AI-Driven Optimization Framework for EAF Operations

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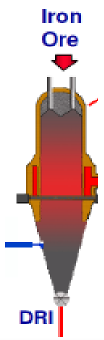
EMSTEEL R&D

Public

Emirates steel process route



Raw Material → **Direct Reduction** → **Steel Making (EAF)** → **Ladle Treatment** → **Billet and beam blank)**

4.2
MTPA

3.6
MTPA

2
MTPA

0.5
MTPA

1.0
MTPA

Emsteel Decarbonization Strategy

Steel Business

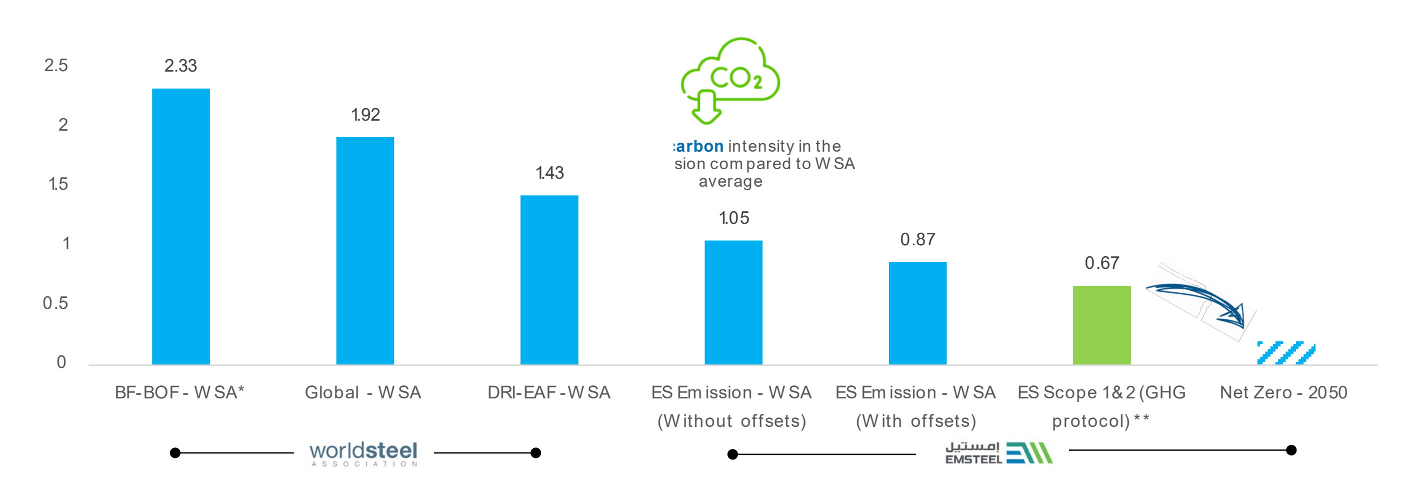
32% Reduction achieved — 40% Reduction Target set

2019	2023	2030
CO2e: 3.2Mt	CO2e: 2.2Mt	CO2e: 1.9Mt

Road to 2030 - Key Initiatives

- Carbon Capture
- Alternative Fuel Switching
- Used recycled Steel Scrap
- Clean and renewable Energy
- Electrification
- Energy Efficiency
- Digital Transformation

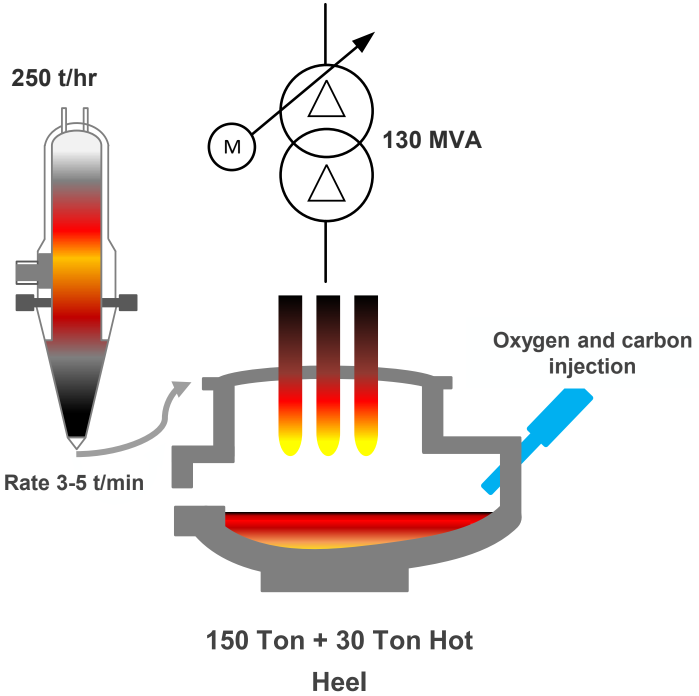
Steel Business performance vs global industry (2024)



Levers deployed in 2024

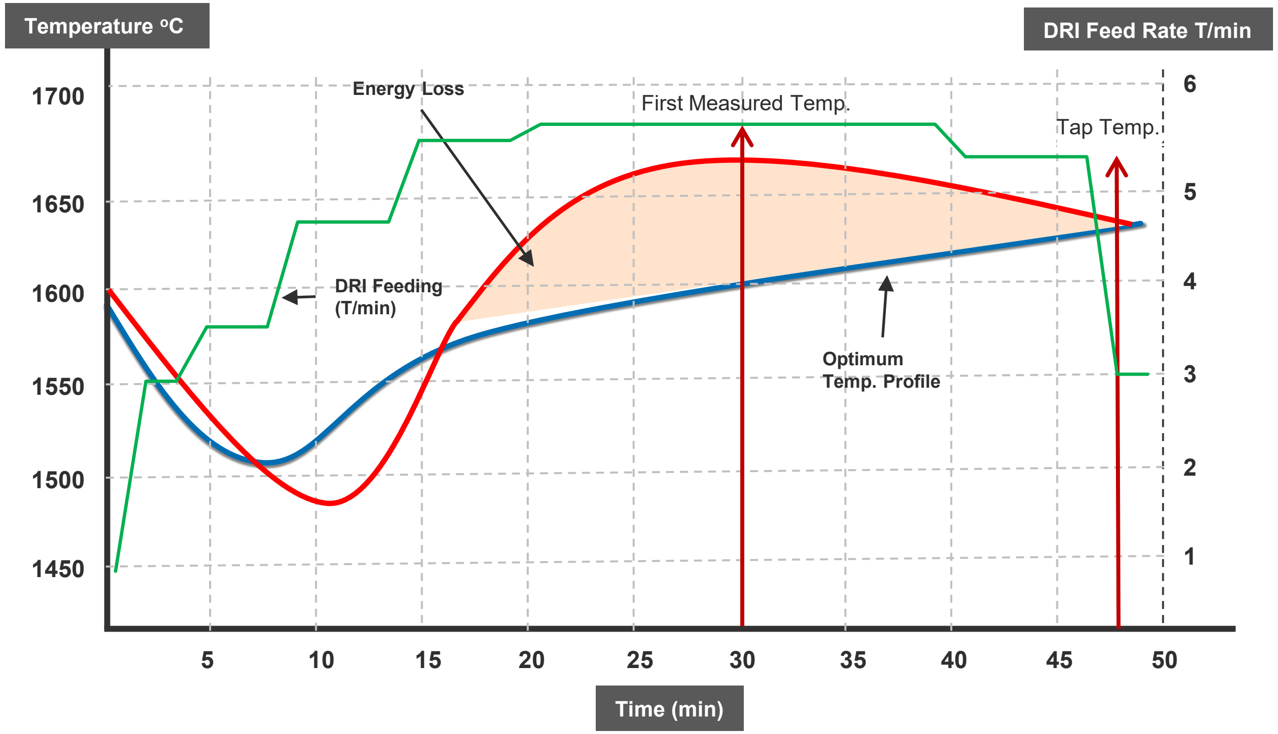
- Increase our clean and renewable electricity through "Energy Attribute Certificates"
- 1st Steel maker worldwide to capture part of our CO2 emissions
- 1st of-a-kind MENA region green hydrogen to green steel pilot facility

Problem Statement



Challenges

- No continuous bath temperature measurement
- No real-time DRI chemistry
- Operator-dependent control adjustments
- Leads to high SEC, temp swings, Slag FeO% variation



EAF Specifications

- Tap weight - 150 Ton
- Transformer capacity -130 MVA
- Charge mix – Hot DRI , Cold DRI and Scrap
- Tap to Tap time – 40-50 Min
- Four injectors (Natural gas, oxygen and carbon)

DRI Composition

- Carbon: 2- 2.5%
- Fe (Metallic) :82-85%
- DRI FeO% :5- 8%
- Hot DRI temp: 400- 450 deg C

Solution Approach (past and future)

Existing Approach

1970s–1980s First Principles & Early Thermal Models
(Two control volumes (gas + slag/bath)
PDEs for scrap heating and melting.

2000–2010 CFD Era Begins (ANSYS / FLUENT / COMSOL)
Arc plasma behavior
Heat transfer & radiation
Electromagnetic fields.

2010–2016 Comprehensive Heat/Mass Transfer Models
3D AC-EAF freeboard modeling.
EAF energy balance modeling

- Off-gas heat flows
- Oxy-fuel burners
- Oxygen lances Coal combustion
- Meier & Pfeifer: melting process modeling with numerical solution comparisons.
- Opitz et al.: detailed radiative heat transfer via discrete ordinate methods.

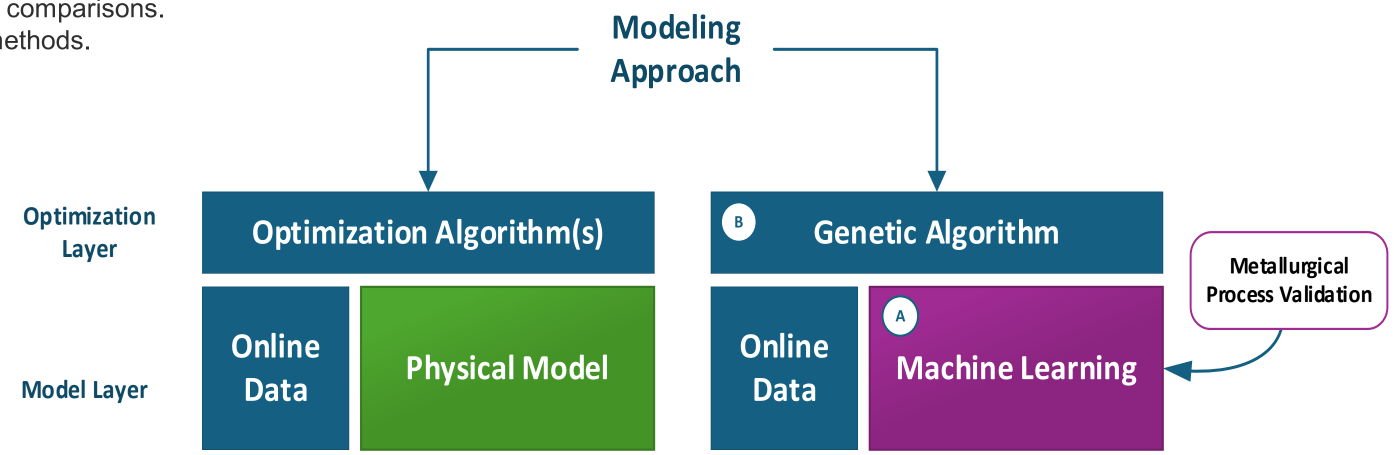
2016–2020 Hybrid Models & Online Optimization
Arc plasma behavior
Heat transfer & radiation
Electromagnetic fields.

2020–2024 Machine Learning & AI-Driven EAF
Models Energy consumption
Arc length estimation
Tap temperature prediction

New Approach

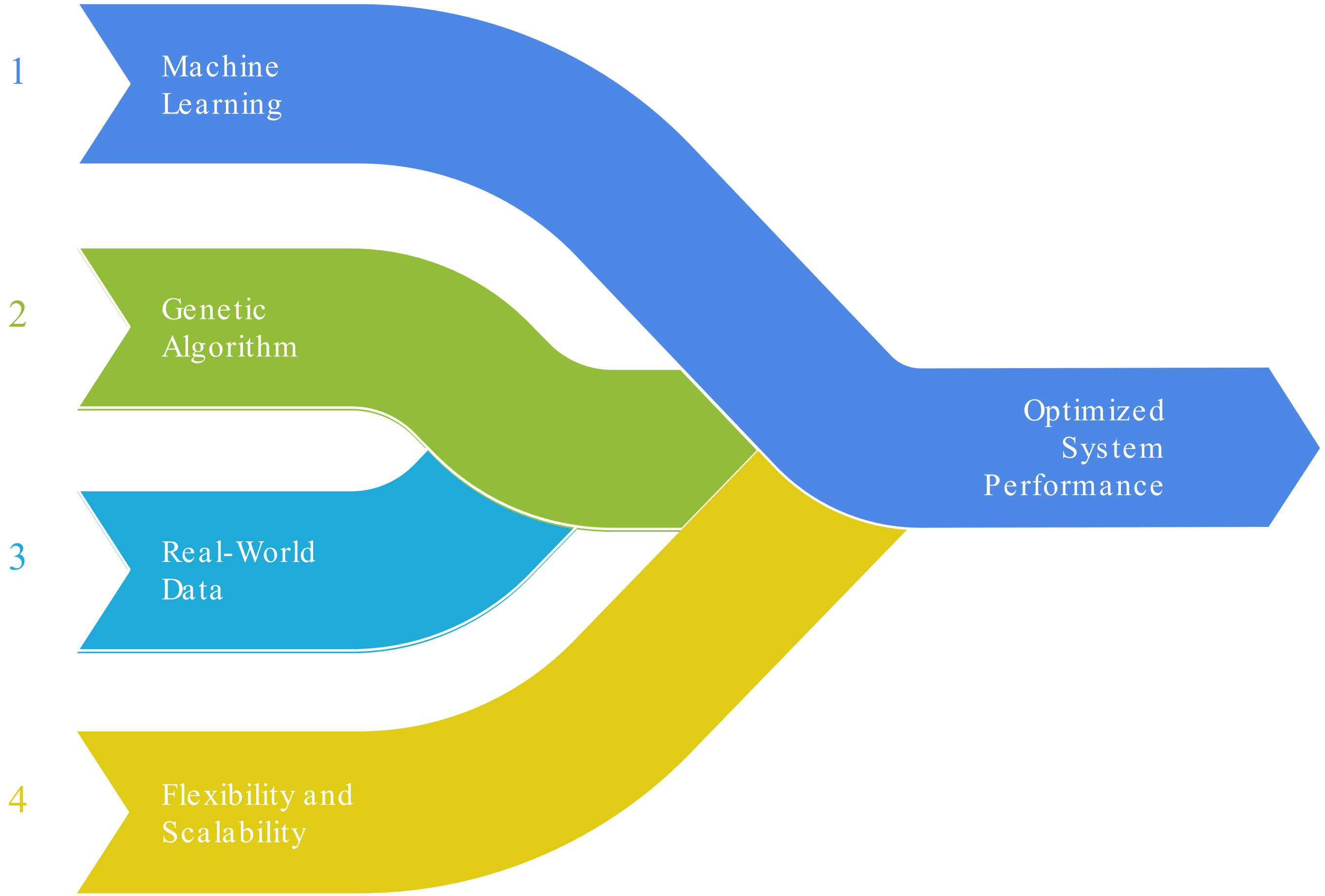
2025 Combining Machine Learning with Genetic Algorithm

Machine learning models can predict specific energy consumption but lack an optimization layer for minimizing the specific energy. Therefore, a Genetic Algorithm (GA) - as an optimization layer on top of the ML model is used to generate the optimal setup (melting profile) that resulted in minimizing specific energy consumption while respecting plant-specific operating constraints.



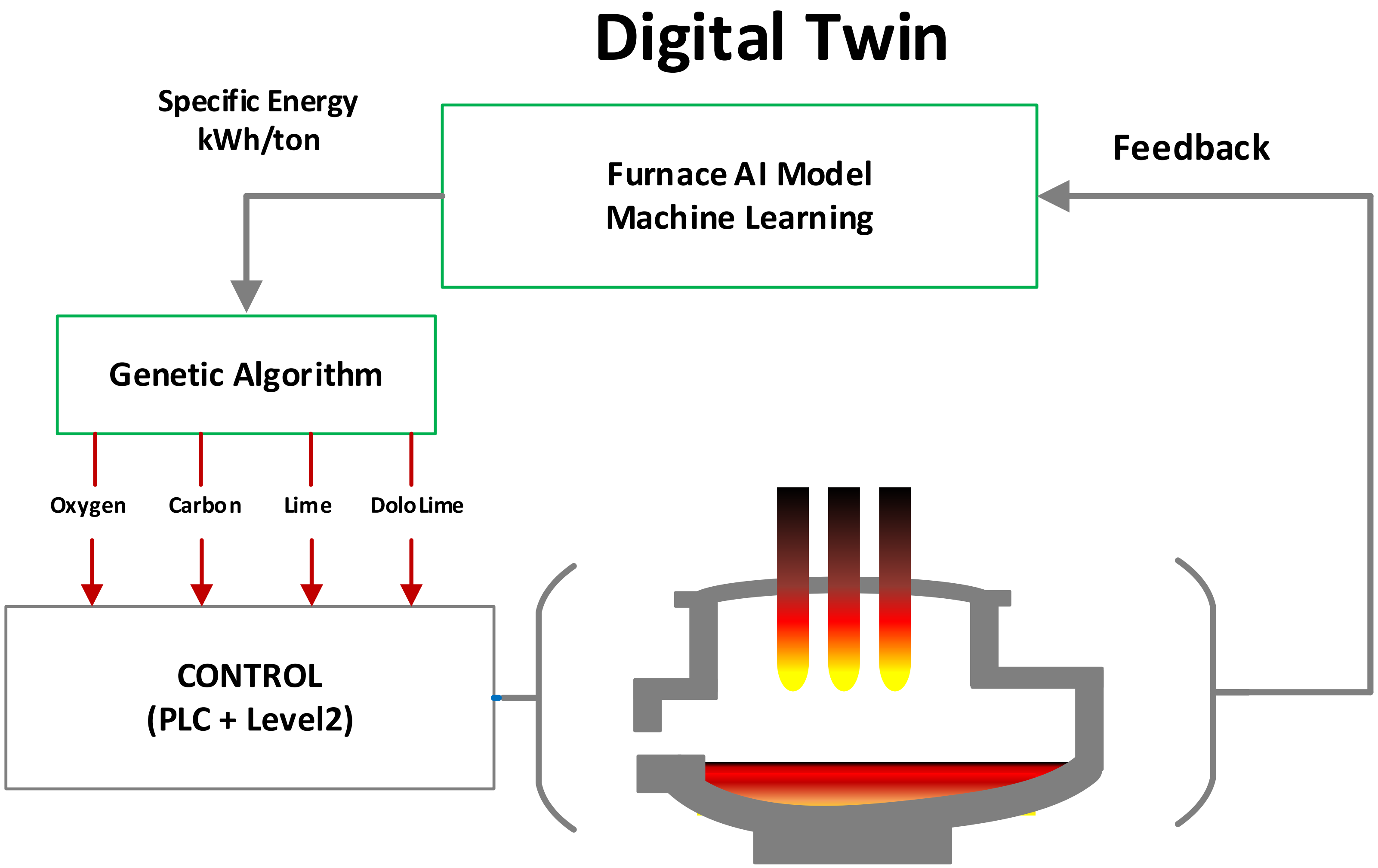
Hybrid Model Benefit

Synergy of ML and GA Optimization



1. Fast, accurate predictions of system performance outcomes.
2. Searches for optimal input variable combinations efficiently.
3. Integrates empirical data for realistic optimization.
4. Adaptable to various industries and optimization problems.

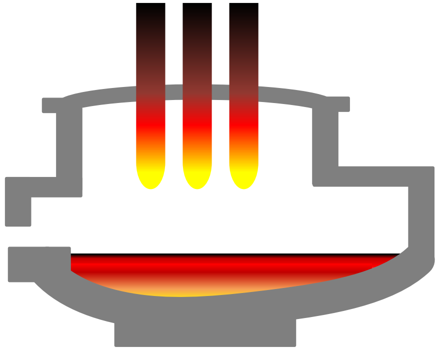
Model Deployment Approach



EAF Energy Balance

Electrical 442.0 kWh (57.5%)

Chemical (C -> CO + CO_2)
326.0 kWh (42.5%)



768 kWh/ton
Total Energy

Steel 380.0 kWh (49.48%)
Slag 57.0 kWh (7.42%)
FeO Reduction 24.0 kWh (3.13%)

Shell, Roof, EBT 81.0 kWh (10.55%)
Flue Gas 226 kWh (29.43%)

Input Energy

Electrical	Chemical
442 kWh/t	**326 kWh/t**

Output Energy

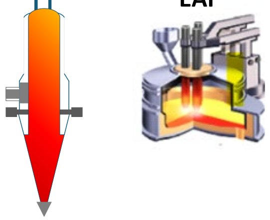
Liquid Steel	DRI FeO Reduction
380 kWh/t	**24 kWh/t**

Shell, roof loss	Slag Loss	Flue gas loss
81 kWh/t	**57 kWh/t**	**226 kWh/t**

Model Design Concept

DRP

EAF



Data Collection

Data Preprocessing and Outlier Removal

Running Different ML Models

- Linear Regression
- Decision Trees
- Support Vector Regression
- Gaussian Process Regression
- Kernel Approximation Regression
- Ensembles of Trees
- Artificial Neural Network

Compare Models Accuracy

R2, RMSE, MAE of each Model

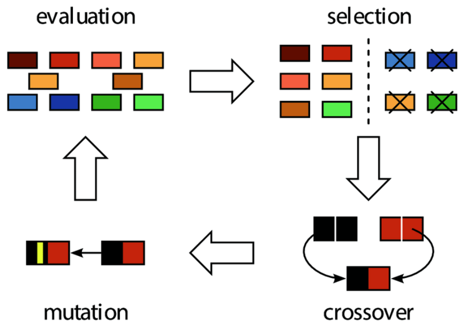
Validating Models

Metallurgical Process Validation

Model Selection

Model Accuracy
+
Metallurgical Principles

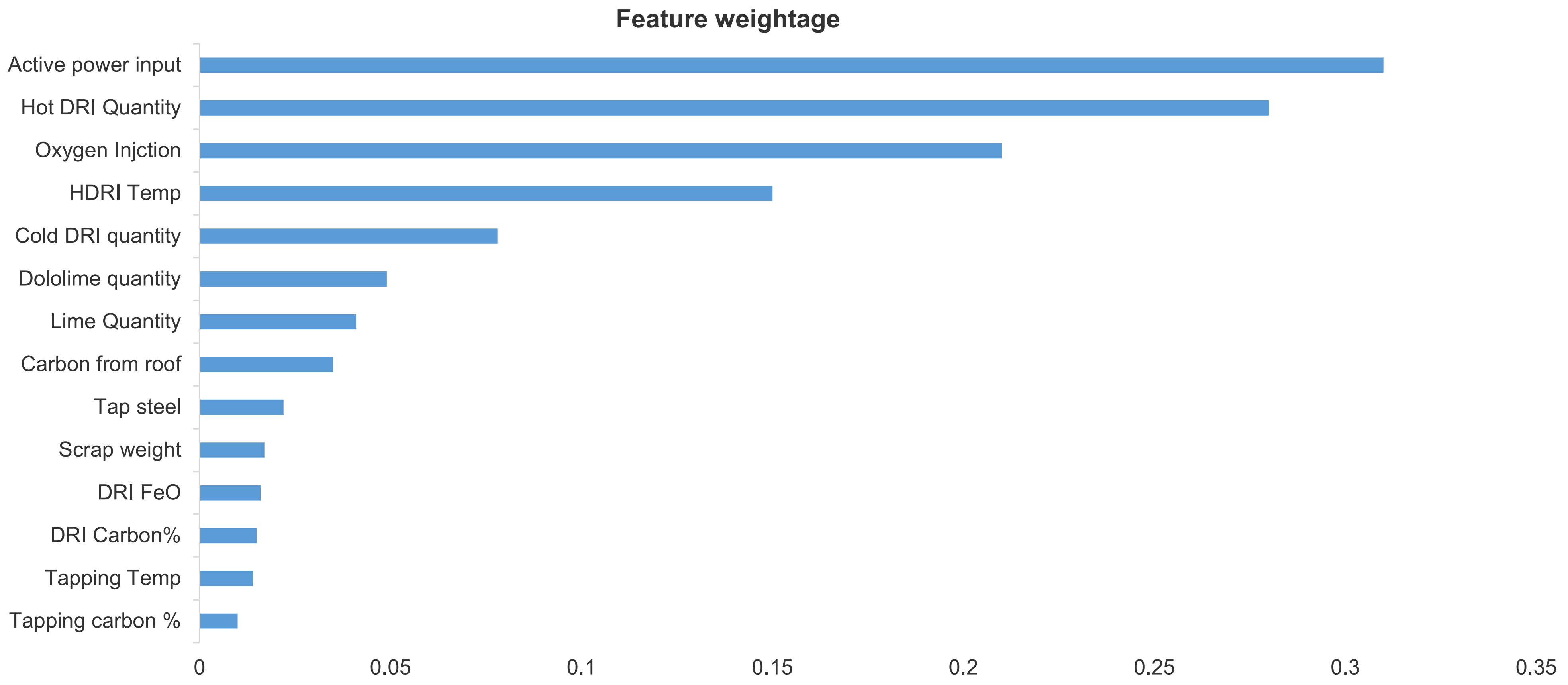
Optimization by genetic algorithm



Optimum Process Parameters to Minimize Specific Energy

Feature selection

R-Relief algorithm was used for feature selection. Highlights the most influential process variables impacting specific energy

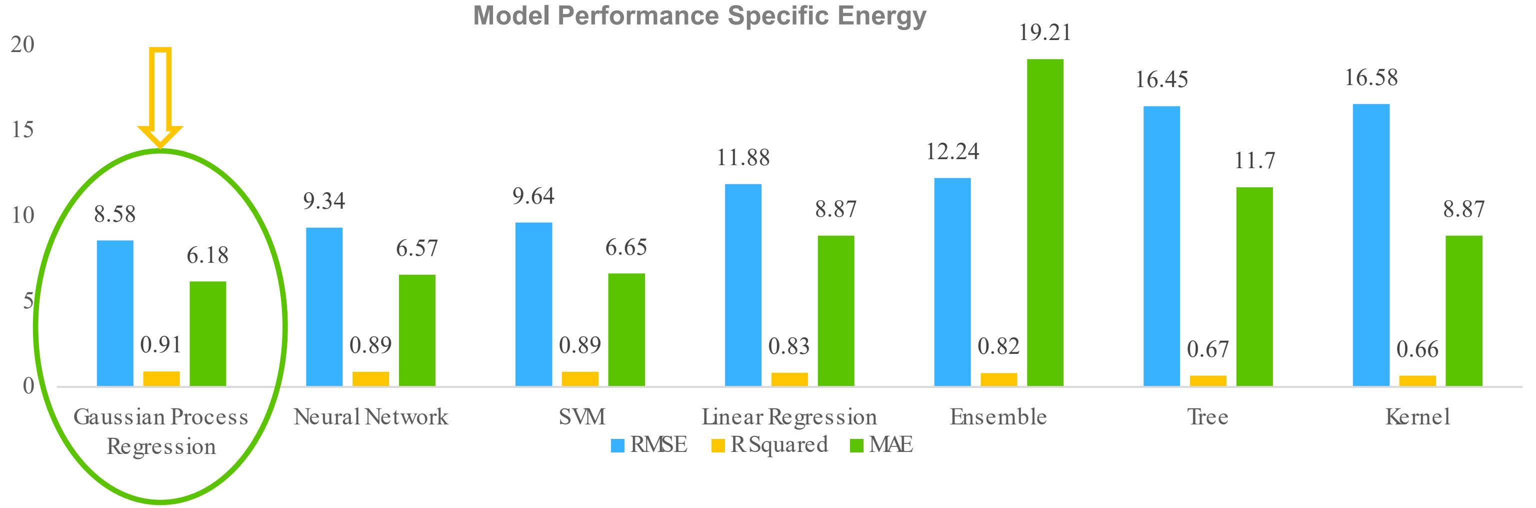


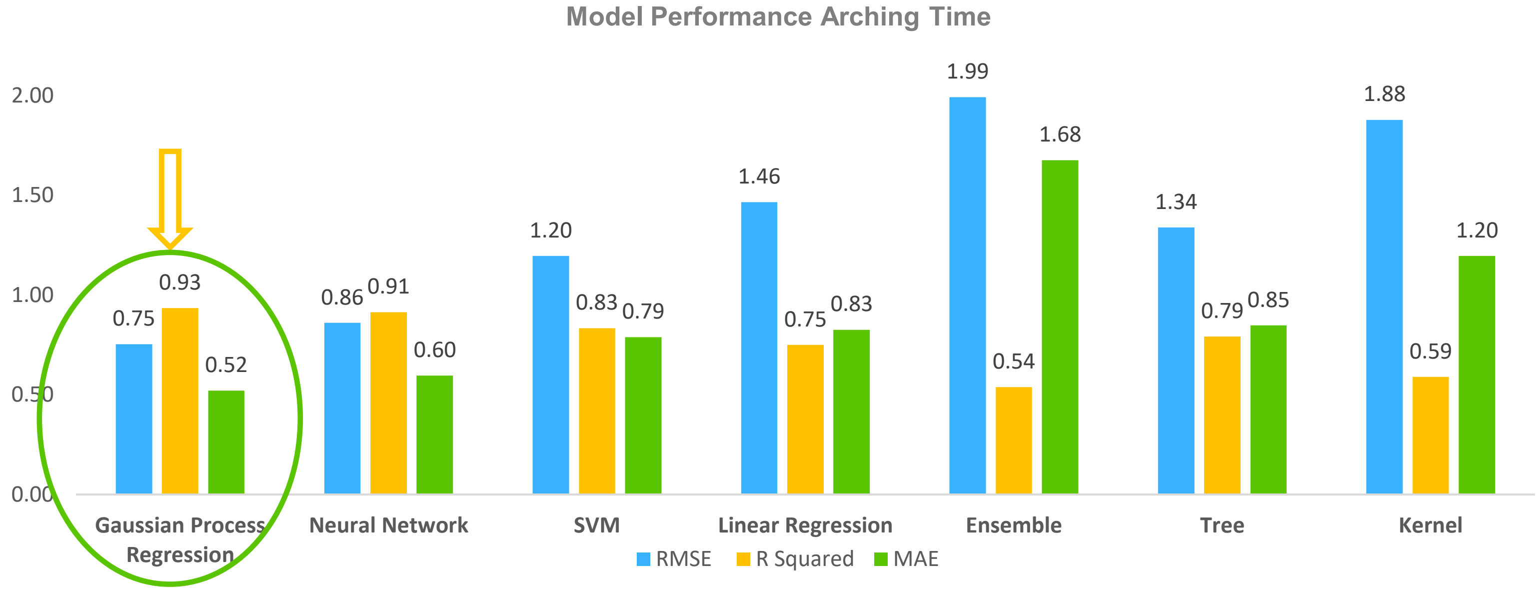
Modeling Performance

Model Tested:

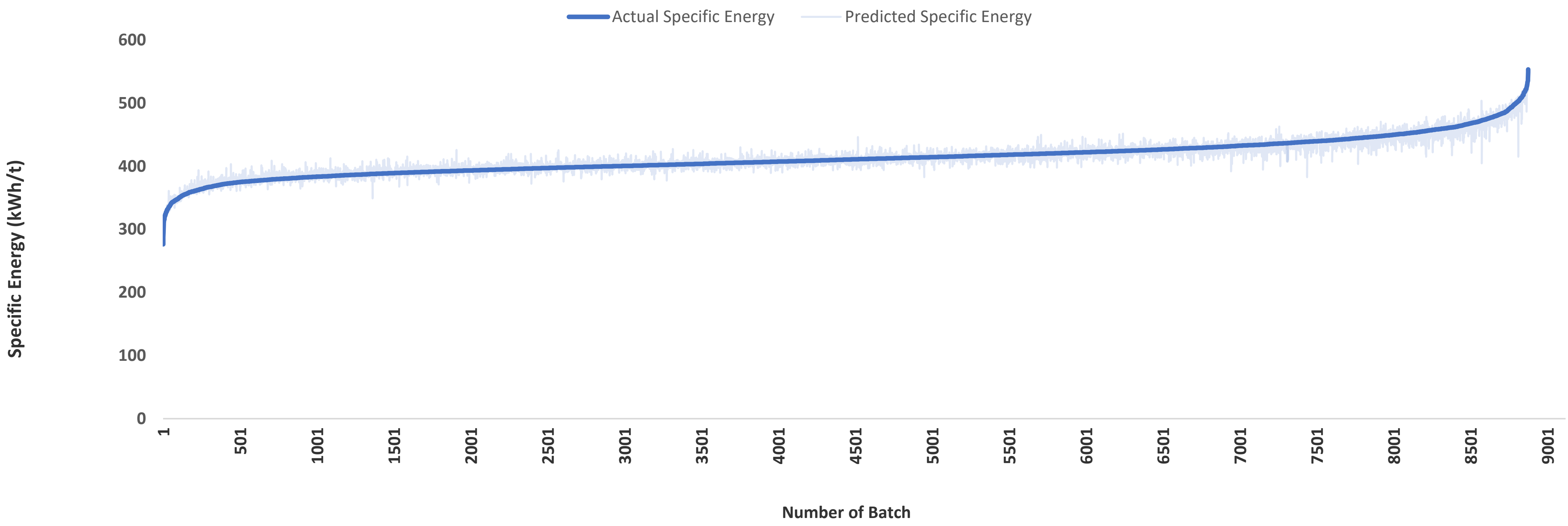
- Linear regression variants
- Decision Trees, SVM, Kernel methods
- Gaussian Process Regression (GPR)
- Ensemble Methods
- Artificial Neural Networks (ANNs)

Best Algorithm Selection:
Gaussian Process Regression (GPR)





Actual vs Predicted Specific energy

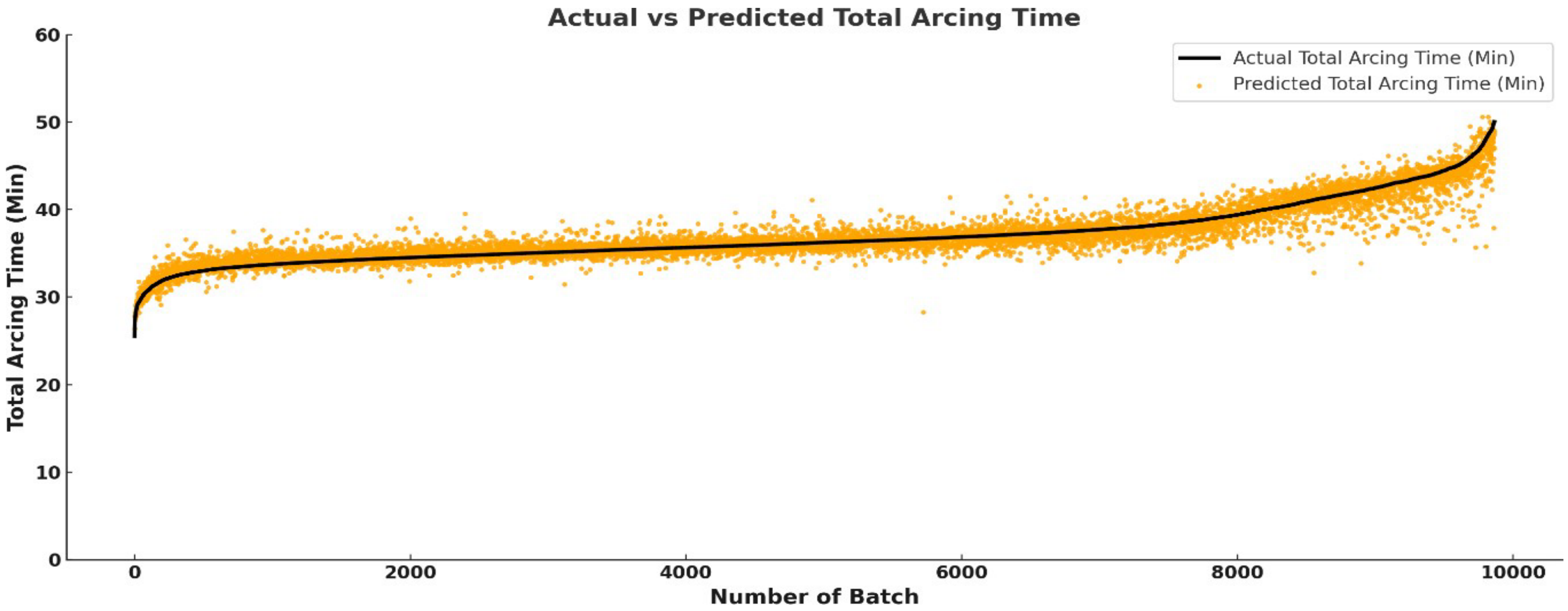


GPR Model result:

Model	R^2	RMSE	MAE
Specific Energy	0.91	8.58	6.18

High overlap of curves
Model generalizes well across 9000 heats

Actual vs Predicted Arcing time

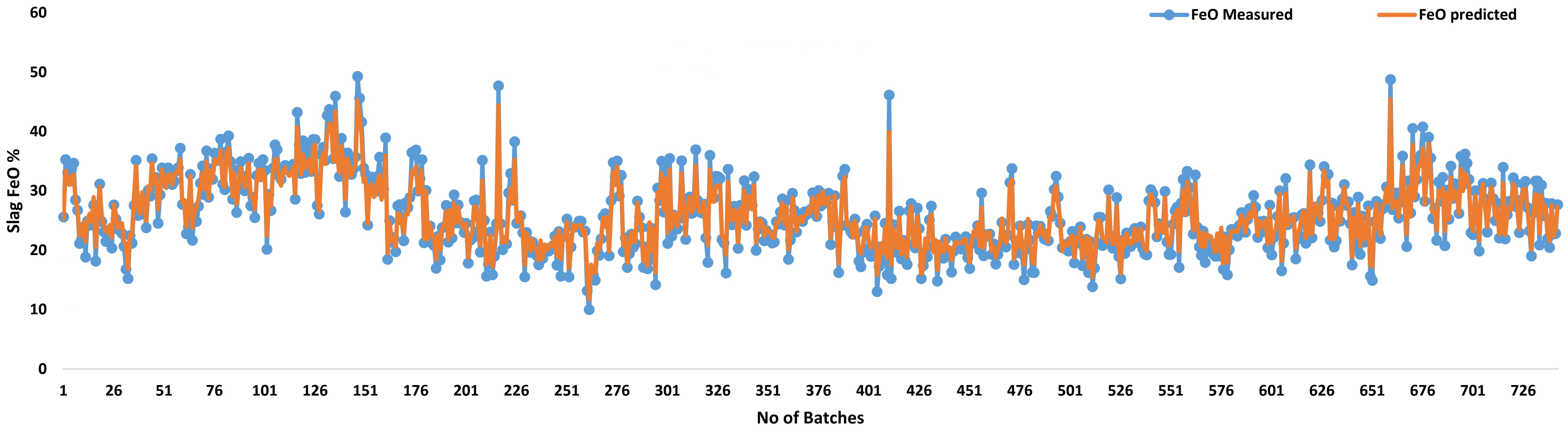


GPR Model result:

Model	R^2	RMSE	MAE
Arching Time	0.93	0.75	0.52

Accurate prediction of Arcing Time
Enables forecasting of productivity improvement

EAF Slag prediction model result

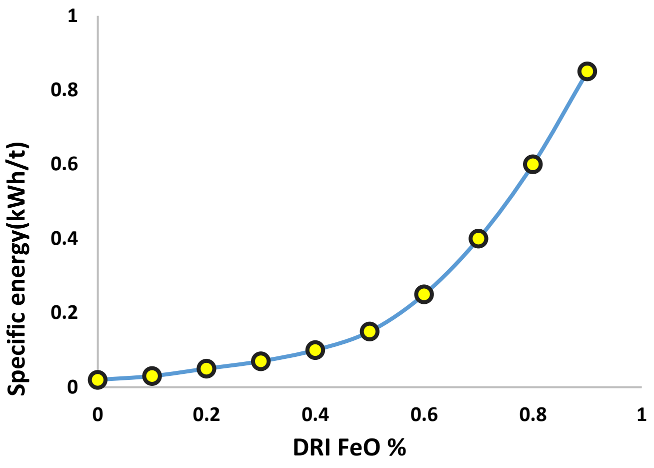


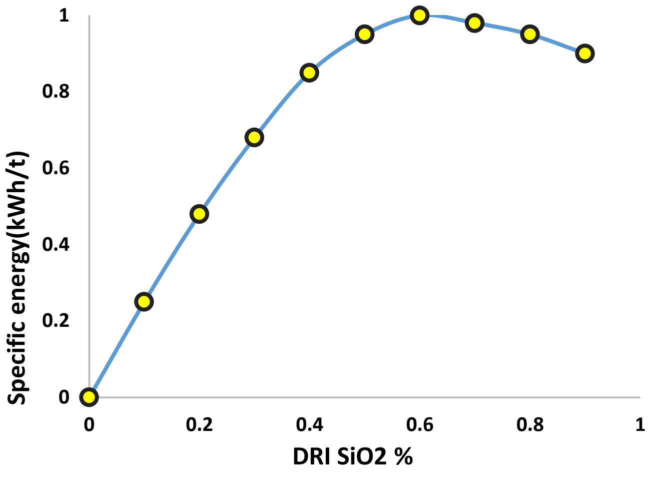
GPR Model result:

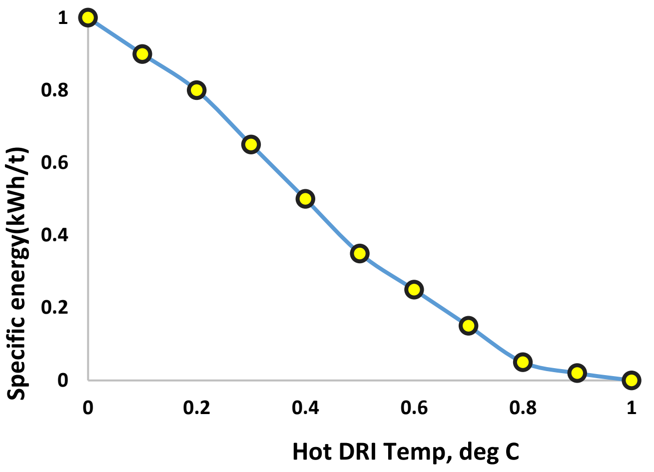
Model	R^2	RMSE	MAE
Slag FeO%	0.87	0.97	0.69

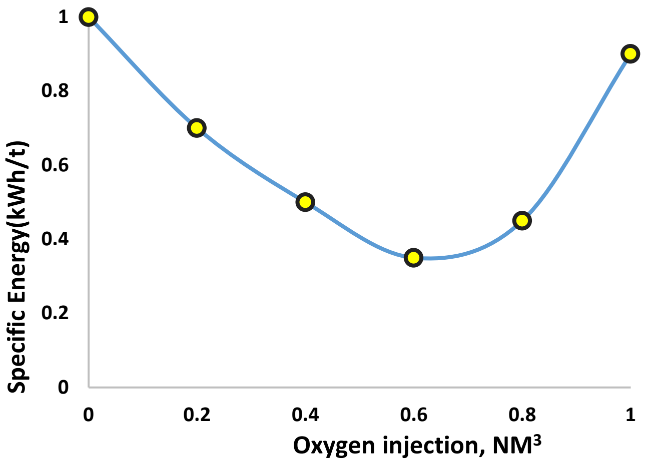
Accurate prediction of Slag chemistry
Supports optimal flux and carbon control

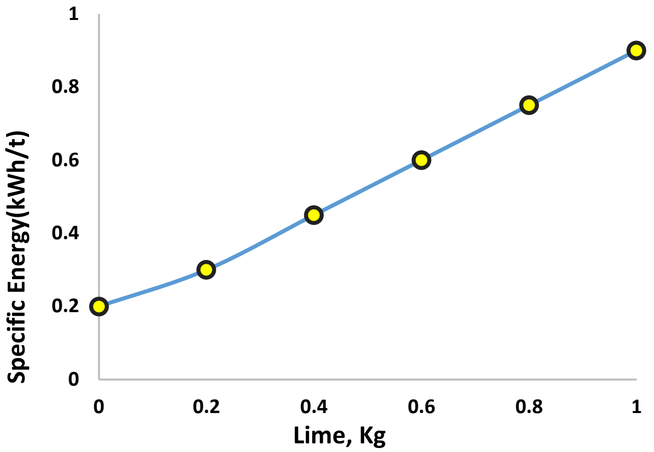
Metallurgical Process validation

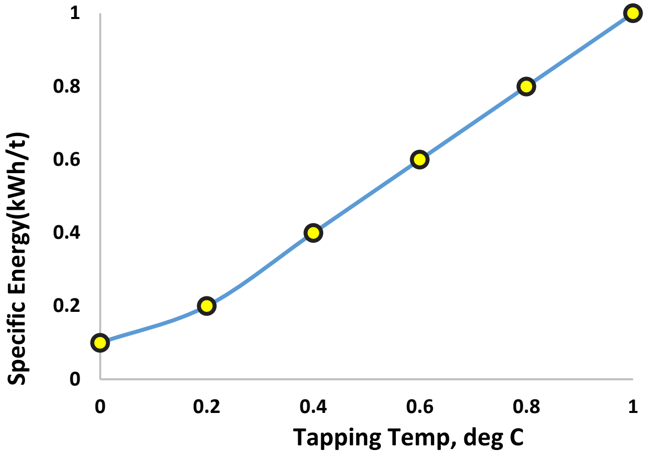






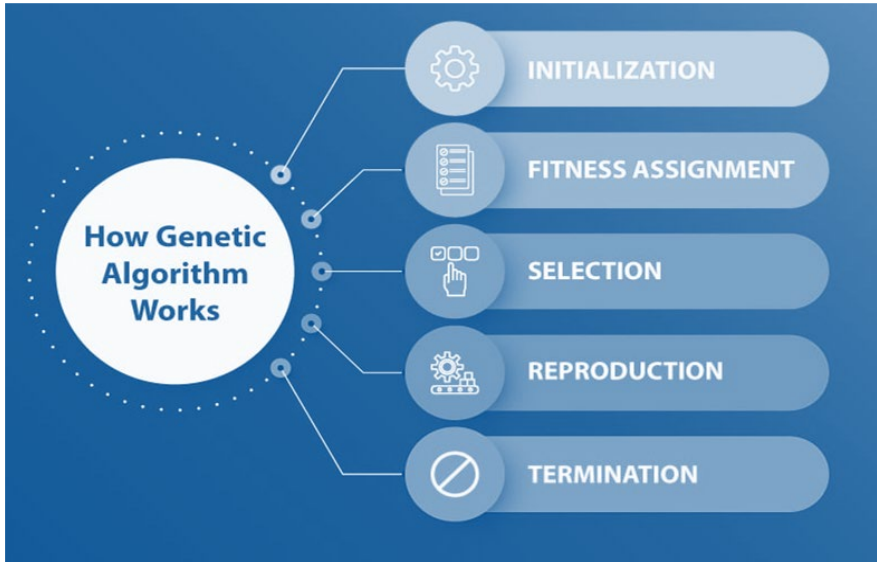






* X and Y axis data are normalized

Genetic algorithm



GA Optimization Initialization

Objective to minimize Specific Energy

Population Size	150
Generation	500
Crossover Fraction	0.8
Mutation Rate	0.05
Optimized Variables	4
Fixed Variables	18

Decision vector $x = [x1....x22]$

Objective Function:

$$\min SEC=f(x)$$

*f(x) is the SEC predicted by ML

GA Constraints

Optimized Variablle(4)

- Oxygen
- Carbon
- Lime
- Dololime

Fixed Variable (18)

- DRI Chemistry
- Process Variable
- Input Power
- Charge Mix

Output

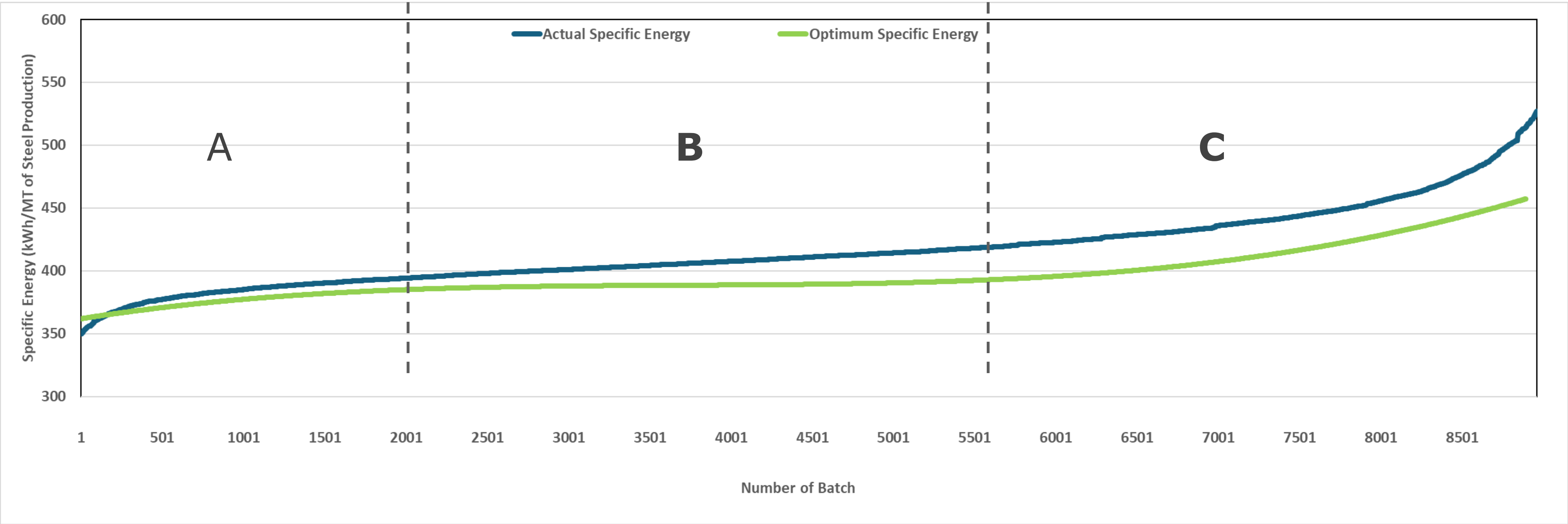
Optimal Parameter Set per Batch

- Optimum Oxygen Injection
- Carbon Injection
- Lime Addition
- Dololime Addition

Lowest Achievable Specific Energy Under real plant constraints

Optimization result

- **GA doesn't get stuck in local minima** → It searches broadly across the solution space.
- **Keeps evolving better solutions** through selection, crossover, and mutation.
- **Reaches the global optimum** → Giving consistently lower specific energy



GA Optimization Benefits

Reduced Specific Energy (SE)

-10 kWh/ton.

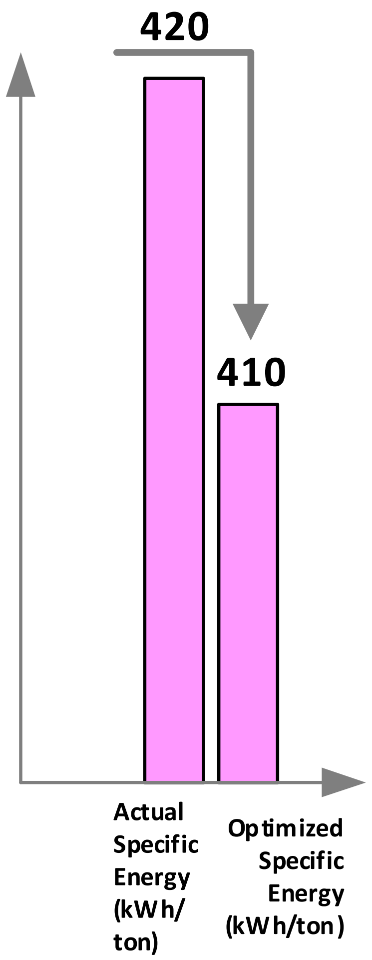
Improved productivity

+7 tons/hour.

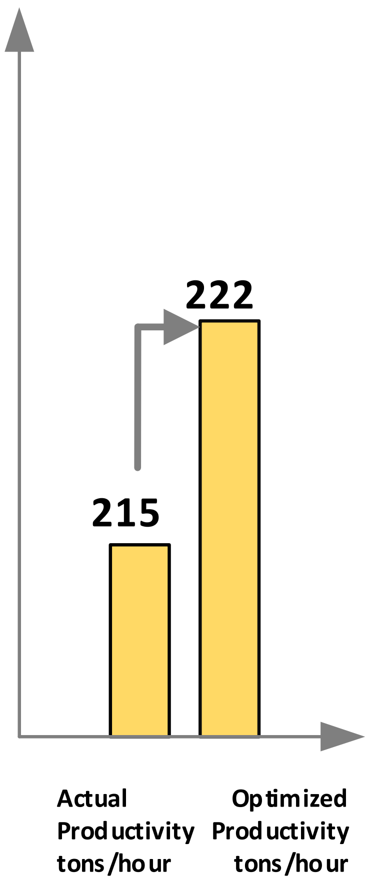
Lowered CO_2 emissions

-10 kg/ton steel.

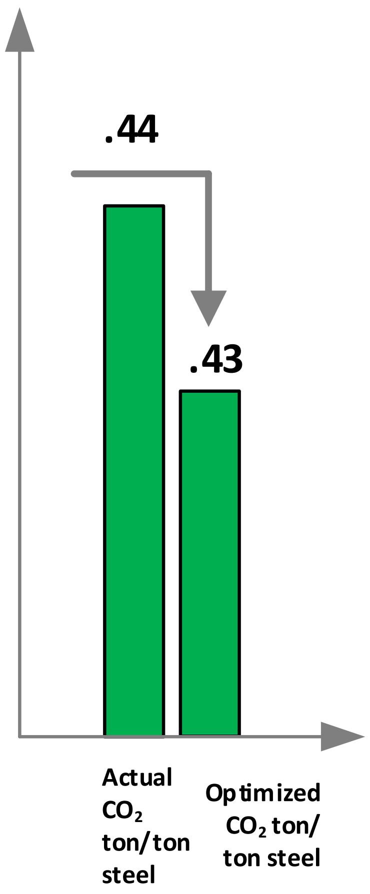
Actual Vs Optimized Specific Energy



Actual Vs Optimized Productivity



Actual Vs Optimized CO_2



Conclusion & Future Works

- Developed a robust hybrid GPR + GA framework delivering highly accurate predictions for specific energy, arcing time, and slag FeO%.
- Domain-informed feature selection and sensitivity analysis ensured strong alignment with metallurgical principles.
- GA optimization achieved 10 kWh/ton energy reduction, 7 tons/hr. productivity increase, and 10 kg/ton CO_2 reduction.
- All optimized recommendations were validated within real plant operating constraints, ensuring practical and safe implementation.
- Outperformed traditional thermodynamic/kinetic models by capturing real-time variability and complex nonlinear interactions, forming a scalable foundation for Industry 4.0.

Future Works

- Extend to dynamic time-series modeling using LSTM for continuous prediction of EAF bath temperature and carbon.
- Develop a full EAF Digital Twin for real-time simulation, control strategy evaluation, and operator decision support.
- Implement multi-objective optimization balancing energy, productivity, yield, and CO_2 emissions.
- Advance toward full Industry 4.0 integration, enabling intelligent, autonomous, and optimized EAF operations.

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Thank You