Optimization-based Real-time Operating Paradigms for Electric Arc Steelmaking

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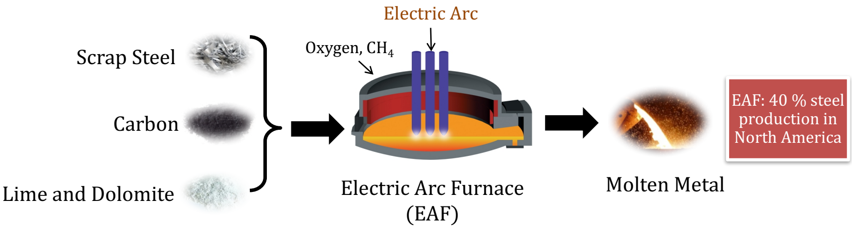
Outline

1. Introduction
   - Electric Arc Furnace Model
2. Real-time Dynamic Optimization Application Paradigms
3. Real-time Advisory System
   - Multi-tiered Optimization
   - Multi-rate Moving Horizon Estimation
   - Case Study 1
4. Real-time Energy Management
   - Economic Model Predictive Control
   - Case Study 2
5. Conclusions and Future Work

Introduction



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

Objectives

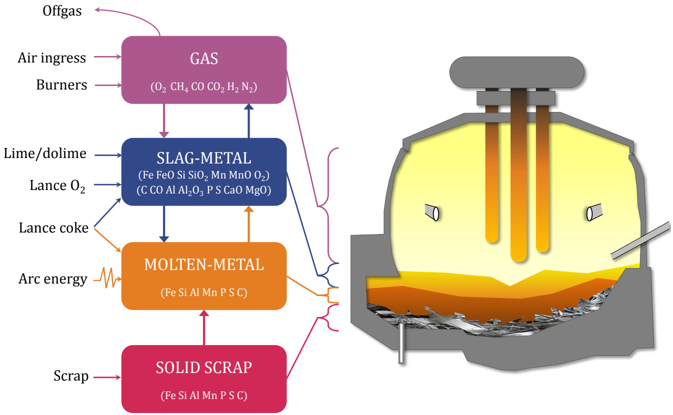
- Develop decision-support tool to determine economically optimal operating policies for EAF

Approach

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

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

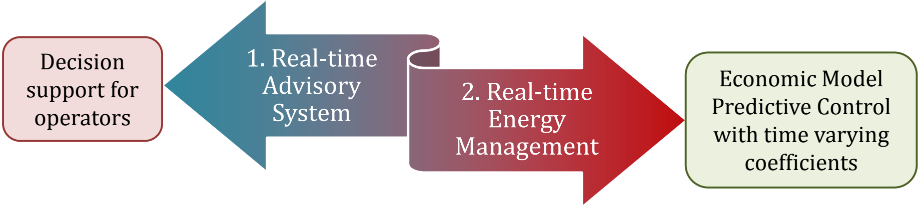


Parameter estimation using plant data

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.

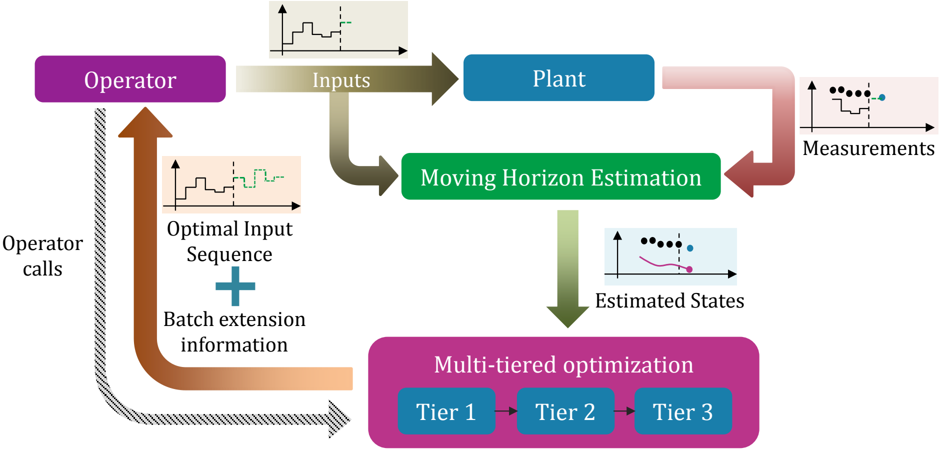
Dynamic Optimization Application Paradigms



Key ingredients

- Dynamic model
- Dynamic optimization
- State estimation
- Novel initialization scheme

Real-time Advisory System



- Model runs in parallel with the plant
- Multi-tiered optimization strategy handles end-point constraints

Economics-based Dynamic Optimization Formulation

Objective function

$$\Phi(t_f) := c_0 M_{steel}(t_f) - \Bigg(c_1 \int_{t_i}^{t_f} P dt + c_2 \int_{t_i}^{t_f} F_{CH_4,brnr} dt + c_3 \int_{t_i}^{t_f} F_{C_{lance}} dt$$

$$+ c_4 \int_{t_i}^{t_f} F_{C_{charge}} dt + c_5 \int_{t_i}^{t_f} (F_{O_2,Jetbox1} + F_{O_2,Jetbox2} + F_{O_2,Jetbox3}) dt$$

$$+ c_6 \int_{t_i}^{t_f} F_{CaO} dt + c_7 \int_{t_i}^{t_f} F_{Dolomite} dt + c_8 \int_{t_i}^{t_f} (F_{1stCharge} + F_{2ndCharge}) dt \Bigg)$$

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

Path constraints: $T_{wall}(t) \le T_{wall}^{max}, \quad T_{roof}(t) \le T_{roof}^{max}$

End-point constraints: $m_{ss}(t_f) \le \delta_{ss}, \quad y_{carbon}(t_f) \le Y_c^{max}$

Multi-tiered Optimization

Multi-Tiered Optimization for end-point constraint handling

Tier 1 — Direct Optimization

- **Move to next tier**
  In response to problem found to be infeasible or maximum number of iterations reached

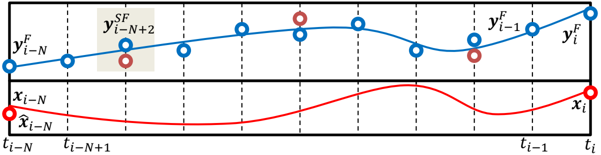
Tier 2 — Feasibility through horizon extension (serial/parallel)

- Solve problems with integral time step extensions
- **Move to next tier**
  If problem found to be infeasible or maximum number of iterations reached for maximum allowed extended problem

Tier 3 — End-point constraint relaxation

- Reformulate the optimization problem by softening the end-point constraints

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:
$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{w}_k,$$
$$\mathbf{y}^F_k = \mathbf{h}^F(\mathbf{x}_k) + \mathbf{v}^F_k, \quad k \in \mathbb{I}_F; \qquad \mathbf{y}^{SF}_k = \mathbf{h}^{SF}(\mathbf{x}_k) + \mathbf{v}^{SF}_k, \quad k \in \mathbb{I}_{SF}$$
$$\mathbf{x}^{LB} \leq \mathbf{x_k} \leq \mathbf{x}^{UB}, \quad \mathbf{w}_k \in W$$

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.

Initialization and implementation

Novel Multi-Tiered Initialization

Background Tiers

1. Generate predicted measurements using model
2. Solve predicted MHE problem & store sol^n
3. Solve predicted economic optimization problems in the multi-tiered optimization strategy & store sol^n

Online Tiers

1. Get actual measurements and use stored sol^n to solve actual MHE problem

If operator triggers optimization

2. Use stored sol^n to solve actual economic optimization problems

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

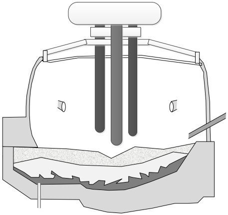
Optimization using IPOPT

Simulation assisted initialization: IDAS (SUNDIALS)

CasADi framework (Python)

Case Study 1

- Length of batch process: 60 minutes
- Estimation horizon: 6 min
- Advisory system'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

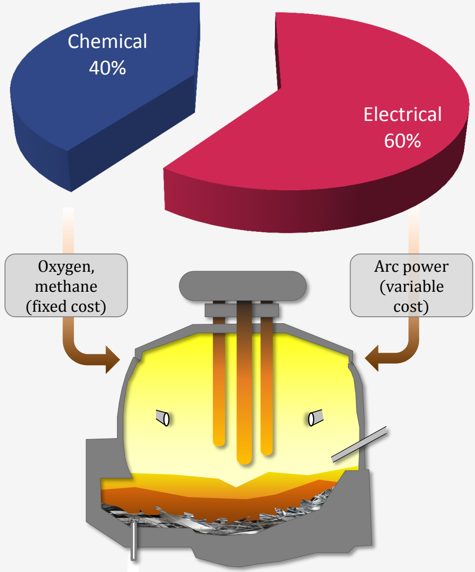
Off-gas compositions (CO, CO_2, O_2, H_2), T_{roof}, T_{wall}	Every 1 min
Slag compositions (FeO, Al_2O_3, SiO_2, MgO, CaO)	t=43 min
Molten-metal temperature and carbon content	t=43 & 47 min

Case Study 1 Results

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Times at which advisory system was called (min)	0	0, 30	0, 30, 40	0, 30, 40, 50, 58
Number of re-optimizations	0	1	2	4
Economic objective function value ($)	9,100	9,360	9,484	9,585
Actual scrap left at 60th minute (kg)	2.8	2.5	2.3	1.0

- Scenario 4 has 5.3% more profit compared to scenario 1.
- End point target achieved without extension when more reoptimizations carried out

Energy Management for Electric Arc Furnace



Optimal electrical and chemical energy usage

↓

Electricity supply dependent on deregulated markets

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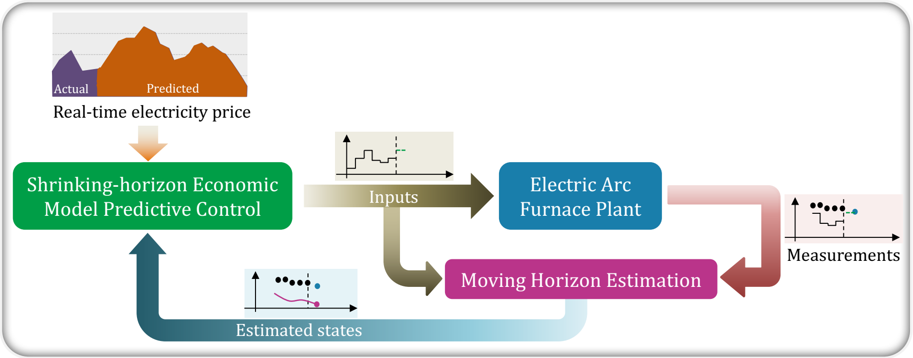
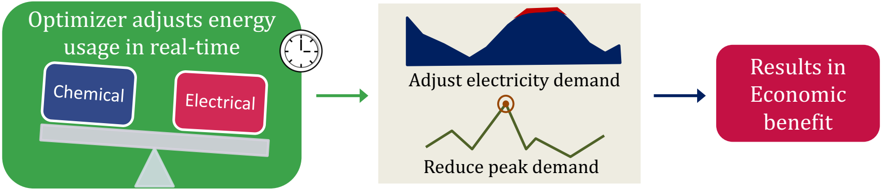
Challenge: Develop efficient energy management strategies in response to external variations

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

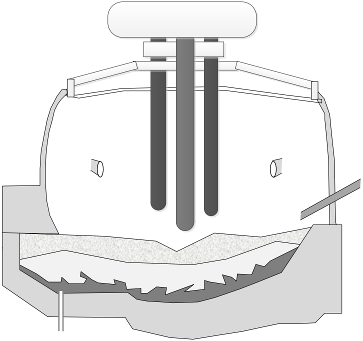
Input constraints:

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

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

Case Study 2

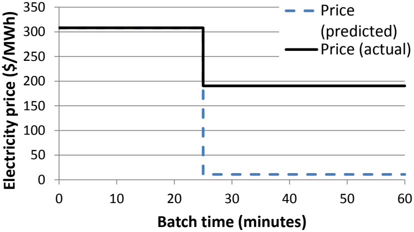
- Realistic electricity price data considered
- Real-Time market (price change every 1 hour)
- Ontario wholesale market



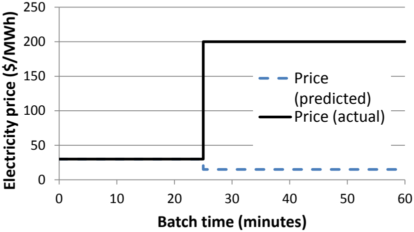
Compare two closed loop results:

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

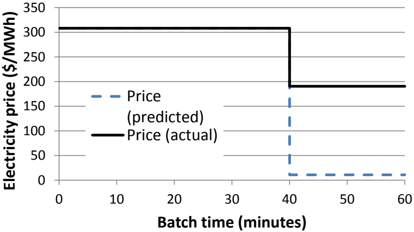
Price Profiles for Case Studies



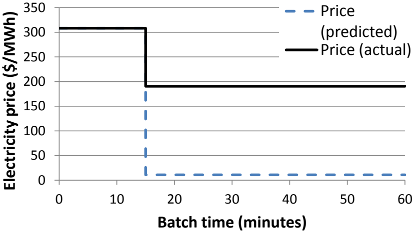
Case Study 1



Case Study 2



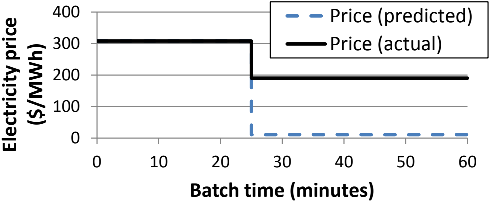
Case Study 3



Case Study 4

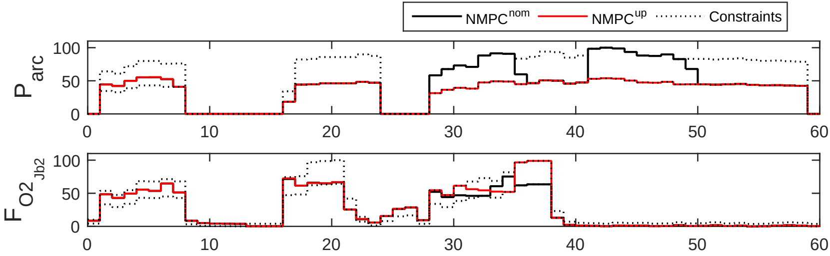
Case Study 2

Peak price decrease with price change at 25th minute



Compare $NMPC^{update}$ & $NMPC^{nominal}$:

Profit increase	4.6%
Decrease in electricity use	23%
Increase in other input use	1.6%
Reduction in peak electricity demand	45%



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

Conclusions and Future Work

1. Introduced real-time dynamic optimization-based advisory system
2. Real-time energy management strategy to reduce energy requirements
   - Optimal energy use while exploiting changing electricity price
3. Case studies demonstrate major economic benefit for both the application paradigms

Average Solve Time | 2.6 seconds

Current and Future Work

1. Variable batch length problem
   - Explore possibility of contraction in batch duration
2. Real-time energy management strategy for 5 and 15 minute market
   - Construct NMPC problem to minimize the peak demand

Acknowledgments

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