# Real-Time Energy Management for Electric Arc Furnace Operation

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# Outline

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3. Implementation
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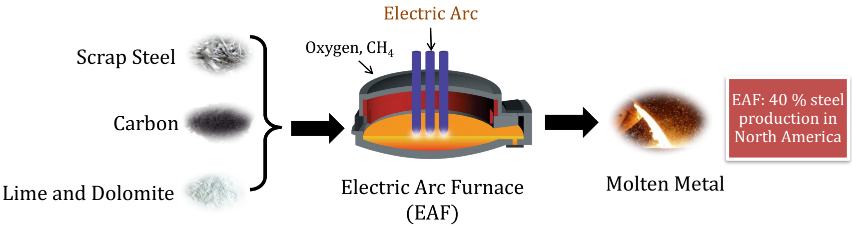
# Introduction




High energy intensive batch process, Low level of automation, Limited measurements

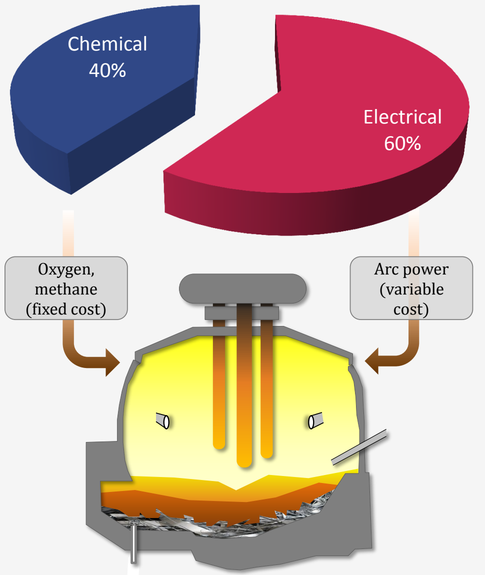
## Objectives

- Develop real-time energy management strategy to determine economically optimal operating policies for EAF

## Approach

- Develop dynamic model and rigorous optimization framework
- Collaborate with industrial partners for model validation, optimization problem formulation and in-plant evaluation

# Energy Management for Electric Arc Furnace



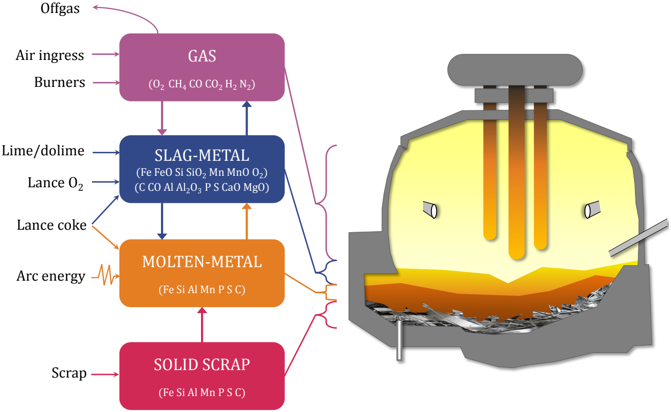

Optimal electrical and chemical energy usage

Electricity supply dependent on deregulated markets

**Challenge**: Develop efficient energy management strategies in response to external variations

# Dynamic First Principles Model of EAF[1]

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

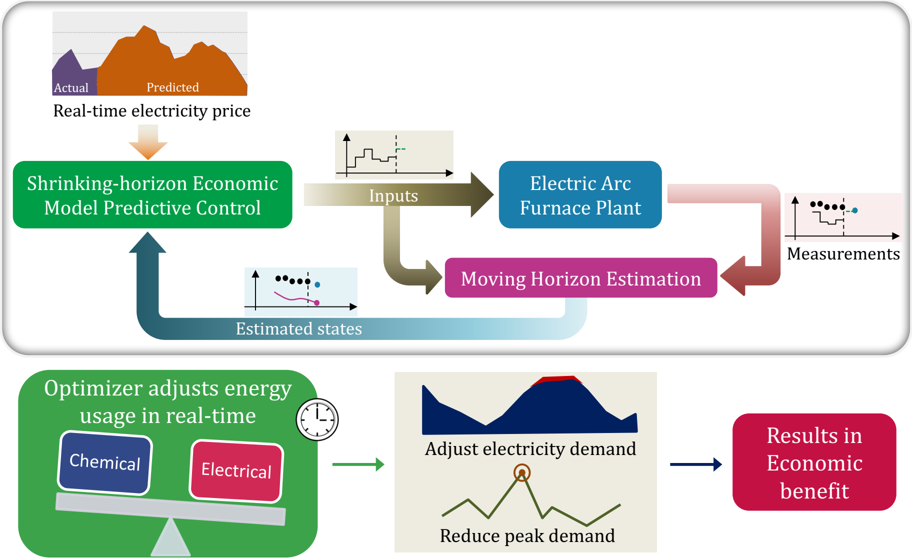



Parameter estimation using plant data

Large scale DAE system: 28 differential & 518 algebraic variables

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

# Real-Time Energy Management




Key idea: Offset high price electricity with chemical energy

# Economic Model Predictive Control

Objective function (with time varying cost coefficients)

$$\max_{\mathbf{u}(t)} \quad c_0 M_{steel}(t_f) - \left( \int_{t_i}^{t_f} c_1(t) P dt + c_2 \int_{t_i}^{t_f} F_{CH_4,brnr} dt \right.$$
$$\left. + c_3 \int_{t_i}^{t_f} (F_{O_2,Jetbox1} + F_{O_2,Jetbox2} + F_{O_2,Jetbox3}) dt \right)$$

Constraints

*Model equations:*

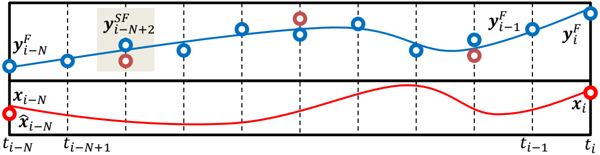
$$\dot{\mathbf{x}}(t) = \mathbf{f}_x(\mathbf{x}(t), \mathbf{z}(t), \mathbf{u}(t)), \quad \mathbf{0} = \mathbf{f}_z(\mathbf{x}(t), \mathbf{z}(t), \mathbf{u}(t))$$
$$\mathbf{y}(t) = \mathbf{h}(\mathbf{x}(t), \mathbf{z}(t), \mathbf{u}(t))$$

*Input constraints:*

$$P^{min}(t) \leq P \leq P^{max}(t), \quad F_k^{min}(t) \leq F_k \leq F_k^{max}(t)$$

**u**: $P$ (Electrical arc power), $F_k$ (Flow rates of natural gas and oxygen)

# Multi-rate MHE[2,3] (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: $\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{w}_k,$

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

$\mathbf{x}^{LB} \leq \mathbf{x_k} \leq \mathbf{x}^{UB}, \ \ \mathbf{w}_k \in W$

Tuning matrices :

$$Q, R \text{ and } S_i \ \left(S_{i+1} = Q + A_i[S_i - S_iC_i^T(R + C_iS_iC_i^T)^{-1}C_iS_i]A_i^{-1}\right)$$

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

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

# Implementation

**Novel Multi-Tiered Initialization**

Background

1. Generate predicted measurements using model
2. Get electricity price forecasts
3. Solve predicted MHE problem & store sol$^n$
4. Solve predicted NMPC problem & store sol$^n$

Online

5. Get actual measurements and use stored sol$^n$ to solve actual MHE problem
6. Use stored sol$^n$ to solve actual NMPC

**Original EAF Model**
gPROMS code: 28 differential states, 518 algebraic vars

Model contraction

28+1* states, 121 alg vars, 397 dependent vars (*disturbance state)

Backward Euler discretization

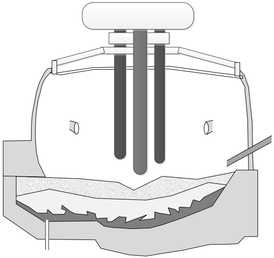
Optimization using IPOPT

Simulation assisted initialization: IDAS (SUNDIALS)

CasADi framework (Python)

# Case Study

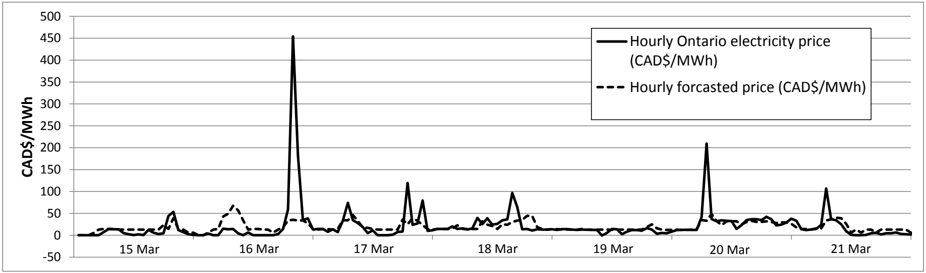
- Realistic electricity price data considered
- Real-Time market (price change every 1 hour)
- NMPC: Shrinking horizon of 60 time steps
- MHE: Moving horizon of 6 time steps
- Multi-rate measurement structure

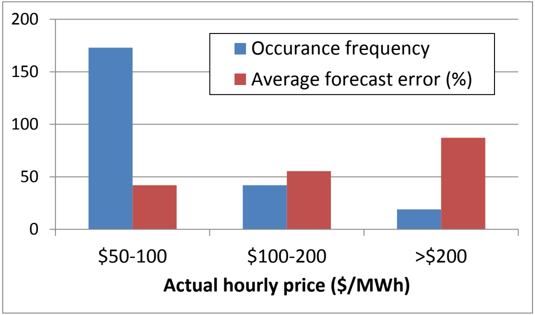


**Compare two closed loop results:**

1. $\text{NMPC}^{\text{nominal}}$: Price profile not updated and forecast price continued to be used even after the change occurs
2. $\text{NMPC}^{\text{update}}$: Price profile updated to reflect actual price obtained from wholesale market

# Actual & Predicted Electricity Prices for Ontario (2016-17)

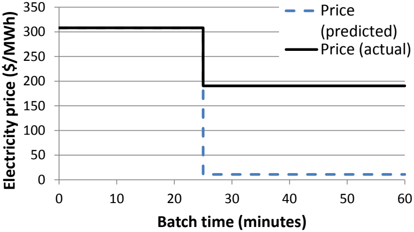


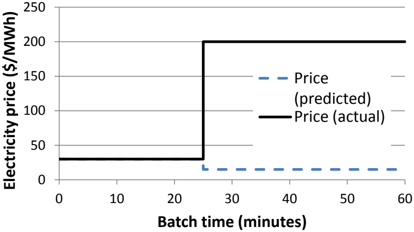

## Price profile charcteristics

- Volatile electricity costs
- High price spikes occur rather frequently
- High forecast error

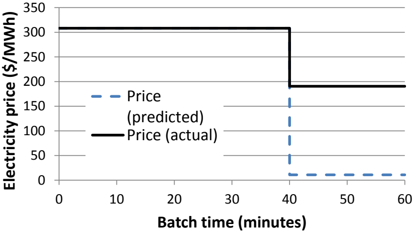
# Price Profiles for Case Studies



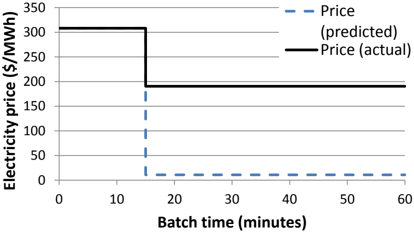

Case Study 1




Case Study 2

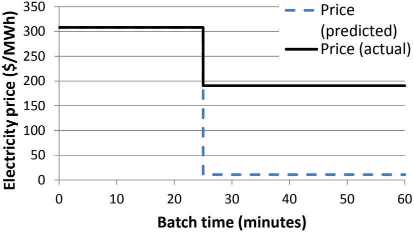



Case Study 3




Case Study 4

# Price Profiles for Case Studies

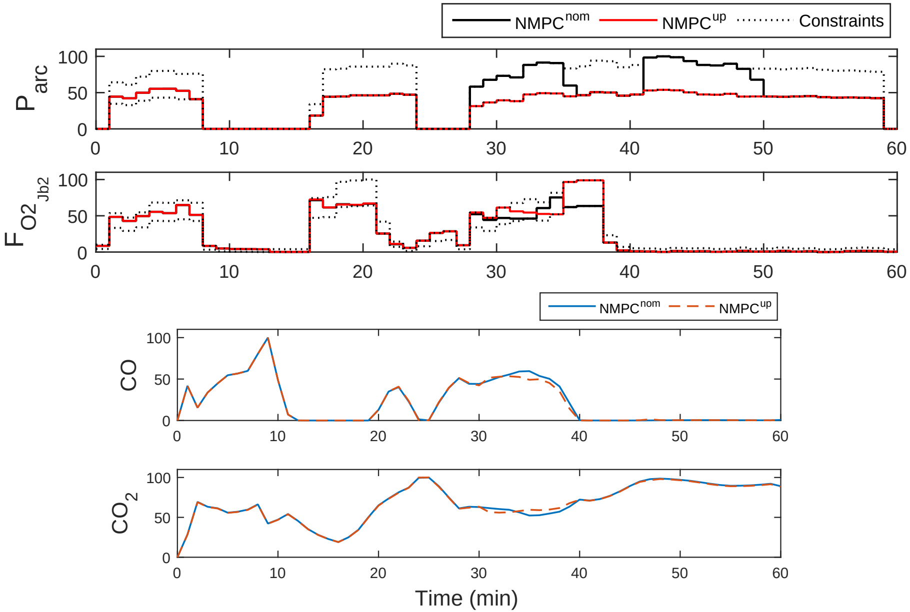



Case Study 1

# Case Study 1 (Compare NMPC$^{update}$ & NMPC$^{nominal}$)

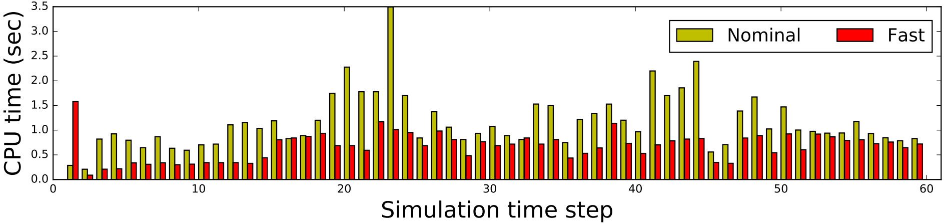
| | |
|---|---|
| Time of electricity price change (min) | 25 |
| Electricity price before the change ($/MWh) | 308 |
| Electricity price after the change ($/MWh) | 190 |
| Predicted electricity price ($/MWh) | 11 |
| Profit increase (%) | 4.6 |
| Decrease in electric power use (%) | 23 |
| Increase in other input use (%) | 1.6 |
| Reduction in peak electricity demand (%) | 45 |

# Case Study 1: Optimal Inputs and Outputs

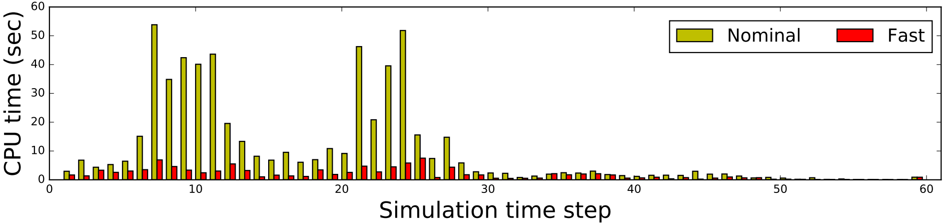


# Case Study 1: Computational Results

MHE:




NMPC:




Average CPU time to solve (sec): 2.6 (novel initialization), 11.2 (nominal)

# Conclusions and Future Work

1. Real-time energy management strategy to reduce energy requirements
   - Optimal energy use while exploiting changing electricity price
2. Case studies demonstrate economic benefit for Real-time Market

| Average Solve Time | 2.6 seconds |
|---|---|

3. Demand peak reduced when changing electricity price profile is used

## Current and Future Work

1. Real-time energy management strategy for 5 and 15 minute market
   - Construct NMPC problem to minimize the peak demand
2. Variable batch length problem
   - Integrate batch control in scheduling

**Acknowledgments**

MACC McMaster Advanced Control Consortium
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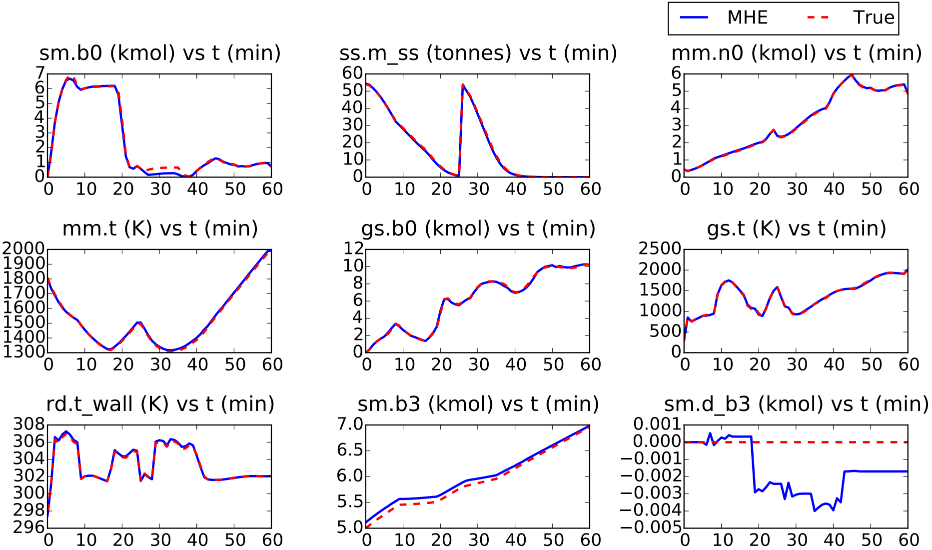
ArcelorMittal
Ontario

# 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 |