Modelling of Fireside Corrosion of Superheaters and Reheaters Following Coal and Biomass Combustion

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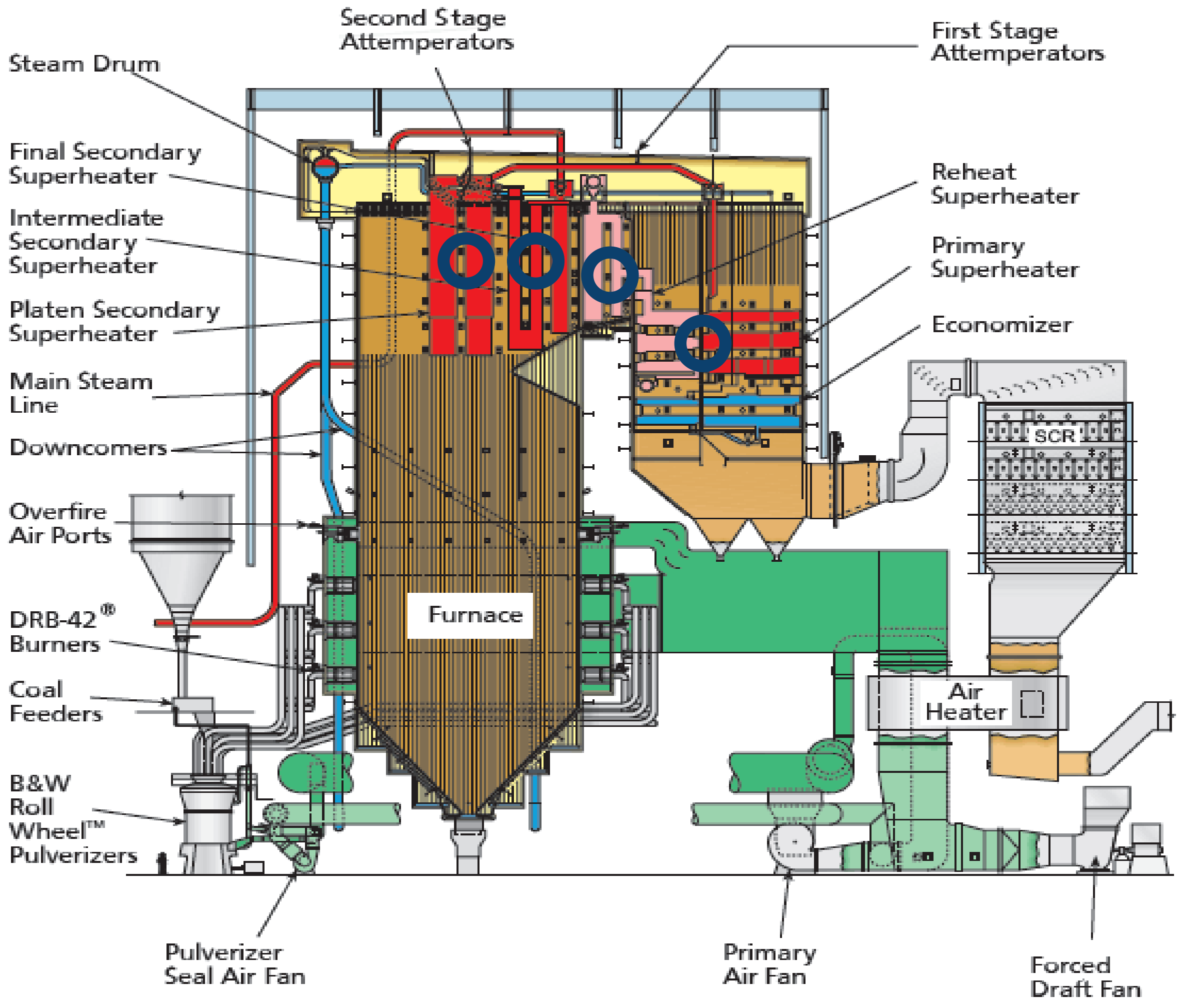
OVERVIEW

➢ **Introduction**
- Fireside corrosion
- Review of existing corrosion models

➢ **Corrosion Dataset**
- Fuel: UK coals / biomass
- Fuel: World traded coals (US, EU)
- Materials: Austenitic, ferritic, nickel-based alloys, coatings and claddings

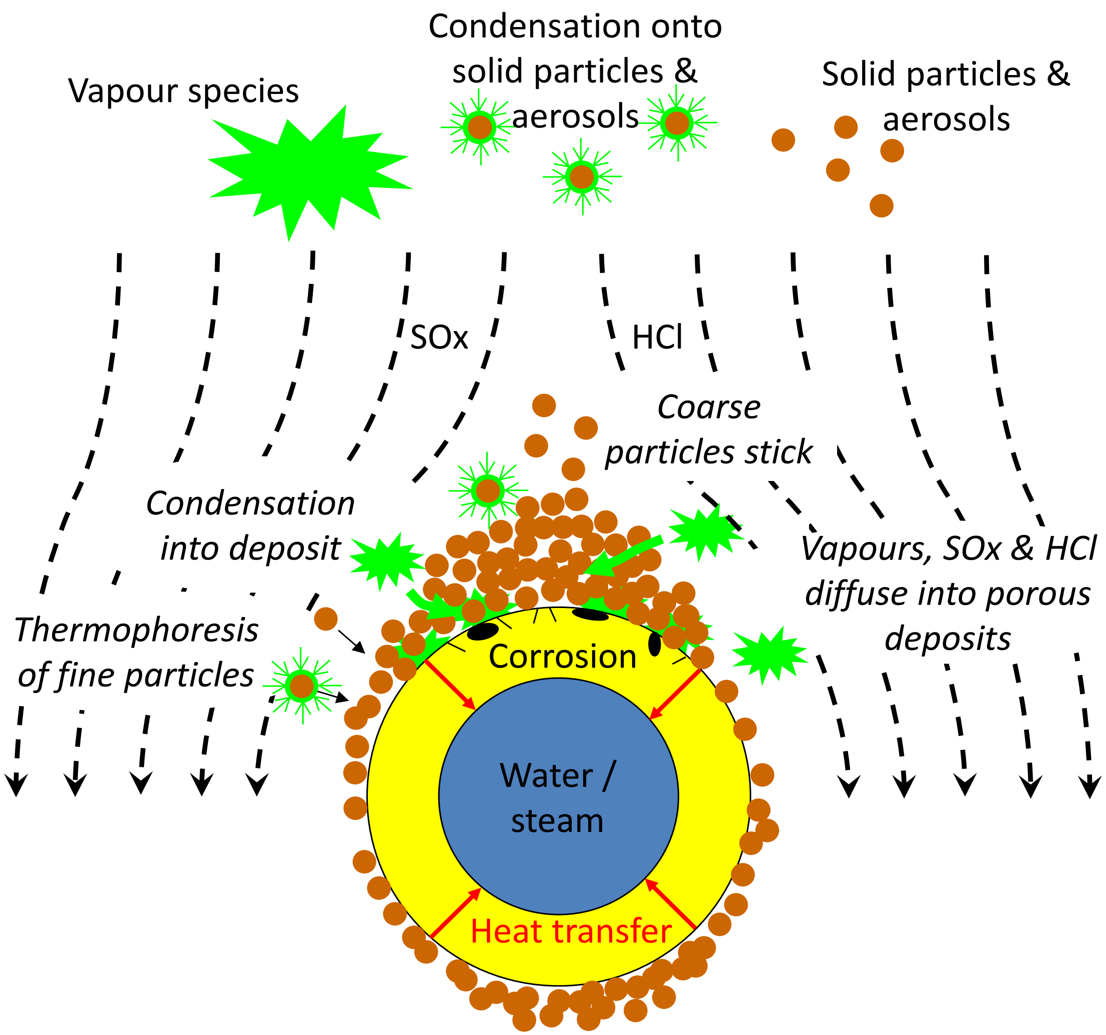
➢ **Data Analysis / Model Development**
- Principal Component Analysis / Principal Component Regression
- Partial Least Squares
- Model suite

PULVERISED COMBUSTION BOILER



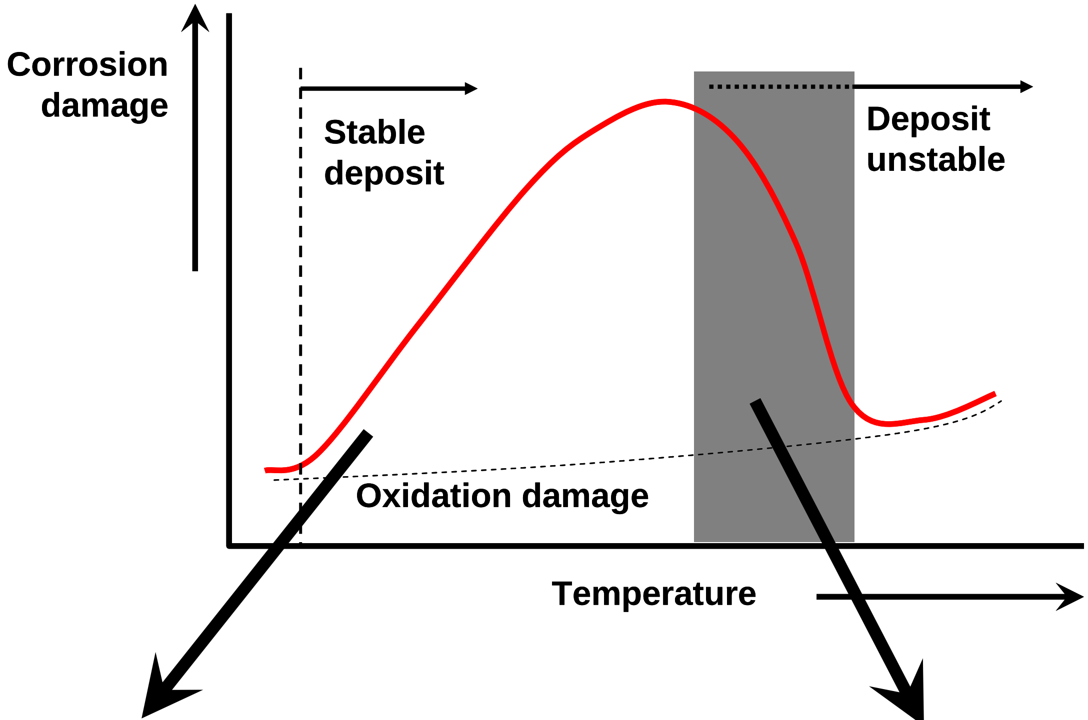
www.tbwes.com/products/subcritical-boilers/

FIRESIDE CORROSION:
Deposition on Superheater / Reheater Tubing



Reference: Simms et al., 2007

FIRESIDE CORROSION:
High Temperature Corrosion Mechanism



CORROSIVE DEPOSITS:
- Sulphate deposits (pyrosulphates, alkali iron trisulphates, mixed sulphates)
- Chloride deposits
- Sulphates-Chlorides-Carbonates (mixed)

DEPOSIT INSTABILITY:
- Vapour condensation dewpoints
- Insufficient SO_3 available to stabilise some phases
- Other phases more stable with temperature change

Reference: Simms et al., 2007

EXISTING CORROSION MODELS

1. **Borio Index:** The index value was derived from a nomograph defining factors including acid-soluble K_2O, Na_2O, CaO and MgO, and Fe_2O_3. The coal corrosivity index derived was of the range 0 - 22 with increasing index denoting increased corrosion.
2. **Raask Index:** i.e. < 0.5 wt % (Na + K) denotes low coal corrosivity; and > 1.0 wt % (Na + K) denotes high coal corrosivity.
3. **PE-8 model:** $Corrosion\ rate\ \left(\frac{nm}{hr}\right) = AB\left({}^{T_g}/_{G}\right)^m\left[\frac{(T_m - C)}{M}\right]^n (\%Cl - D)$
4. **Modified PE-8 model:**

   $$Corrosion\ rate\ (nm/hr) = exp[(r/T_m) + s(\%Cr_{alloy}) + t(T_g - T_m) + u + v(\%Cl_{fuel})]$$
5. **Laboratory Test Equation:**

   $$Corrosion\ rate\ (nm/hr)$$

$$= \exp[(a/T_m) + b + c(HCl) + d(SO_x) + e(Na + K)_{dep}\% + f(\%S_{dep}) + g(\%Cl_{dep})]$$

References: Borio et al., 1968[1]; Clapp, 1991[2]; James et al., 2007[3,4, 5]; Lant et al., 2010[3,4]; Wright and Shingledecker, 2015[1,2,3]

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CORROSION DATASET
Input Parameters from Plant Data

ALLOYS	Austenitic, Ferritic, Coatings/Claddings
FUEL	Coal (UK, US, EU); Biomass
OPERATING CONDITIONS	Metal Temperature, Gas Temperature
TUBE POSITION	Leading (facing gas flow), Non-leading

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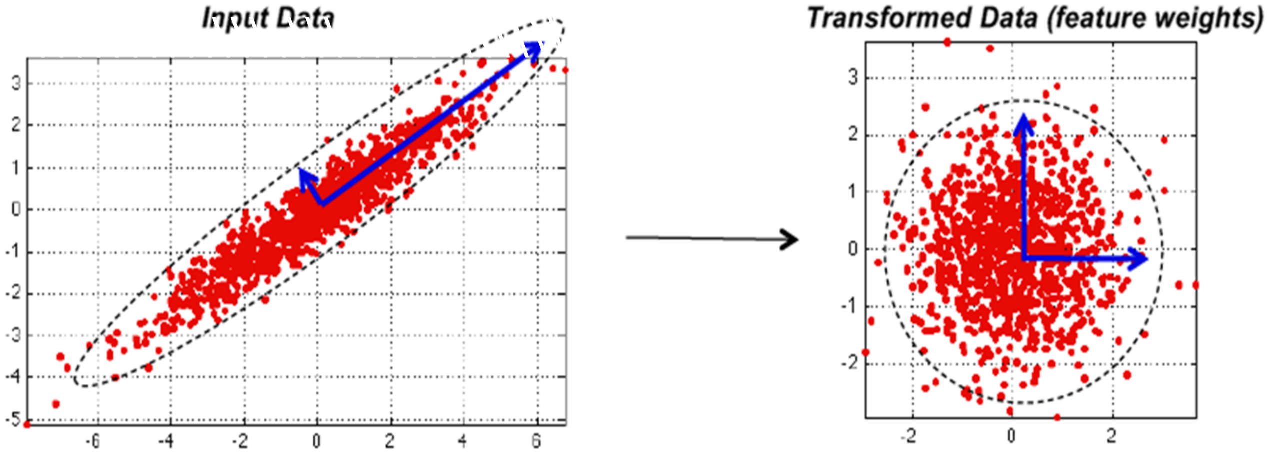
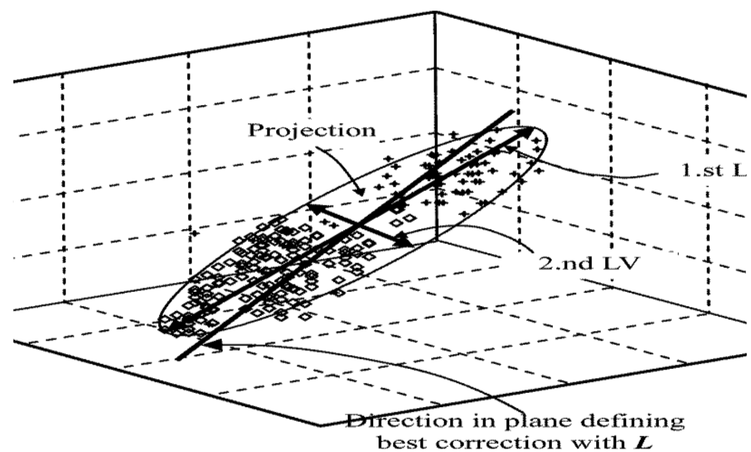
MODEL DEVELOPMENT: Principal Component Analysis / Partial Least Squares



PCA is employed to reduce the dimensionality of a set of variables while retaining maximum variance

PLS extracts linear functions of the predictor dataset that has maximum covariance with the dependent variable (corrosion rate)



Reference: PCA illustration - Transformation of input data using PCA (University of Illinois, 2000)

MODEL STRUCTURE

Arrhenius Equation:

Activation Energy

Rate Constant

$$K = Ae^{\frac{-E_a}{RT}}$$

Kelvin Temperature

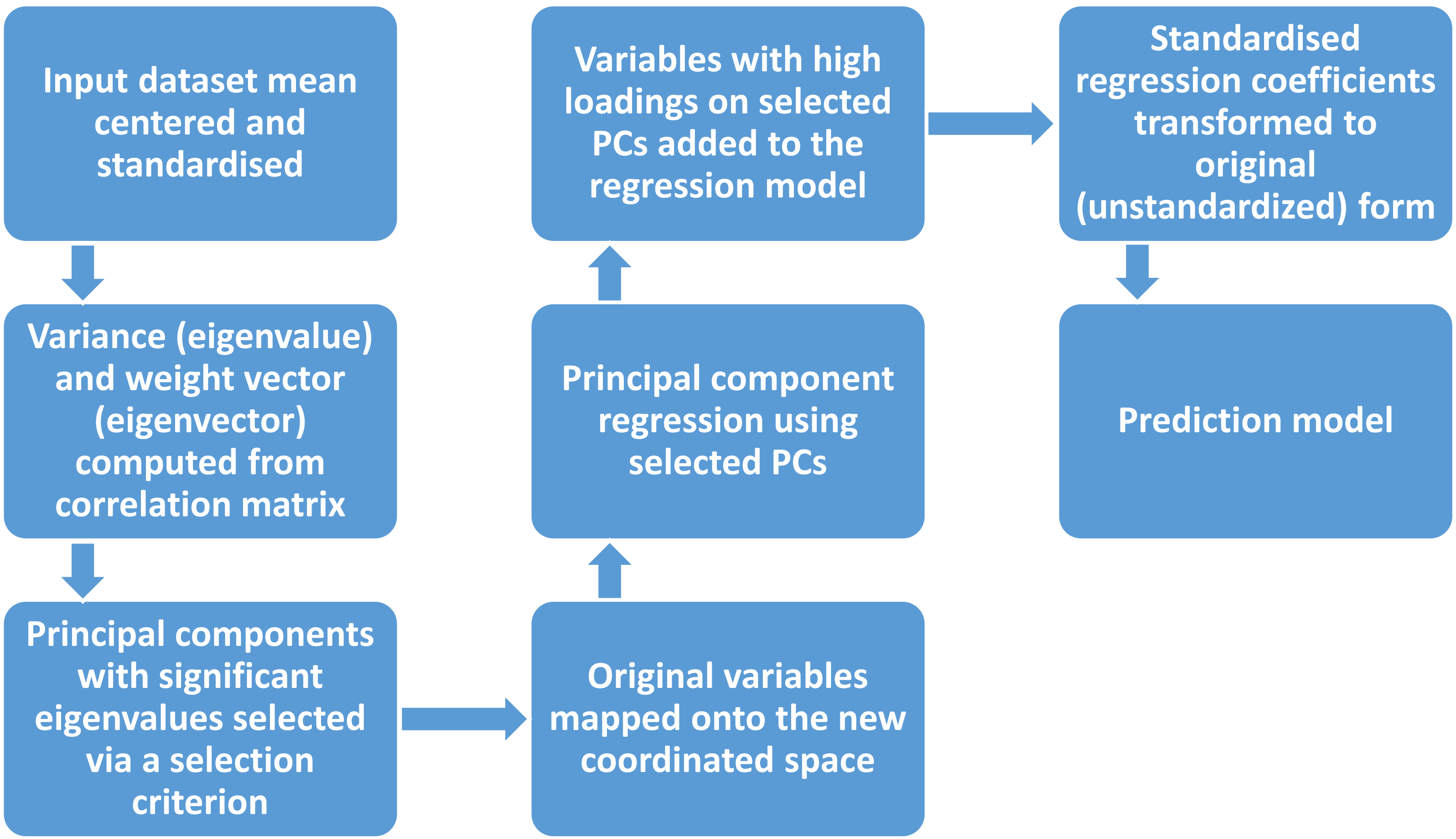
Pre-exponential Factor

Gas Constant

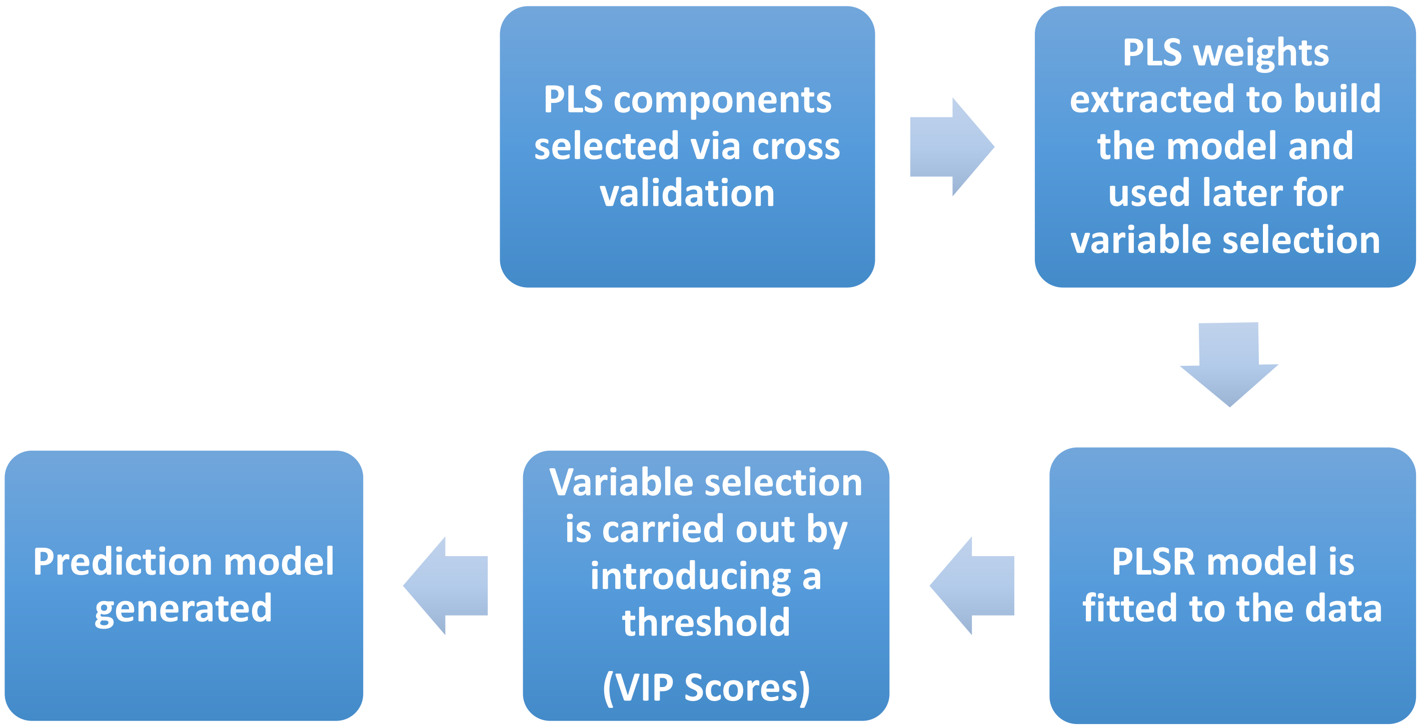
Taking the natural logarithm on both sides gives: $\boldsymbol{In\,K = In\,A - \frac{E_a}{RT}}$

$$\underbrace{In\,y}_{\substack{\text{Corrosion rate}\\ (\mu\text{m.(khr)}^{-1})}} = \overbrace{In(\beta_o)}^{\text{Constant}} + \underbrace{\beta_1 x_{1i}}_{\substack{\text{1000/Metal}\\ \text{temperature , } T_m\\ \text{(1000/K)}}} + \underbrace{\beta_2 x_{2i}}_{\substack{\text{Alloy composition}\\ \text{(wt \%)}}} \ldots.\ldots\ldots + \overbrace{\beta_k x_{ki}}^{\text{Fuel composition (wt \%)}} \ldots. + \underbrace{\varepsilon_i}_{\text{Residual error}}$$

PRINCIPAL COMPONENT ANALYSIS



PARTIAL LEAST SQUARES

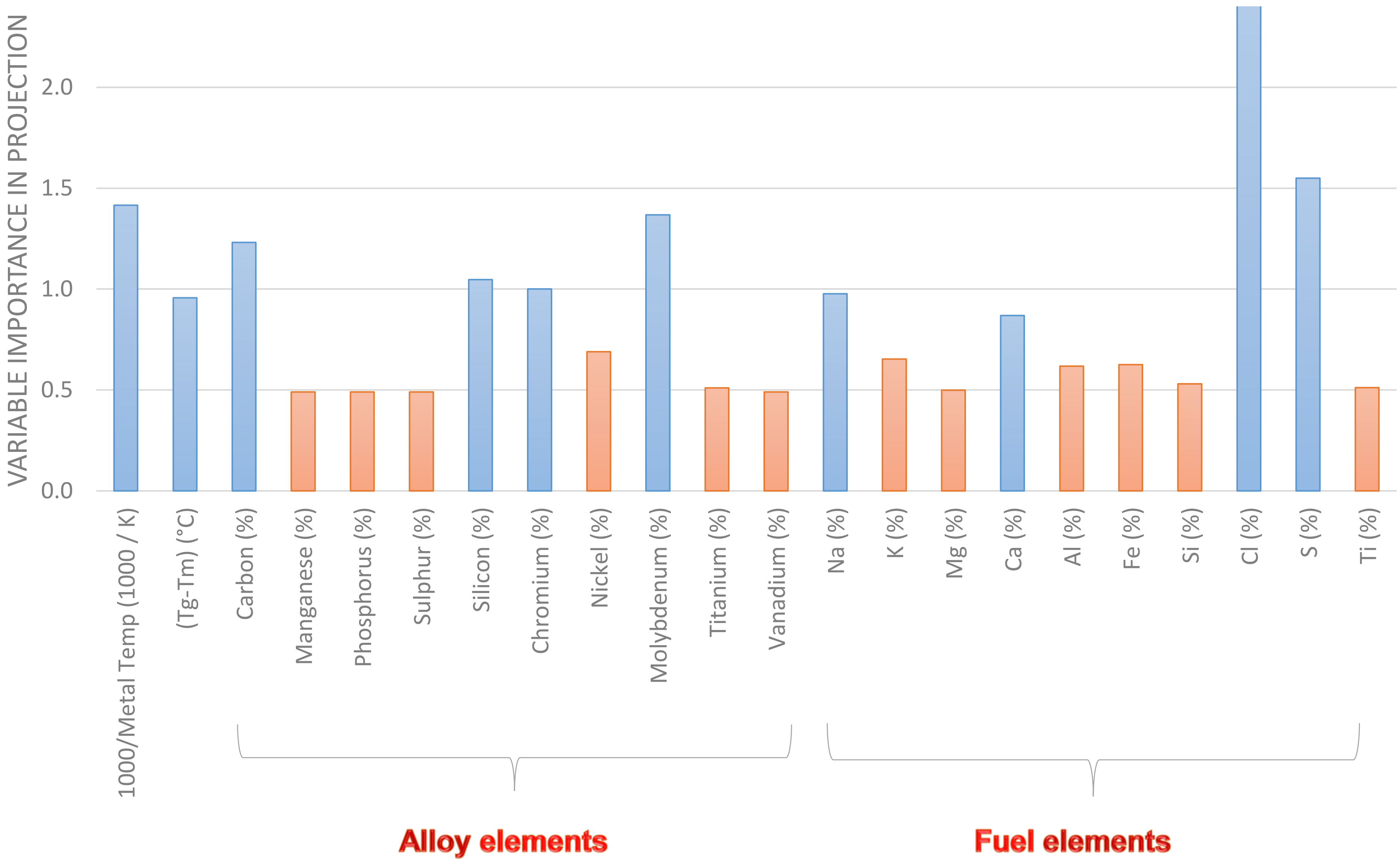


Reference (VIP scores): Mehmood et al (2012); Farres et al (2015)

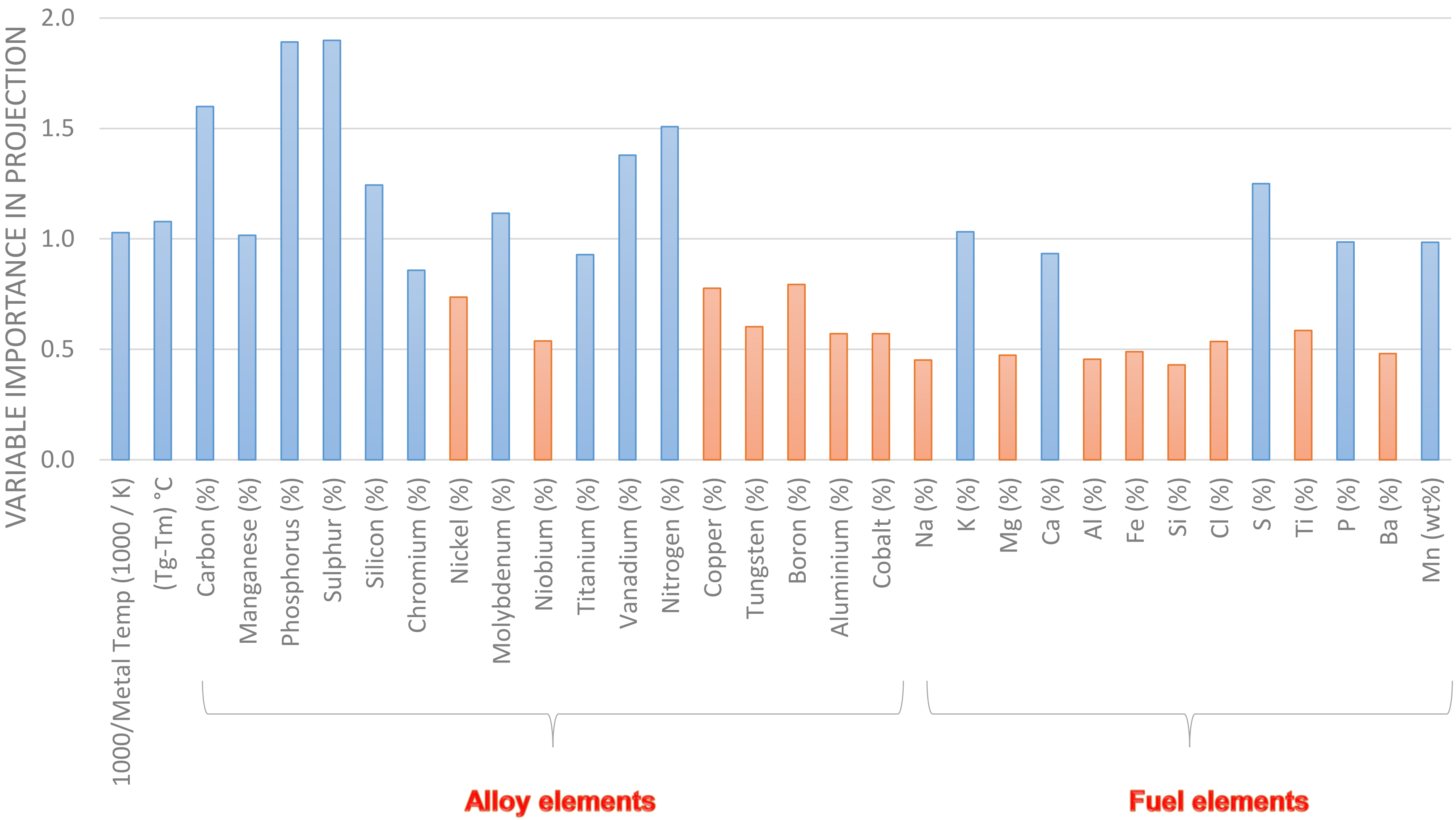
MODEL SUITE

Model	Materials	Tube Position	Fuel
Model 1	Austenitic Fe based	Leading	Midland and North Eastern Region UK Coals
Model 2		Non-leading	
Model 3	Ferritic	Leading	Midland and North Eastern Region UK Coals
Model 4		Non-leading	
Model 5	Austenitic Fe based	Position not specified	Biomass - Clean wood pellets, waste wood and forestry waste
Model 6	Ni based alloys		
Model 7	Ferritic		
Model 8	Coatings and claddings		
Model 9	Austenitic Fe based		US Coal – Eastern and Western Bituminous coal
Model 10	Ni based alloys		
Model 11	Coatings and claddings		
Model 12	TP316, HR3C		10-20% Wood/CCP, Daw Mill Coal

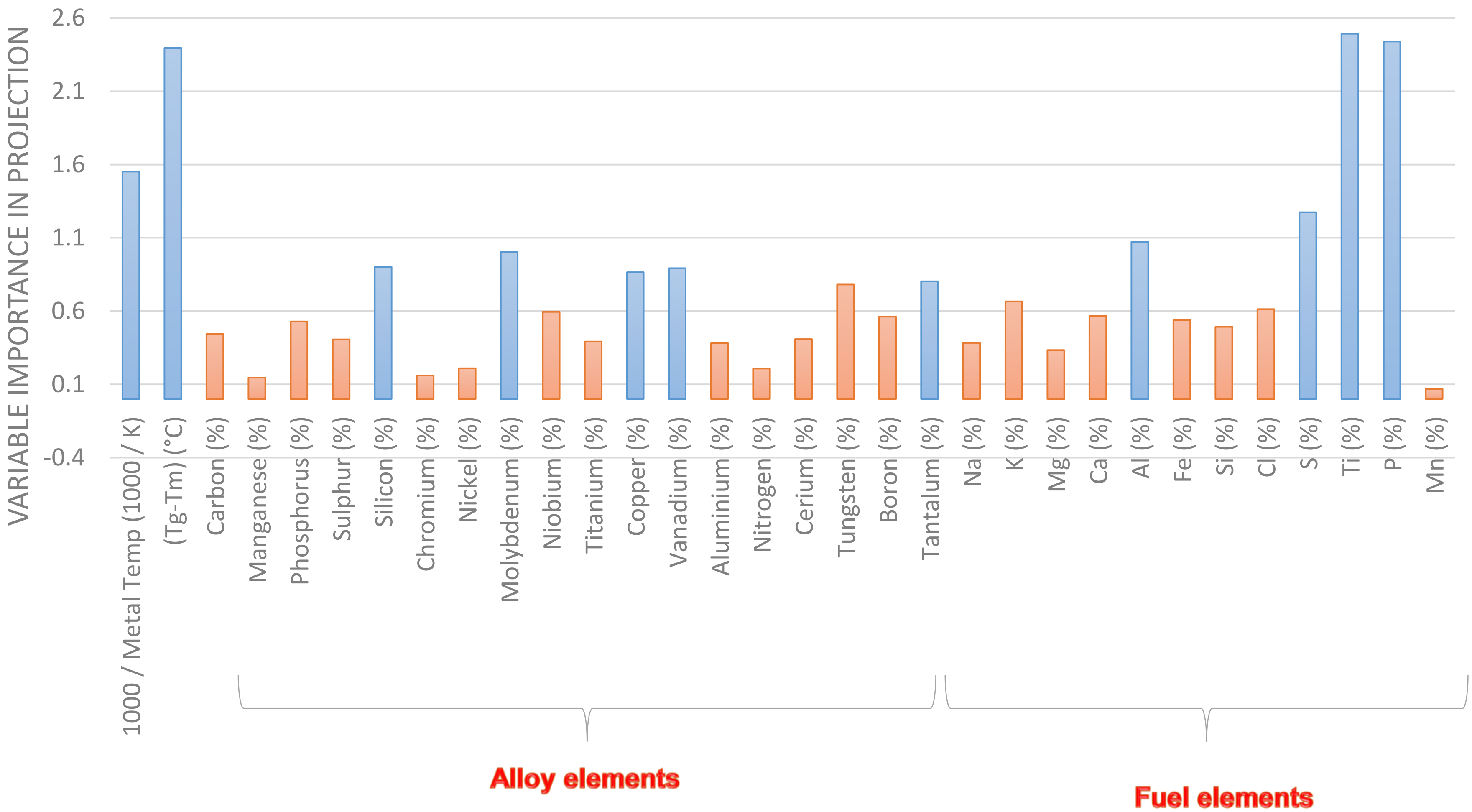
PLS – VARIABLE SELECTION FOR MODEL BUILDING (MODEL 1, UK COAL DATA)



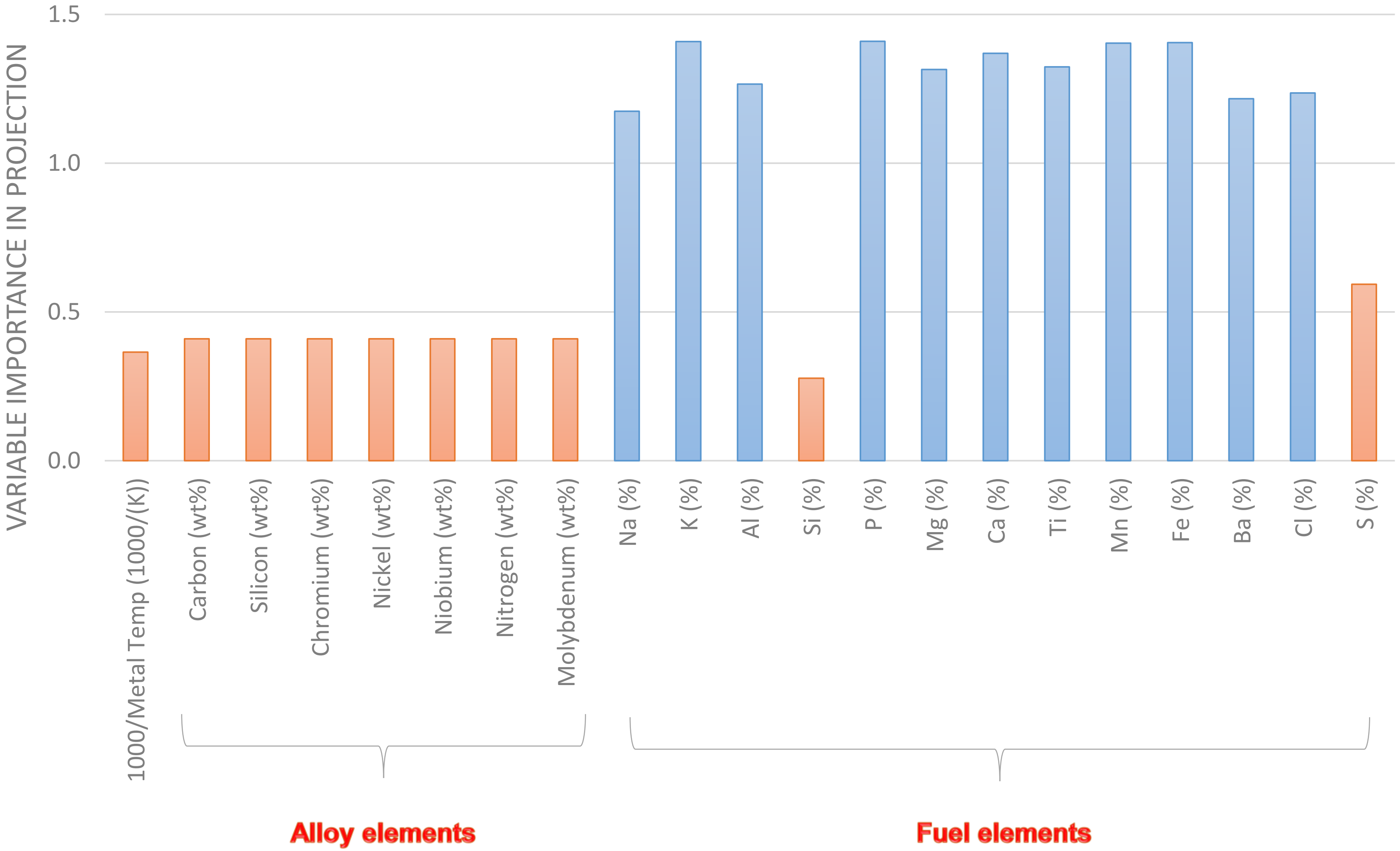
PLS – VARIABLE SELECTION FOR MODEL BUILDING (MODEL 5, UK BIOMASS DATA)



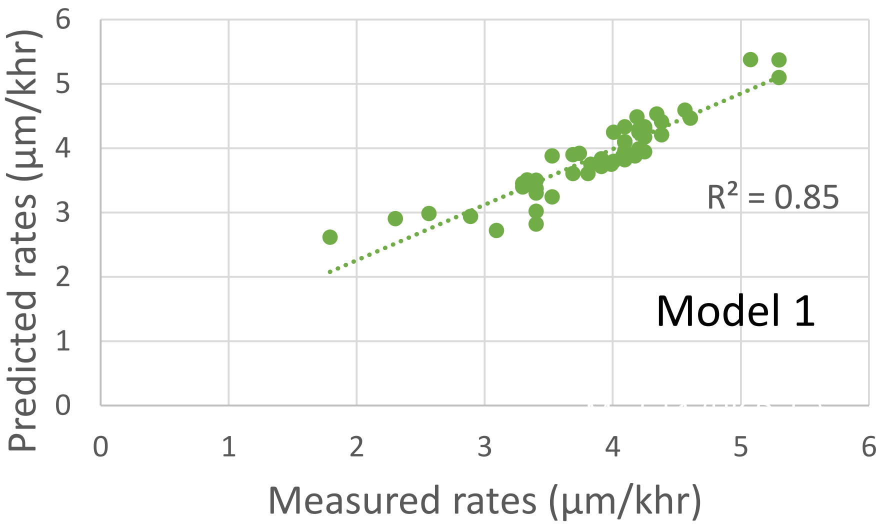
PLS – VARIABLE SELECTION FOR MODEL BUILDING (MODEL 9, US COAL DATA)

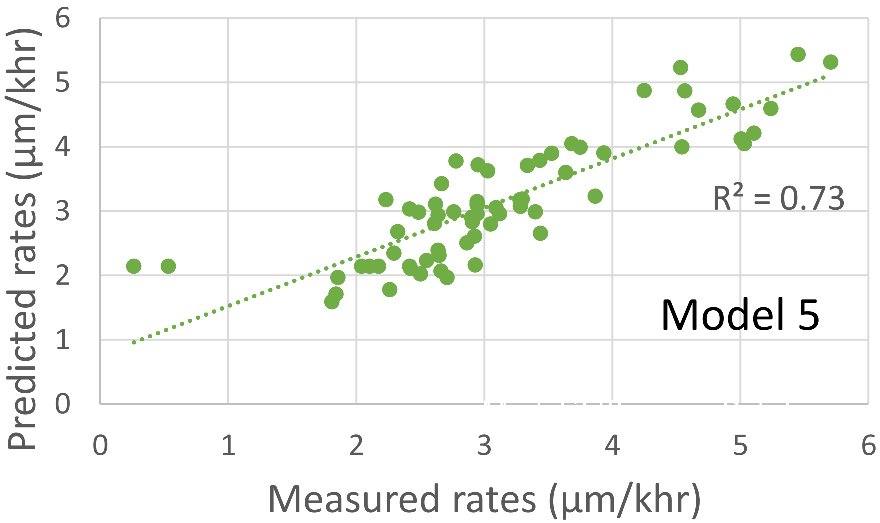


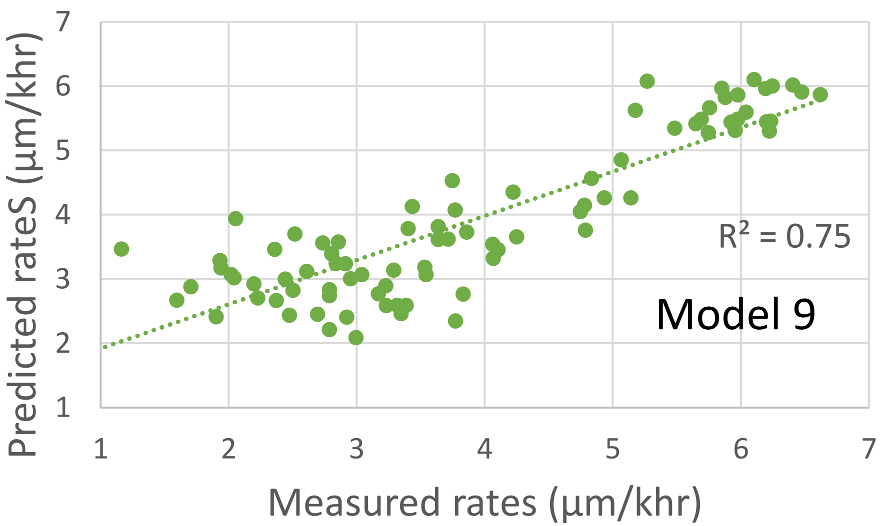
PLS – VARIABLE SELECTION FOR MODEL BUILDING (MODEL 12, UK CO-FIRING DATA)

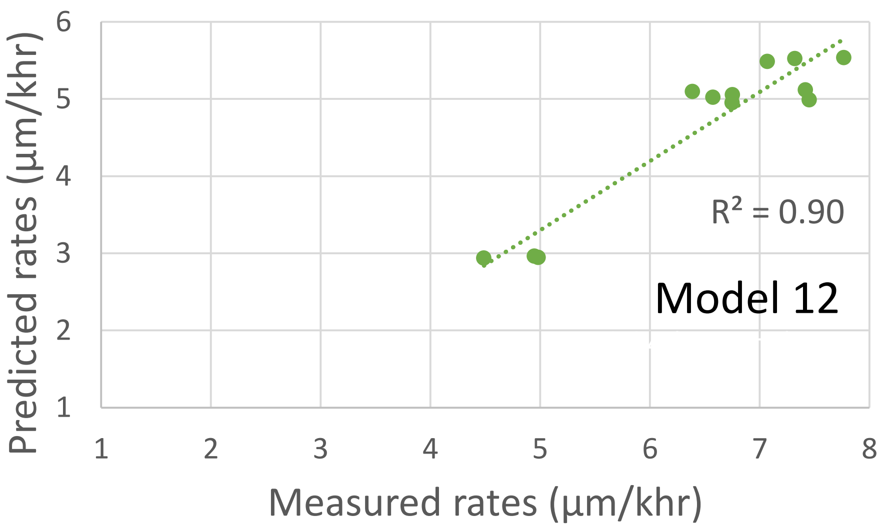


COMPARISON OF PREDICTED AND MEASURED CORROSION RATES USING PLS









CONCLUSIONS

- The analysis suggests a sulphur dominated fireside corrosion dependent on the fuel Cl and Na levels in UK data; for biomass data (comprising mainly wood pellets), alkali sulphate interaction with fireside corrosion dependent mainly on K, Ca and Ti; a fireside corrosion model dependent on Cl, K, Mg, S and P in co-firing data, and the corrosion model from US data is dependent mainly on the fuel's sulphur content.
- Variable selection for fireside corrosion models is in line with conclusions from previous investigations – for instance; chloride influence in UK coals.
- PLS on average produced better predictive models than PCA, and with fewer latent variables compared to PCA. On PCA, the more latent variables (or PCs) selected, the better the model performance; this is not the case for PLS so there is less chance of overfitting the data.
- PCA also includes more predictor variables with negligible effects on the corrosion rate compared to PLS

ACKNOWLEDGEMENTS

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  – Dr. Joy Sumner

THANK YOU

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