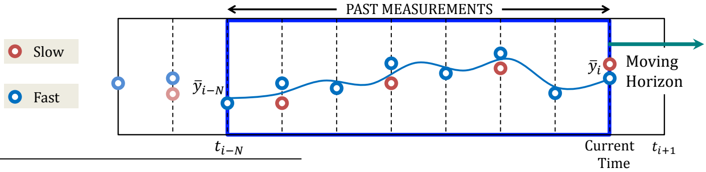
Kalman Filters (KF)
since 1960s

Extended KF, Unscented KF

Prediction

Correction

We apply MHE with irregular sampling:



[1] Rao, C.V., Rawlings, J.B. and Lee, J.H., (2001). Automatica, 37(10), 1619-1628.

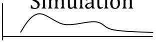
Dynamic Optimization Solution Methods

Sequential

Optimization

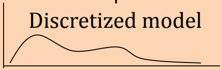
Input profile

Simulation

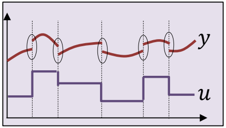


Simultaneous

Optimization
+
Discretized model



Multiple-shooting



Commercial code: **gPROMS**

- Robust solver for large DAE system with complex dynamics
- Less sensitive to initialization than simultaneous method

- Extensively explored for MHE applications[2,3]
- Tools: AMPL (IPOPT), MUSCOD II

- Better solution time
- Sensitive to initialization
- Easy incorporation of constraints

MHE in gPROMS? → As a parameter estimation problem![4]

How to initialize MHE problems? → Use the time between sampling times!

Key challenge: Online computational complexity for large scale application

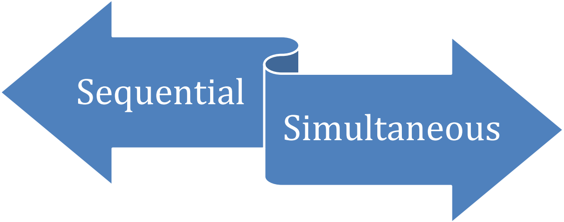
[2] Zavala, V.M. and Biegler, L.T., (2001). Computers & Chemical Engineering, 33(1), 379-390.

[3] Kraus, T., Kuhl, P., Wirsching, L., Bock, H.G., and Diehl, M. (2006). 2006 IEEE International Conference, 377-382.

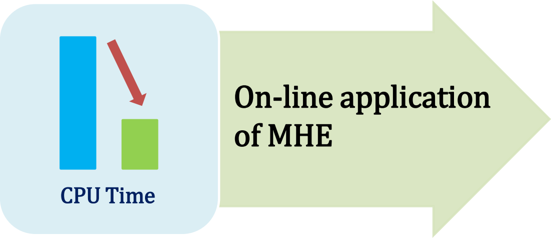
[4] Shyamal, S. and Swartz, C.L.E, (2016). 2016 DYCOPS-CAB, 1175-1180.

Objectives

- **Application of multi-rate MHE for EAF**
- **Compare 2 implementation strategies:**

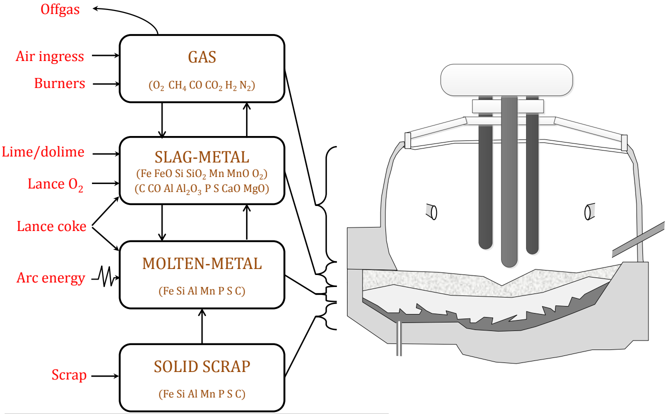


- **Development of implementation/computation enhancement strategies**



Dynamic First Principles Model of EAF[5]

- Multi-zone System: Chemical equilibrium within slag and gas zones (reactions limited by mass transfer)
- Mass and energy balances; diffusion and heat transfer relationships

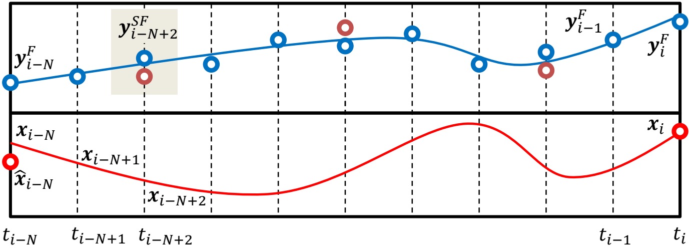


Parameter estimation using plant data

DAE system in gPROMS: 28 differential & 518 algebraic variables

[5] MacRosty, R. D. & Swartz, C. L. E. (2005). Ind.Eng.Chem.Res., 44, 8067-8083.

Multi-rate MHE (w/ Batch MHE)



$$\min_{\mathbf{x}_{i-N},\mathbf{w}_k} \sum_{k=i-N}^{i-1} \underbrace{||\mathbf{w}_k||^2_{Q^{-1}}}_{\text{Model noise}} + \sum_{\substack{k=i-N\\k\in\mathbb{I}_F}}^{i} \underbrace{||\mathbf{v}^F_k||^2_{(R^F)^{-1}}}_{\text{Measurement noise (only fast)}}$$

$$+ \sum_{\substack{k=i-N\\k\in\mathbb{I}_{SF}}}^{i} \underbrace{||\mathbf{v}^{SF}_k||^2_{(R^{SF})^{-1}}}_{\text{Measurement noise (fast+slow)}} + \underbrace{||\mathbf{x}_{i-N} - \hat{\mathbf{x}}_{i-N}||_{S_i^{-1}}}_{\text{Initial state discrepancy}}$$

Subject to: $\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{w}_k, \quad \ldots(1)$

$\mathbf{y}^F_k = \mathbf{h}^F(\mathbf{x}_k) + \mathbf{v}^F_k, \;\; k \in \mathbb{I}_F; \qquad \mathbf{y}^{SF}_k = \mathbf{h}^{SF}(\mathbf{x}_k) + \mathbf{v}^{SF}_k, \;\; k \in \mathbb{I}_{SF}$

State constraints, $\mathbf{w}_k \in W$

Tuning matrices : Q, R and S_i (with EKF update)

Sequential Approach: Model Noise Approximation

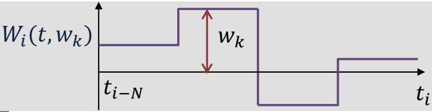
gPROMS does not permit direct specification of **w** as in eq. (1)

Discrete values of process noise

$w_{i-N}, w_{i-N+1}, \dots, w_{i-1}$

Term in MHE objective function:
$\sum_{i-N}^{i-1} ||w_k||^2_{Q^{-1}}$

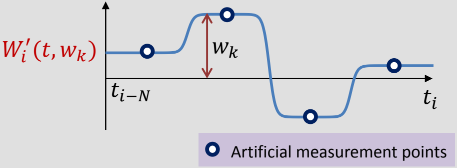
Discontinuous piecewise constant function



Continuous function with $\{w_{i-N}, w_{i-N+1}, \dots, w_{i-1}\}$ as parameters

Approximation based on **tanh** function:

$$W_i'(t, w_k) = \frac{1}{2}(w_{i-N} + w_{i-1} + \sum_{k=i-N}^{i-2} (w_{k+1} - w_k) \tanh \frac{\alpha}{\delta t}(t - t_k))$$



Term in MHE objective function:
$\sum_{i-N}^{i-1} ||W_i'(t_{k+\delta t/2}, w_k) - 0||^2_{Q^{-1}}$

Parameter Estimation Framework

Objective function

$$\min_{\mathbf{x0}_i, \mathbf{w}_k} \sum_{\substack{\text{past time} \\ \text{history}}} ||\mathbf{W}_i'(t_{k+\frac{\delta t}{2}}, \mathbf{w}_k)||^2_{Q^{-1}} + \sum_{k \in \mathbb{I}_F} \left| \begin{matrix}\text{Noise of fast} \\ \text{measurements}\end{matrix} \right|^2_{(R^F)^{-1}}$$

$$+ \sum_{k \in \mathbb{I}_{SF}} \left| \begin{matrix}\text{Noise of slow and} \\ \text{fast measurements}\end{matrix} \right|^2_{(R^{SF})^{-1}} + \underbrace{J_i}_{\sqrt{\left(\begin{matrix}\text{Initial state} \\ \text{discrepancy}\end{matrix}\right)^2_{S_i^{-1}}}}{}^2$$

Constraints

- Nonlinear Model: $\dot{\mathbf{x}}(t) = \mathbf{f}(\cdot) + \mathbf{W}_i'(t, \mathbf{w}_k)$, Algebraic equations
- Model noise function: $\mathbf{W}_i'(t, \mathbf{w}_k) = \tanh$ approximation function
- Equations to express initial condition as parameters
- Bounds on initial state and model noise parameters

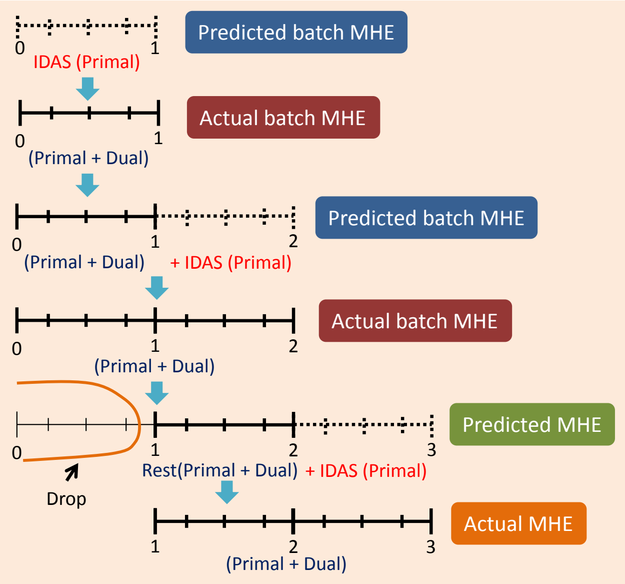
Iinitialization Scheme for Simultaneous Approach

1 Disturbance-free simulation of model to get predicted measurements

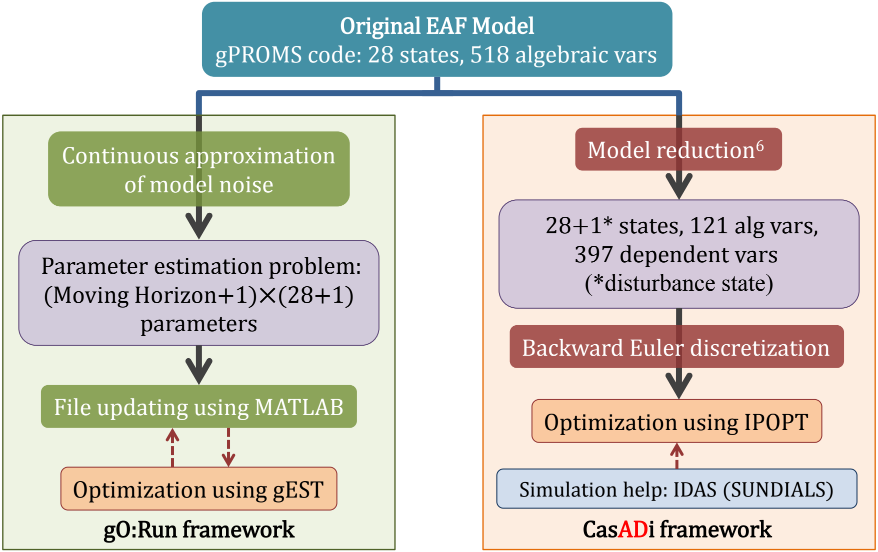
2 Solve the predicted MHE problem

3 Use the solution of predicted solve to initialize actual MHE problem

4 Solve actual MHE problem



Implementation

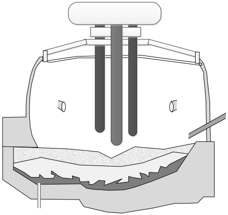


Plant simulation for both schemes in **CasADi**

[6] Eliminate algebraic variables and equations by transforming them into outputs.

Case Study

- Length of batch process: 60 minutes
- Estimation horizon: 6 min
- MHE's ability demonstrated in presence of
  - Plant-model mismatch
  - Unknown initial conditions of states
  - Measurement noise



- Structure of slow and fast measurements:

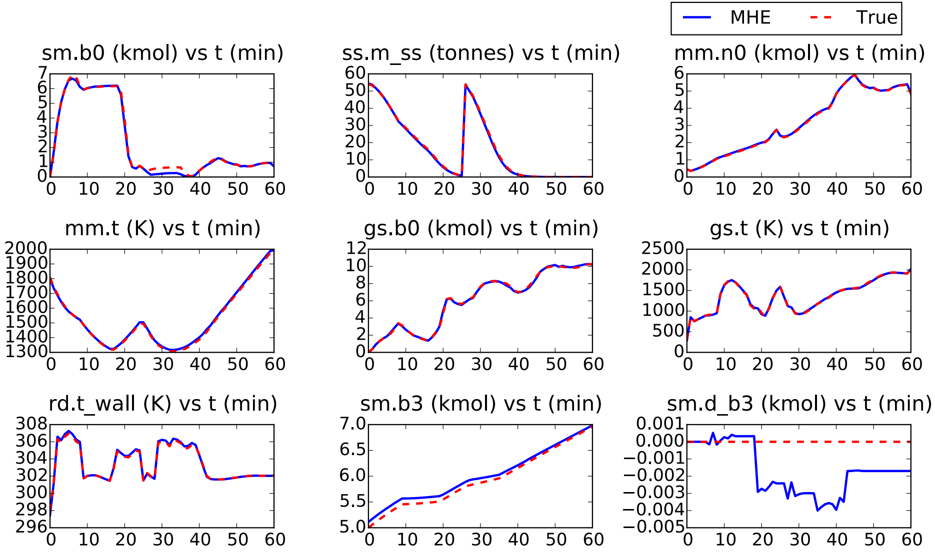
Time (min)	0 . . . 42	43	44 . . . 46	47	48 . . . 60
Number of measured variables	6	**13**	6	**8**	6

Off-gas compositions (CO, CO_2, O_2, H_2), T_{roof}, T_{wall}	Every 1 min
Slag compositions (FeO, Al_2O_3, SiO_2, MgO, CaO)	t=43 min
Molten-metal temperature and carbon content	t=43 & 47 min

- System observable (Lowest observability metric[7] value: 7×10^{-07})

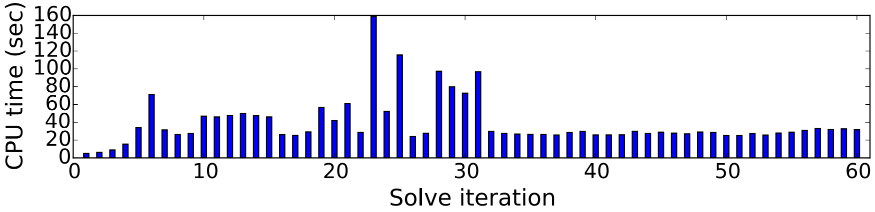
[7] Ji, L. and Rawlings, J.B., (2015). Computers & Chemical Engineering, 80, 63-72.

Results (State Estimates)

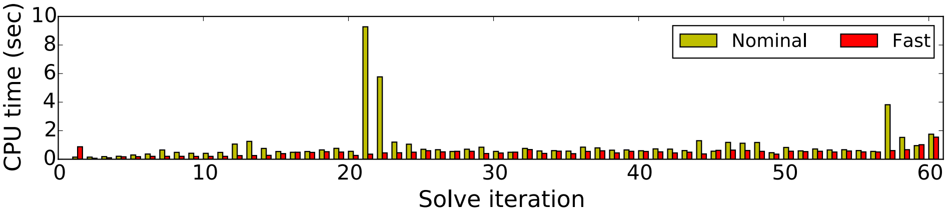


sm.b0: C in slag	ss.m_ss: Solid scrap mass	mm.n0: C in Molten metal
gs.b0: C in gas	sm.b3: Mn in slag	sm.d_b3: Disturbance state

Computational Results



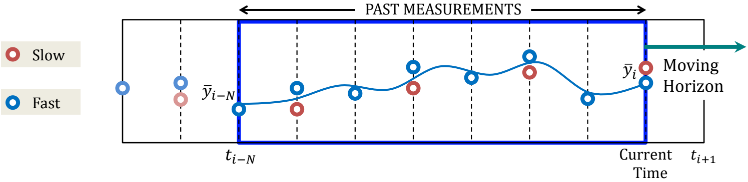
Sequential method using `gO:Run/gEST`: Average CPU time: 39 sec



Simultaneous method using `CasADi/IPOPT`:
Average CPU time: 1 sec (nominal MHE), 0.5 sec (fast MHE)

Summary

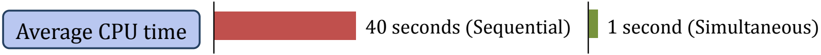
1. Multi-rate MHE implemented for EAF operation using `CasADi` and `gPROMS`: demonstrated excellent performance
2. MHE formulation can readily include multi-rate measurements



3. Presented novel initialization scheme for MHE

1 Get predicted measurements → 2 Solve the predicted MHE problem → 3 Use the solution to initialise actual MHE

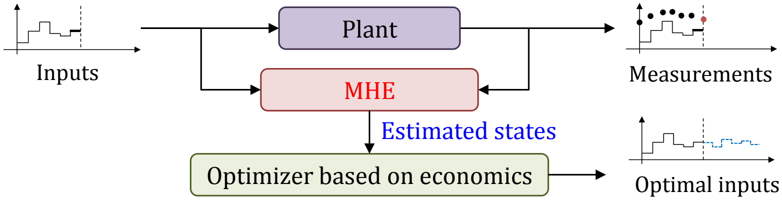
4. Simultaneous approach showed better computational performance



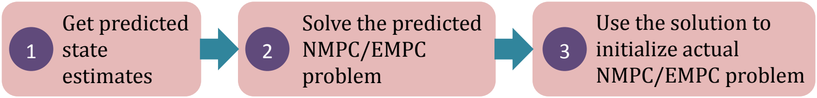
5. 50% solve time reduction due to better initialization of MHE

Current Work and Future Directions

1. Incorporate MHE within real-time optimization framework



2. Explore effects of increased frequency of slow measurements
3. Use information from optimization solve to update arrival cost[8]
4. Embed MHE within NMPC/EMPC application
5. Apply the initialization scheme for NMPC/EMPC



[8] López-Negrete, R. and Biegler, L.T., (2012). Journal of Process Control, 22(4), 677-688.

Acknowledgements

- McMaster Advanced Control Consortium

MACC
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- McMaster Steel Research Center (SRC)

McMaster University