Dynamic Optimization of Electric Arc Furnace Operation with State Estimation as a Decision Support Tool

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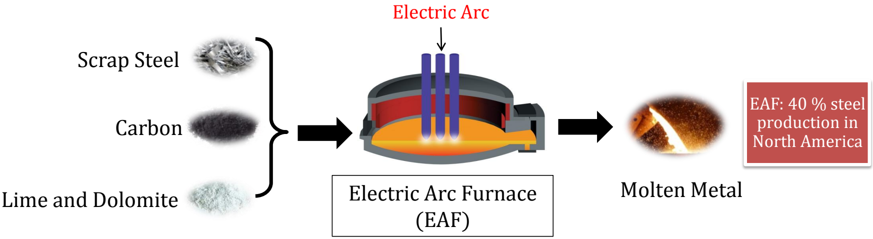
Motivation

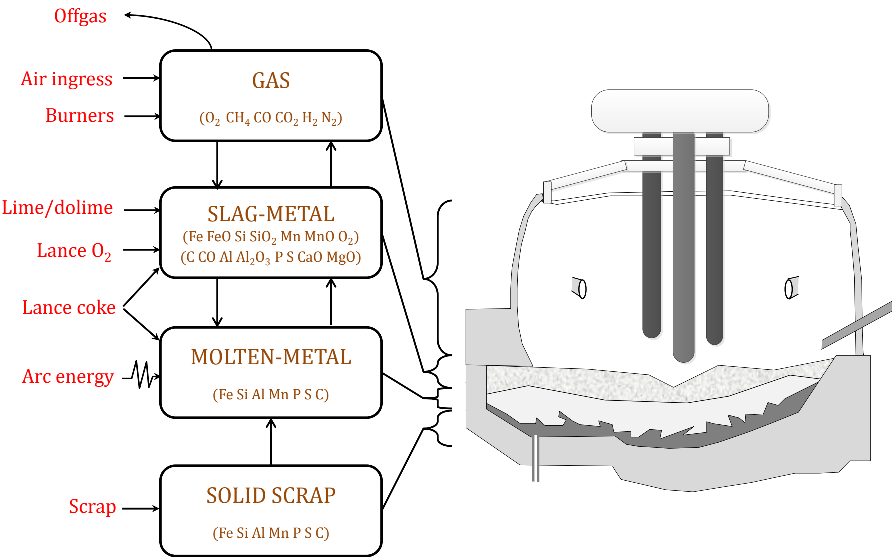


High energy intensive batch process

Objective: Develop a decision-support tool to determine economically optimal policies for EAF operation

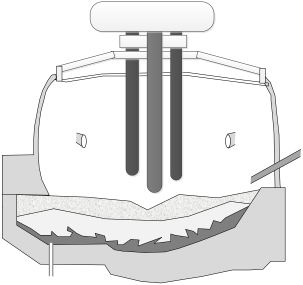
Outline

Electric Arc Furnace (EAF) Modeling Paradigm



EAF Dynamic Model[1]

- Chemical equilibrium within zones
- Reaction limited by mass transfer
- Mass and energy balances
- Equilibrium, diffusion and heat transfer relationships
- Parameter estimation using plant data



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

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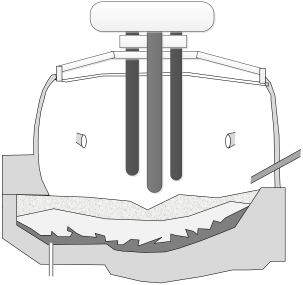

- DAE system within gPROMS
- 30 differential and 1050 algebraic variables

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

Dynamic Optimization Formulation and Solution

Find: Input trajectories that

Maximize: $\text{Selling price of steel} \times M_{steel} - \sum_{inputs} \text{Cost price} \times \int_{t_0}^{t_f} \text{Input}$

Subject to: DAE Model

Input, operational and product quality constraints

[2] Chong, Z. (2012). Ph.D. thesis, McMaster University

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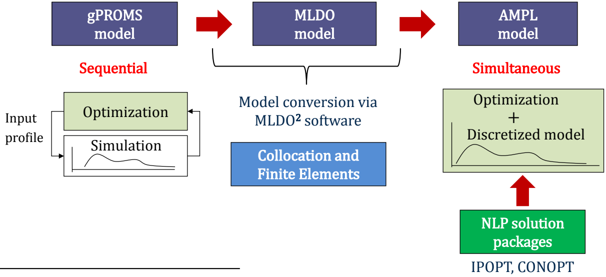

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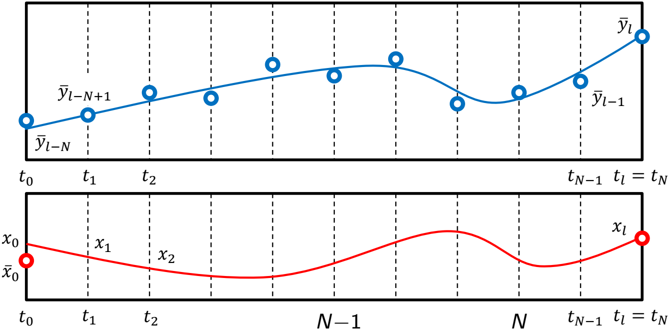
Moving Horizon Estimation (MHE)



$$\min_{x_0, w_k} \; ||(x_0 - \bar{x}_0)||_P^2 + \sum_{k=0}^{N-1} ||w_k||_Q^2 + \sum_{k=0}^{N} ||v_k||_R^2$$

$$\text{s.t.} \quad x_{k+1} = f_k(x_k, w_k), \qquad x_k \in \mathbb{X}$$

$$\bar{y}_{k+l-N} = h_k(x_k) + v_k$$

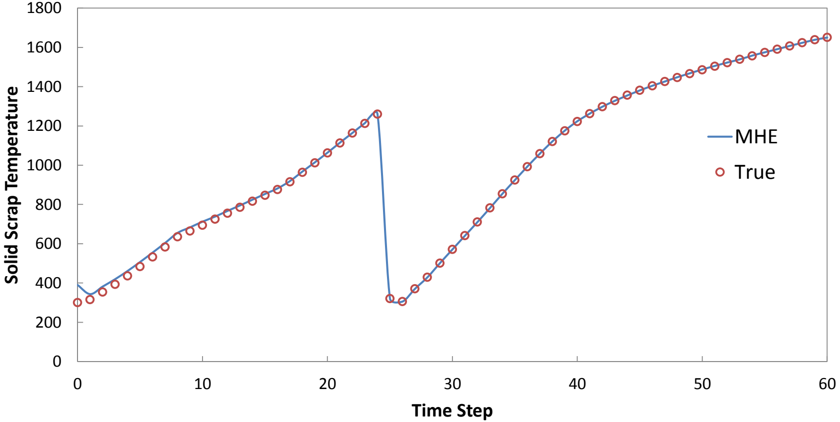
Continuous Time → Simultaneous Collocation Approach

MHE Solution Strategy

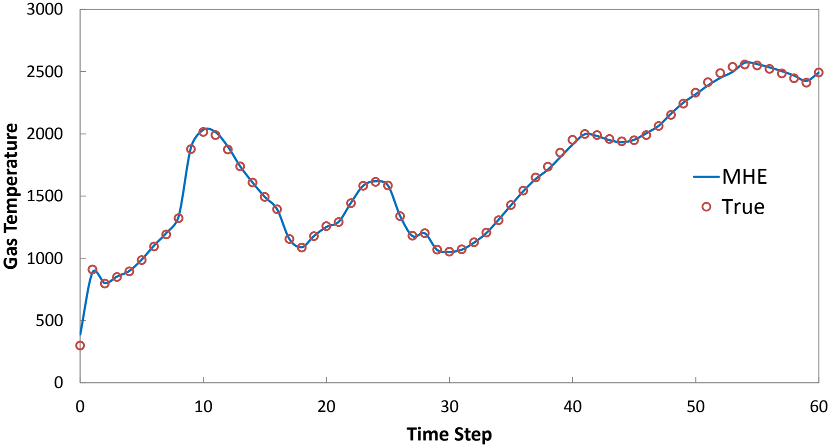
- Discretized DAE Model $\rightarrow$ Large Scale & Sparse NLP
- NLP solver: IPOPT with linear solver ma27
- No plant-model mismatch
- Challenge: Discontinuity due to 2 charges of scrap (0 & 25 min)

State variables	30
Measured state variables	13
Estimation Horizon (min)	10
Total Horizon (min)	60
Sample Time (min)	1

State Variable Profile (Solid Scrap Temperature)

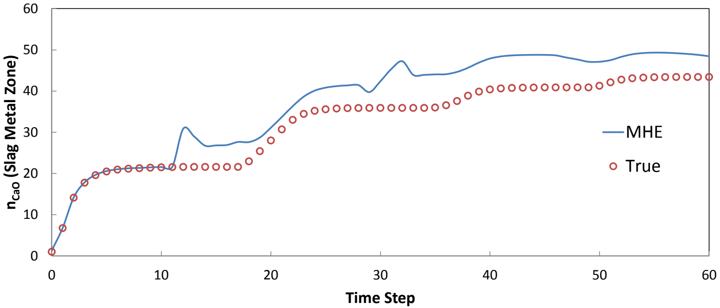


State Variable Profile (Gas Zone Temperature)



Unresolved Issues

- Observability analysis: Solutions Satisfy Second Order Conditions then System Locally Observable[3]



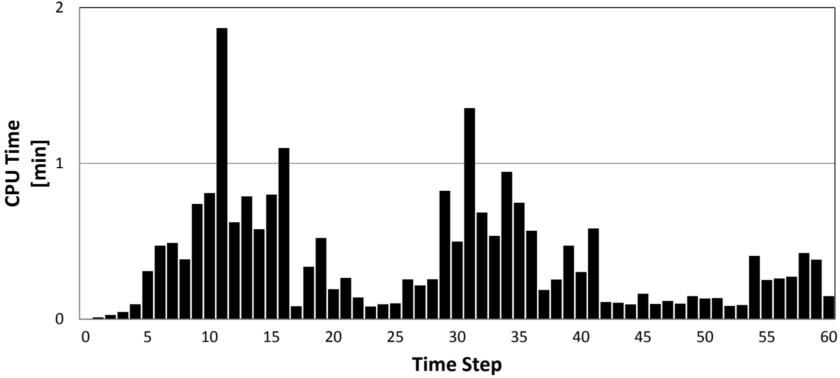
- Use of actual measurements rather than measured states
- Estimator tuning
- Infrequent observation of certain measurements

[3] Zavala, V.M. & Biegler, L.T. (2009) Computers & Chemical Engineering 33.10 : 1735-1746.

Computational Result

Performance of NLP Solver in background

Average Solution Time: 23 sec



Application

Off-line

Dynamic optimization

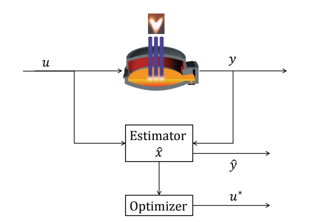
- Initial conditions specified
- Constraints specified by user
- Selected inputs could be fixed

Dynamic Simulation

- All inputs fixed
- System trajectories computed
- Useful for what-if studies

Real Time

- Model runs in parallel with plant
- Dynamic optimization or simulation
- States/model parameters inferred using plant measurements



Conclusions

1. EAF dynamic model successfully translated into AMPL, with minor simplifying assumptions
2. Dynamic Optimization completed
3. MHE implemented with no plant-model mismatch

Future Work

1. Moving horizon state estimation
    - Quantify the observability
    - MHE with parametric mismatch and measurement noise
    - Detailed performance evaluation
    - Fast MHE optimization solution using NLP sensitivity
    - Nonlinear Model Predictive Control (NMPC)
2. Evaluation of decision support tool on simulated plant
    - Detailed model with perturbed parameters to serve as plant
    - Real-time system with state estimation applied under various scenarios of disturbances and model mismatch
    - Performance evaluated and compared against typical operating strategies
3. Evaluation on industrial plant

Acknowledgements

- McMaster Advanced Control Consortium

  MACC
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- McMaster Steel Research Center (SRC)

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