



# Sequential estimation of kinetic parameters for nutraceutical degradation using the Arrhenius model

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# Nutraceuticals

- Nutraceutical compounds are food components having health promoting, disease preventing or medicinal properties
- Nutraceuticals found in grains, oils, fruits, vegetables, and animal products
- Anthocyanins are a nutraceutical
- Anthocyanins are sensitive and unstable at high temperatures



# Objectives

-  Simultaneous estimation of kinetic degradation parameters of anthocyanins in grape pomace
-  Sensitivity analysis and sequential estimation of thermal and kinetic parameter

# Overview of the process

Can Sealing

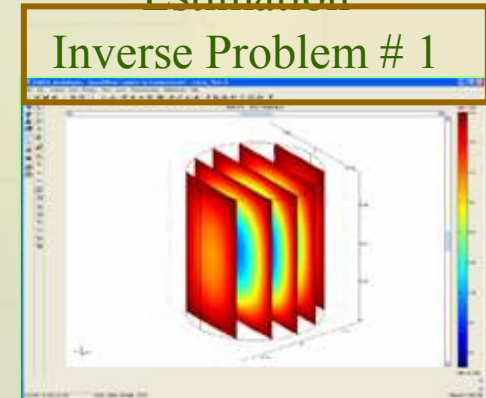


Retorting at different times



Thermal parameter Estimation

Inverse Problem # 1



Extraction of anthocyanins



HPLC analysis



Kinetic parameter Estimation

Inverse Problem # 2



# Inverse Problem # 1

## Estimation of thermal parameter

Two-dimensional axi-symmetric heat conduction

$$\frac{1}{r} \frac{\partial}{\partial r} \left( k(T) r \frac{\partial T}{\partial r} \right) + \frac{\partial}{\partial z} \left( k(T) \frac{\partial T}{\partial z} \right) = C(T) \frac{\partial T}{\partial t}$$

$$\frac{1}{r} \frac{\partial}{\partial r} \left( \alpha(T) r \frac{\partial T}{\partial r} \right) + \frac{\partial}{\partial z} \left( \alpha(T) \frac{\partial T}{\partial z} \right) = \frac{\partial T}{\partial t}$$

$$\alpha(T) = \left( \frac{(T_2 - T)}{(T_2 - T_1)} \times \alpha_1 \right) + \left( \frac{(T - T_1)}{(T_2 - T_1)} \times \alpha_2 \right)$$

# Boundary Conditions

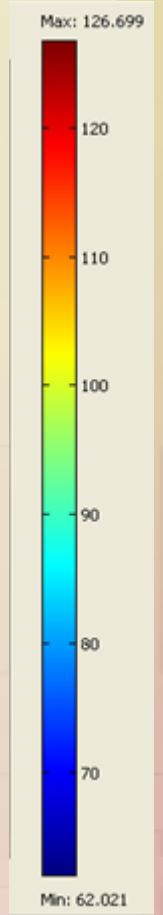
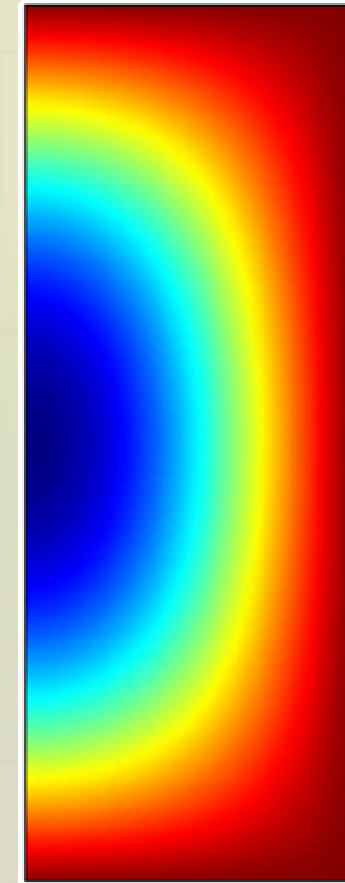
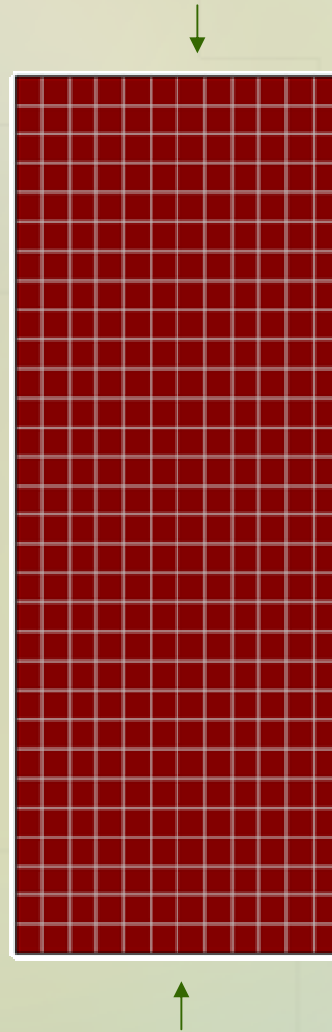
$$\frac{\partial T}{\partial r}(0, z, t) = 0 \quad T(r, z, 0) = T_i \quad \frac{\partial T}{\partial z}(r, H, t) = 0$$

$$-k \frac{\partial T}{\partial r}(R, z, t) = h(T(R, z, t) - T_\infty)$$

$$-k \frac{\partial T}{\partial z}(r, 0, t) = h(T(r, 0, t) - T_\infty)$$

# Temperature Profile of the can

Axial symmetry →



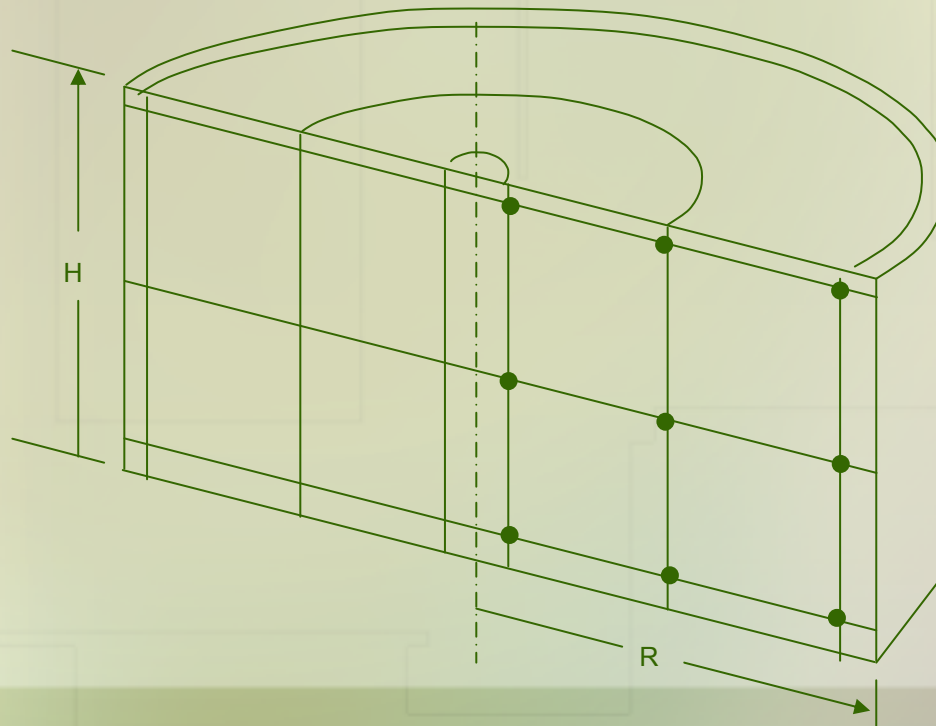
# Mass Average Anthocyanin Inverse Problem # 2

$$C_{\text{pred}} = 2C_0 \iint e^{-k_r} \int_0^t \frac{-E_a}{R} \left( \frac{1}{T(r,z,t)} - \frac{1}{T_r} \right) dt \, r \, dr \, dz$$



# Estimation of Kinetic Parameters

- Trapezoidal method for Integral over time
- 3-point Gauss method for integral over space



# Estimation of Kinetic Parameters

## Inverse Problem # 2

Nlinfit  
( $K_r, E_a$ )



$$SSQ = \sum_{i=1}^n [\bar{C}_{\text{obs}, i} - \bar{C}_{\text{pred}, i}]^2$$

## Inverse Problem # 1

Nlinfit  
( $\alpha$ )



$$SSQ = \sum_{i=1}^n [T_{\text{obs}, i} - T_{\text{pred}, i}]^2$$

# Scaled Sensitivity

- A scaled sensitivity for parameter can be represented as

$$X_{p_i} \equiv p_i \frac{\partial y}{\partial p_i}$$

Finite difference method

$$X_{p_i} \equiv p_i \frac{y(p_i + \delta b) - y(p_i)}{\delta b}$$

- Useful when comparing several parameters in a model

# Sequential Estimation

Updating parameters as the new observations are added

“On-line” method of parameter estimation for dynamic processes

The mathematic form is derived from MAP estimation

$$S_{MAP} = (Y - \tilde{Y})^T \psi^{-1} (Y - \tilde{Y}) + (\beta - \mu_\beta)^T V_\beta^{-1} (\beta - \mu_\beta)$$

If  $V_\beta$  is diagonal with large diagonal components, ML and OLS estimates can be approximated.

# Sequential Estimation

Original  
Data



$$\begin{pmatrix} t_1 & Y_1 \\ t_2 & Y_2 \\ t_3 & Y_3 \\ t_4 & Y_4 \\ \vdots & \vdots \\ t_n & Y_n \end{pmatrix}$$



$$(E_a \quad k_r)$$

# Algorithm

$$e(b^*) \quad X(b^*)$$

$$K_{i+1} = P_i X_{i+1}^T (X_{i+1} P_i X_{i+1}^T + \phi_{i+1})^{-1}$$

$$e_{i+1} = (Y_{i+1} - X_{i+1} b_i)$$

$$b_{i+1}^* = b_i^* + K_{i+1} \{e_{i+1} - X_{i+1} (b_i^* - b)\}$$

$$P_{i+1} = P_i - K_{i+1} X_{i+1} P_i$$

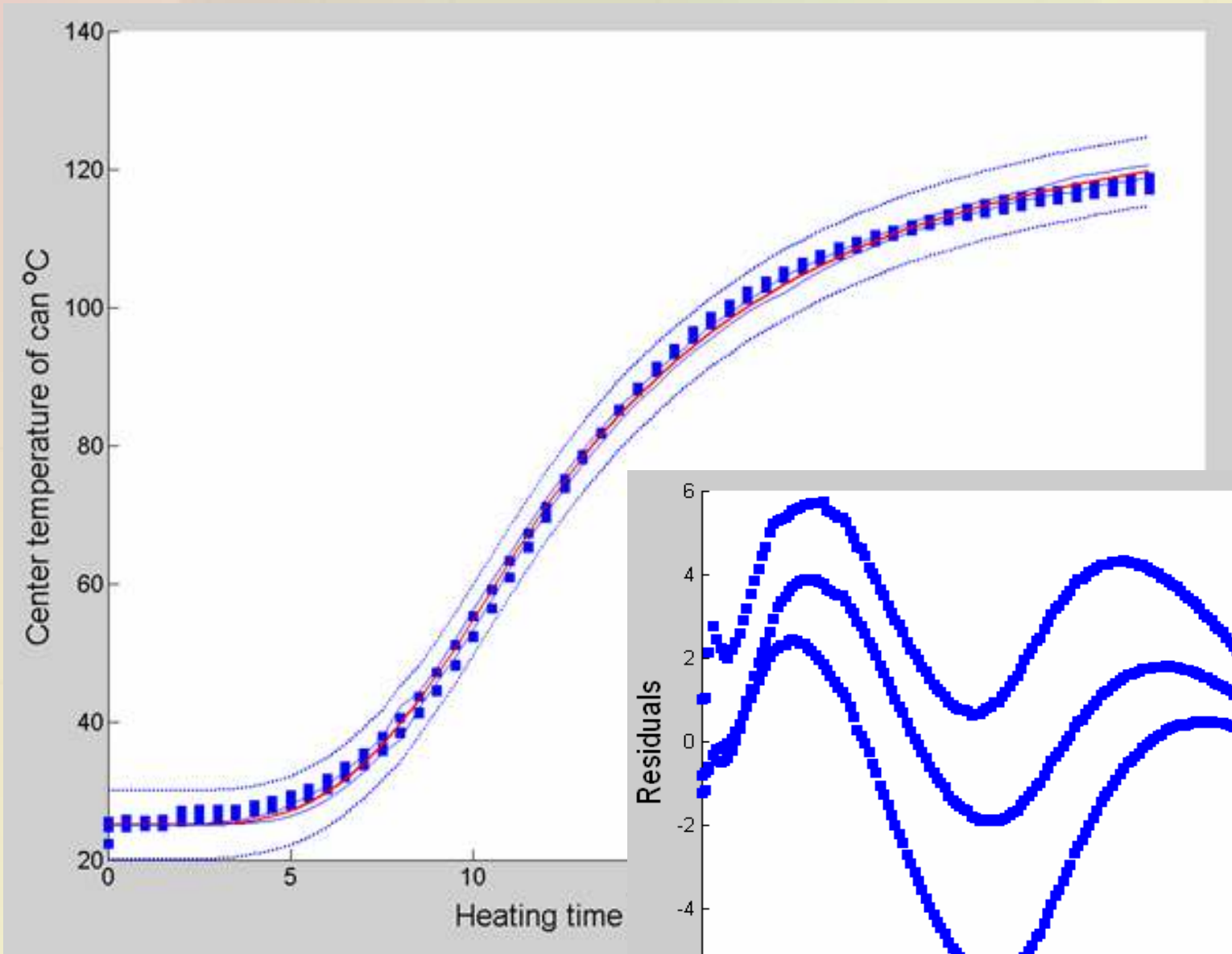
# Sequential Cont'd

- If there is prior information, iteration starts with

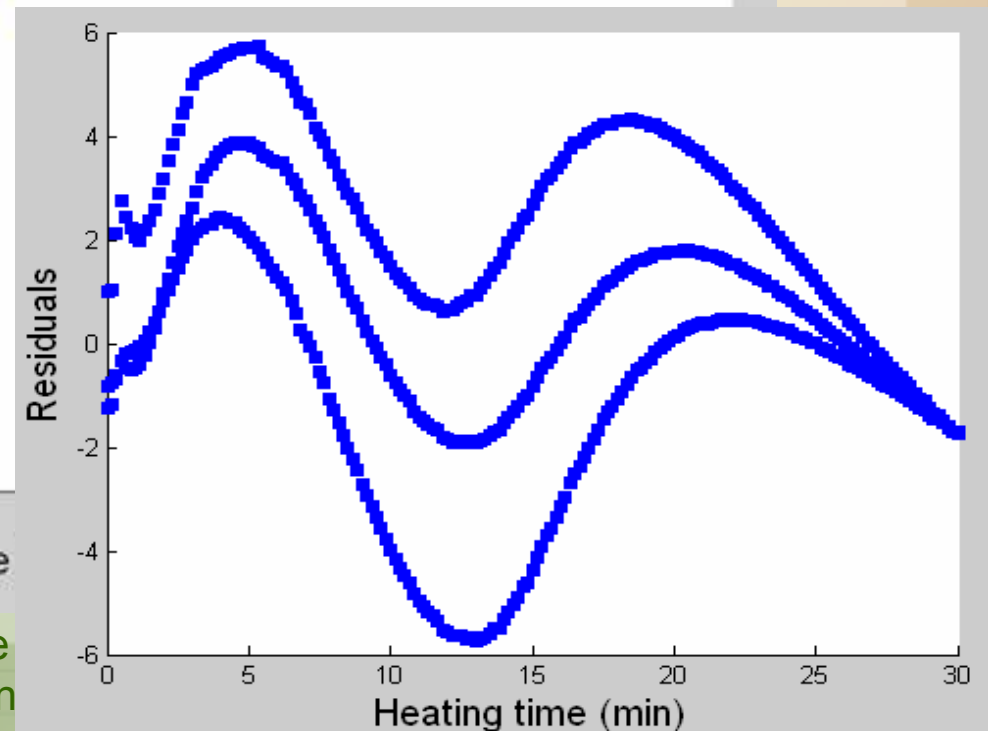
$$b = \mu \text{ and } P(0) = V_{\beta}$$

- If there is no prior information, P can be diagonal matrix with large diagonal terms
- Model building tool

# Result - Thermal Parameters



Example of predicted temperature temperature (triplicate runs) in can

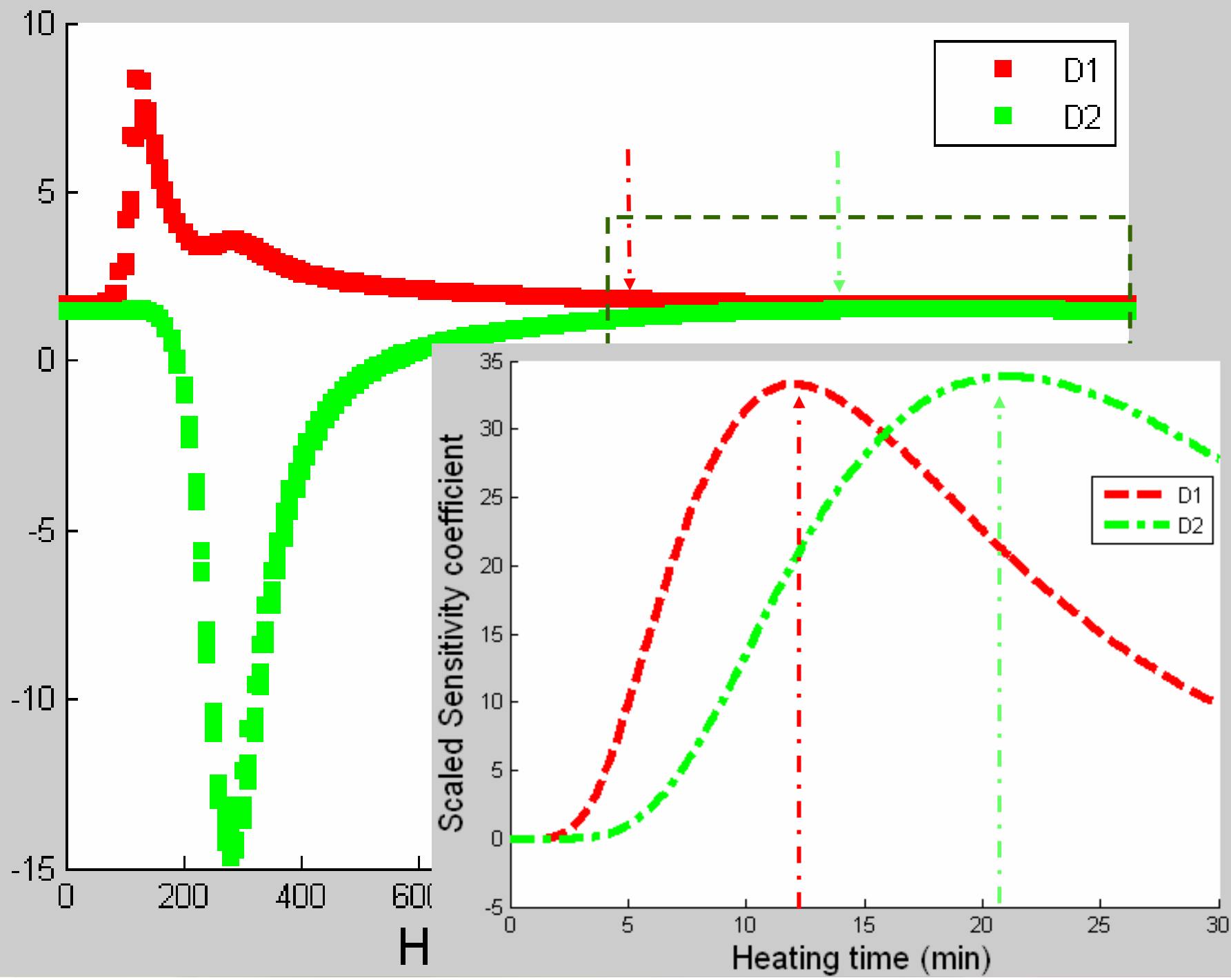


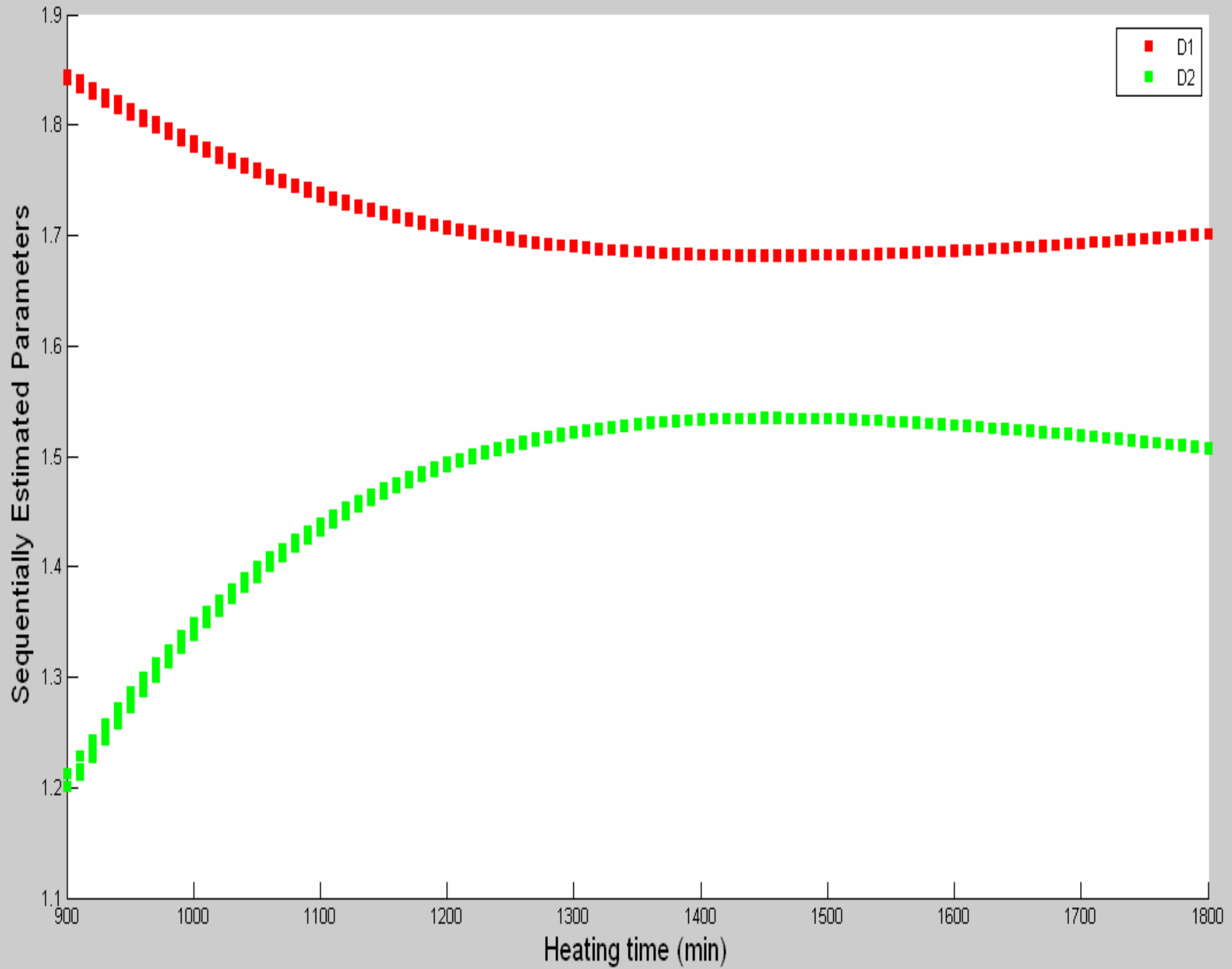


# Estimates of thermal diffusivity parameters

Parameter	Parameter Estimates	Standard Error	Correlation coefficient	95% asymptotic confidence interval	RMSE
$\alpha_1$ at 80 °C	$2.32 \times 10^{-7}$	$0.0054 \times 10^{-7}$	0.260	$2.31 \times 10^{-7}, 2.33 \times 10^{-7}$	2.21
$\alpha_2$ at 120 °C	$2.51 \times 10^{-7}$	$0.014 \times 10^{-7}$		$2.49 \times 10^{-7}, 2.54 \times 10^{-7}$	

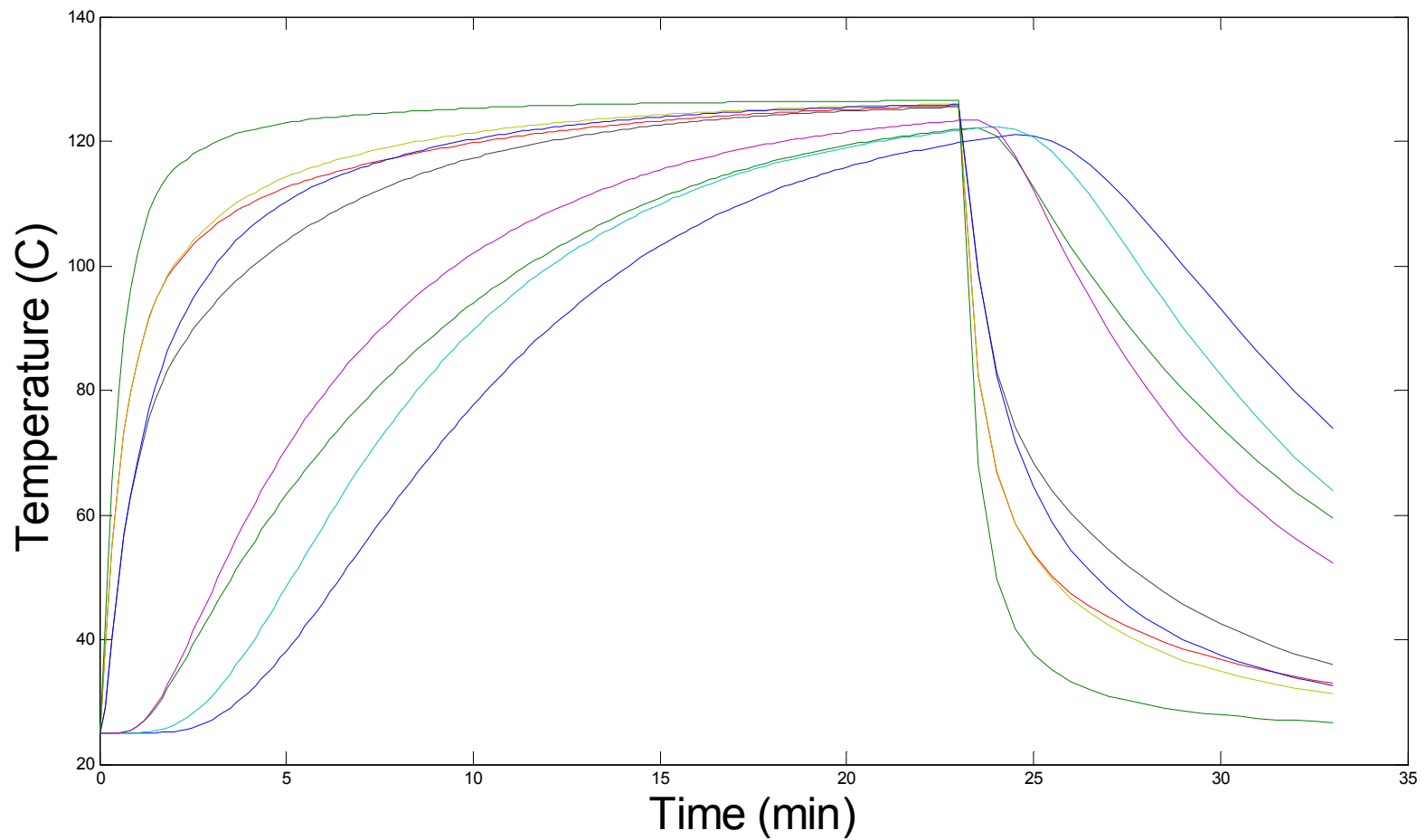
Sequentially Estimated Parameters

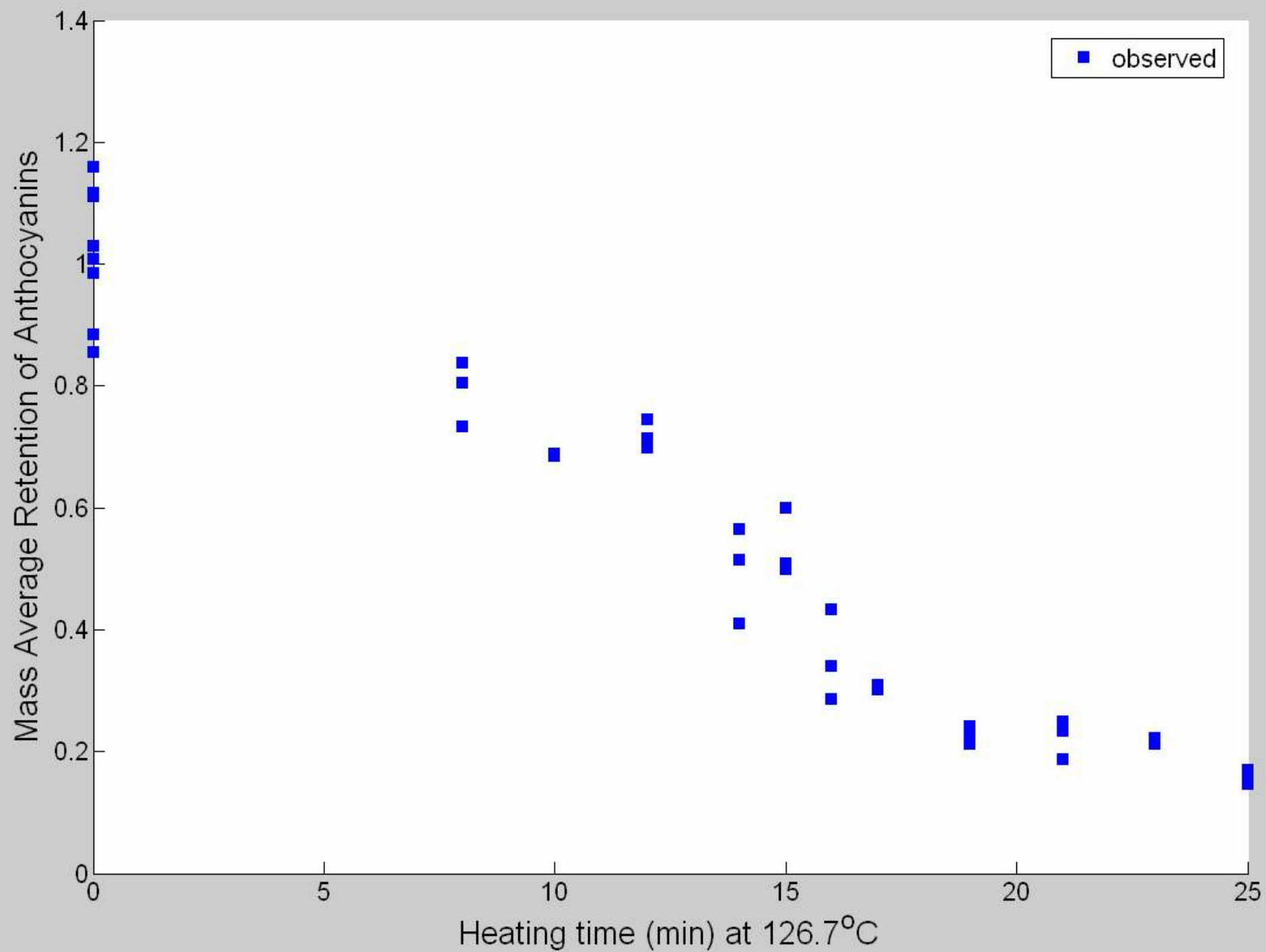


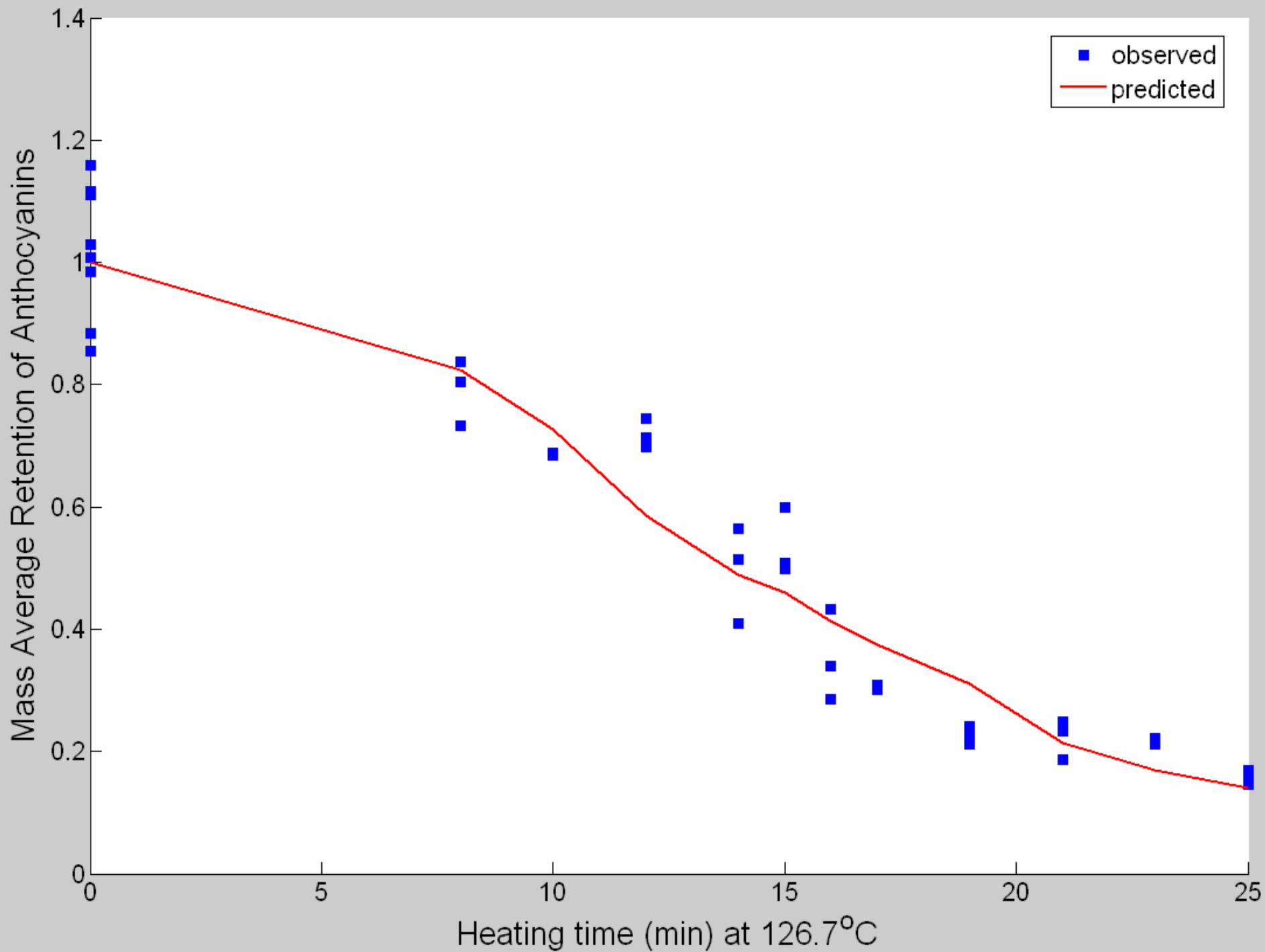


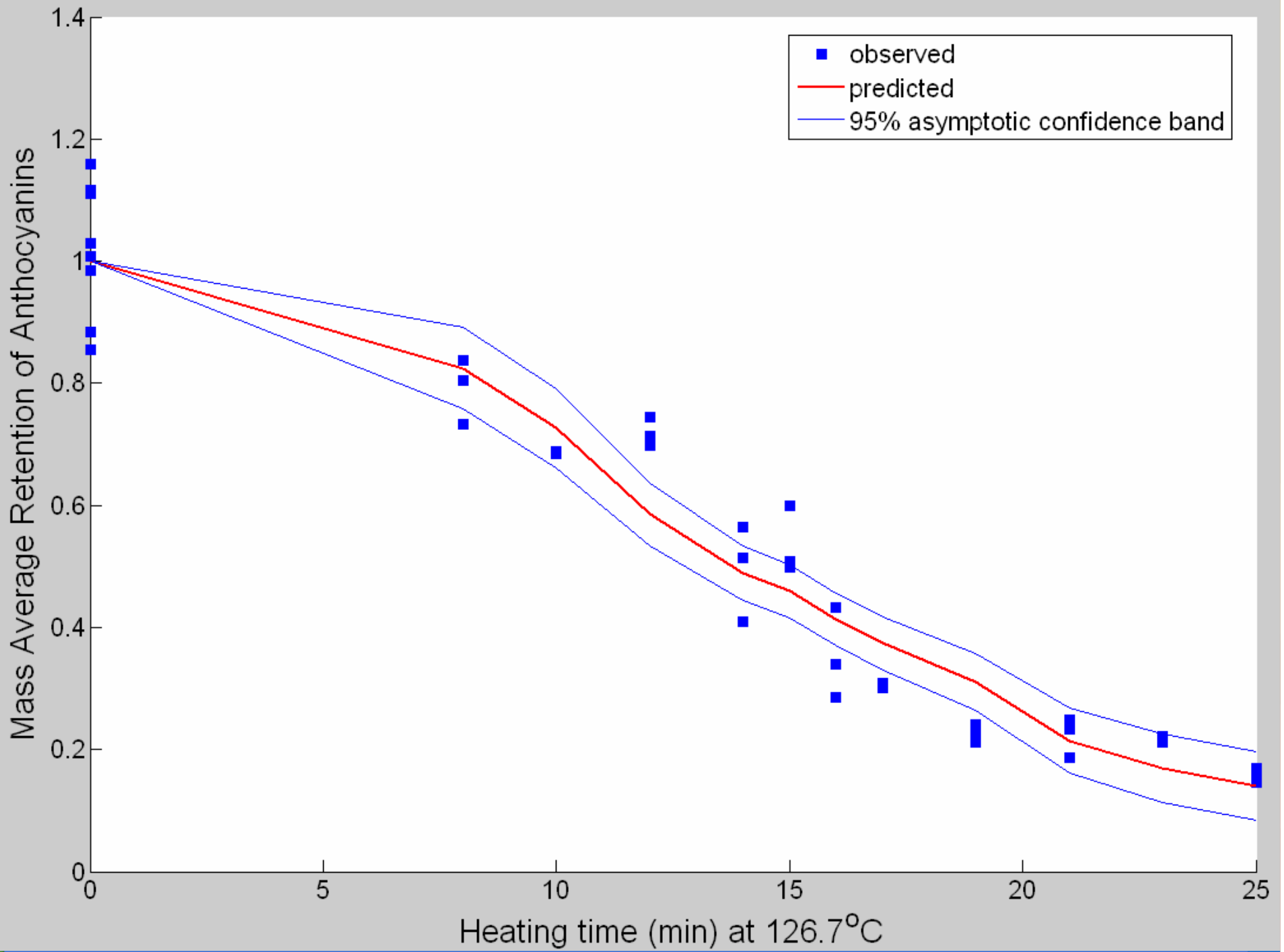
# **Result - Kinetic Parameters**

# Temperature Profile at 9 Gauss Points Inside Can

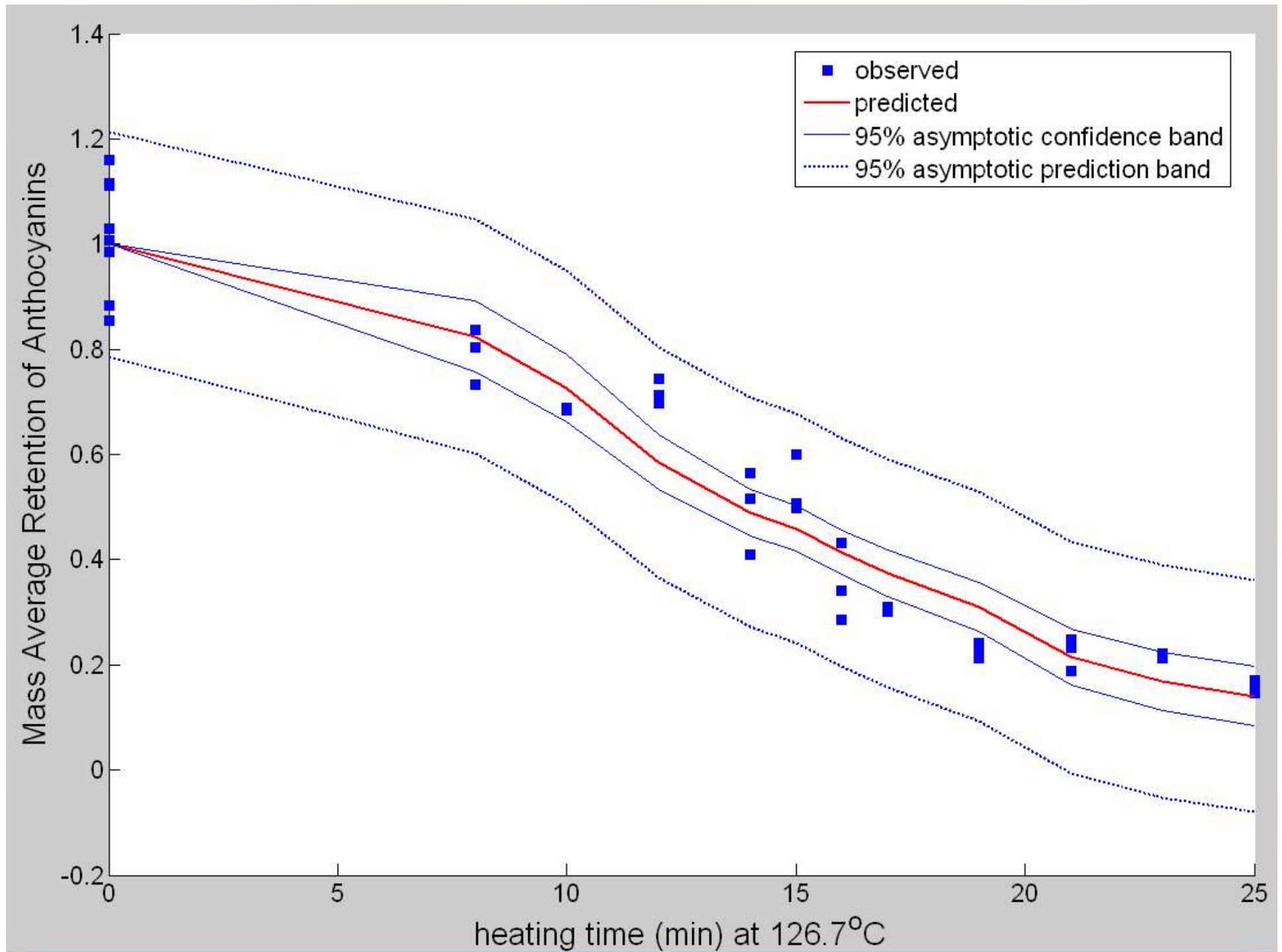




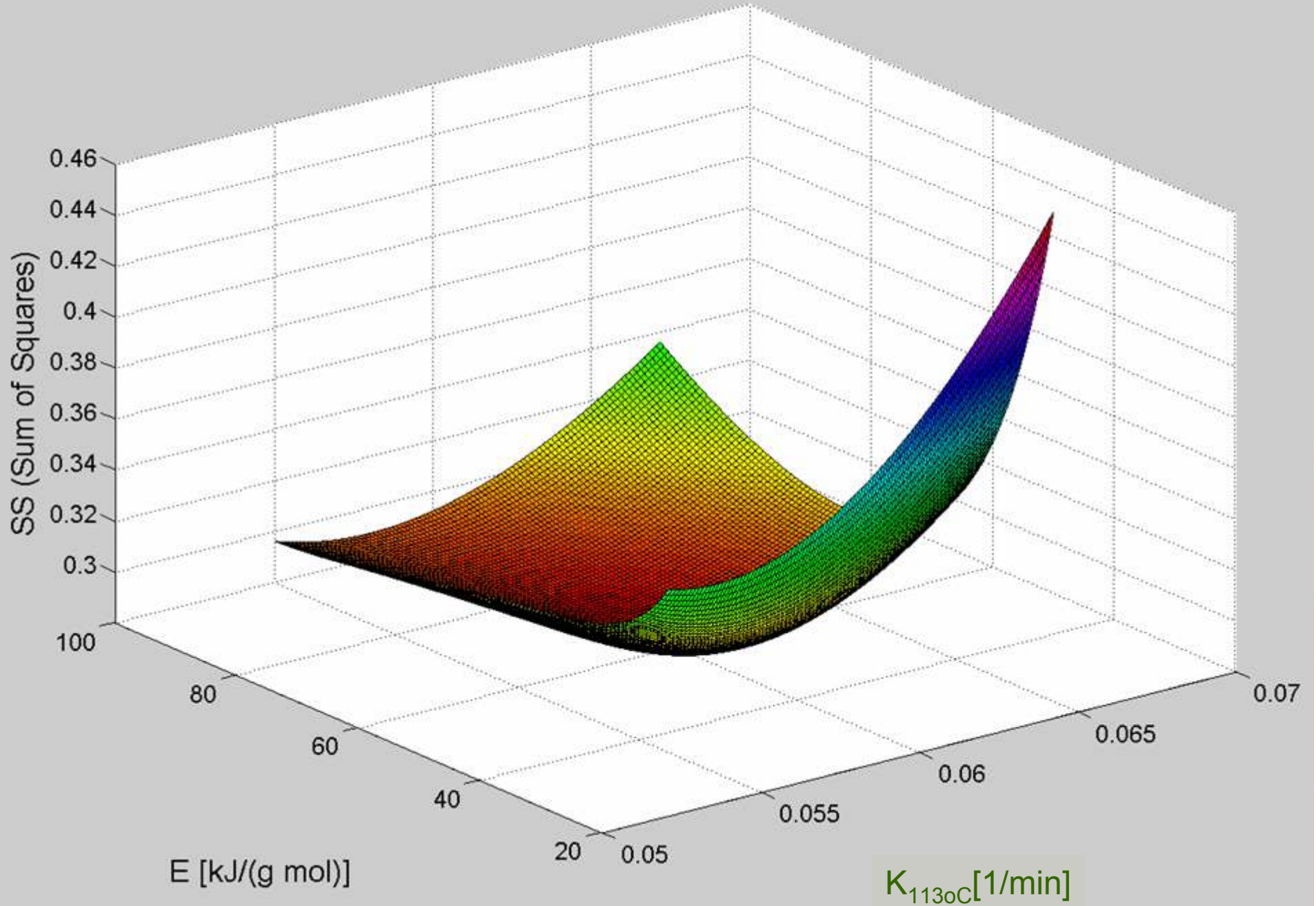








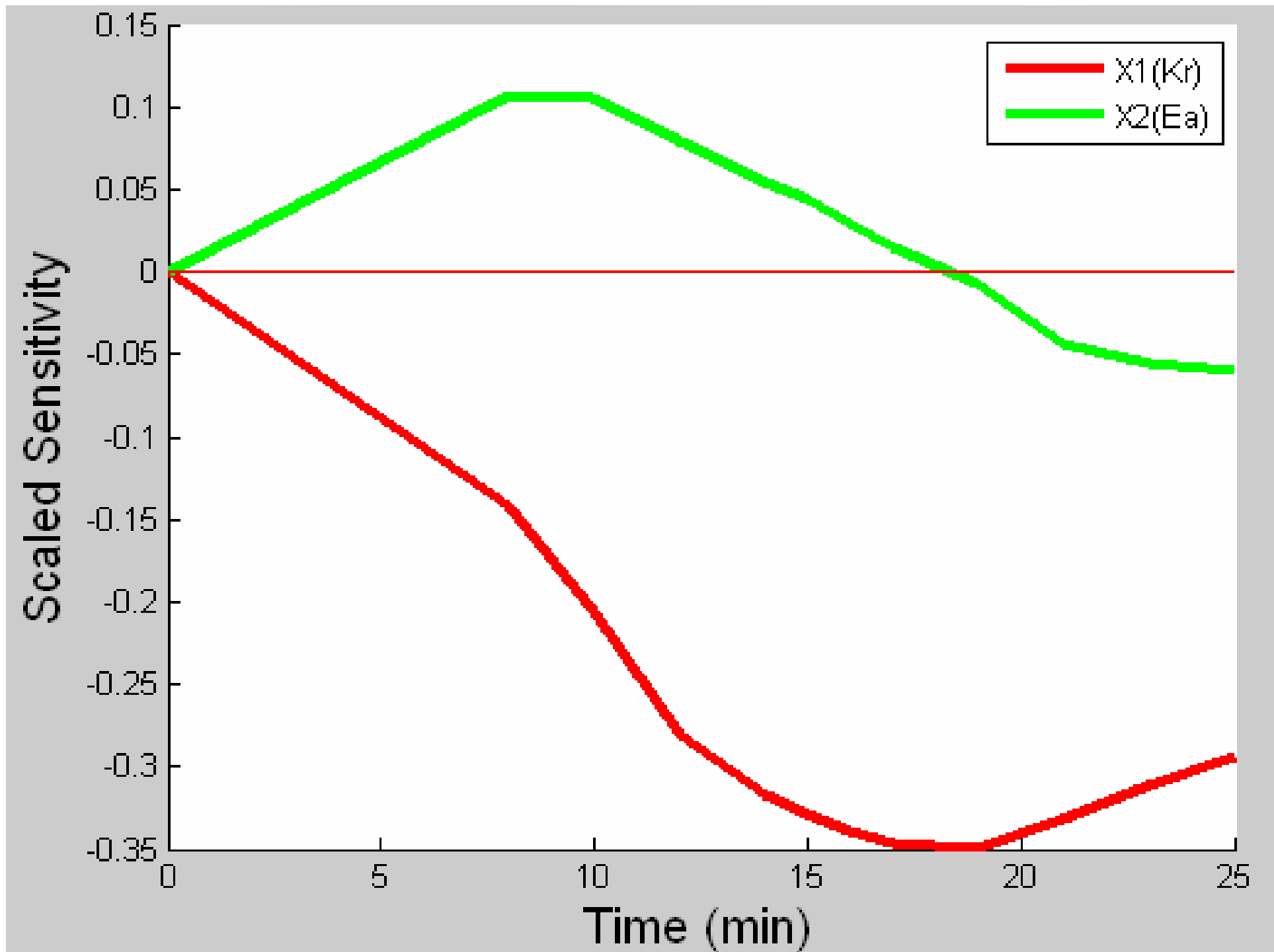
Surface plot of SS

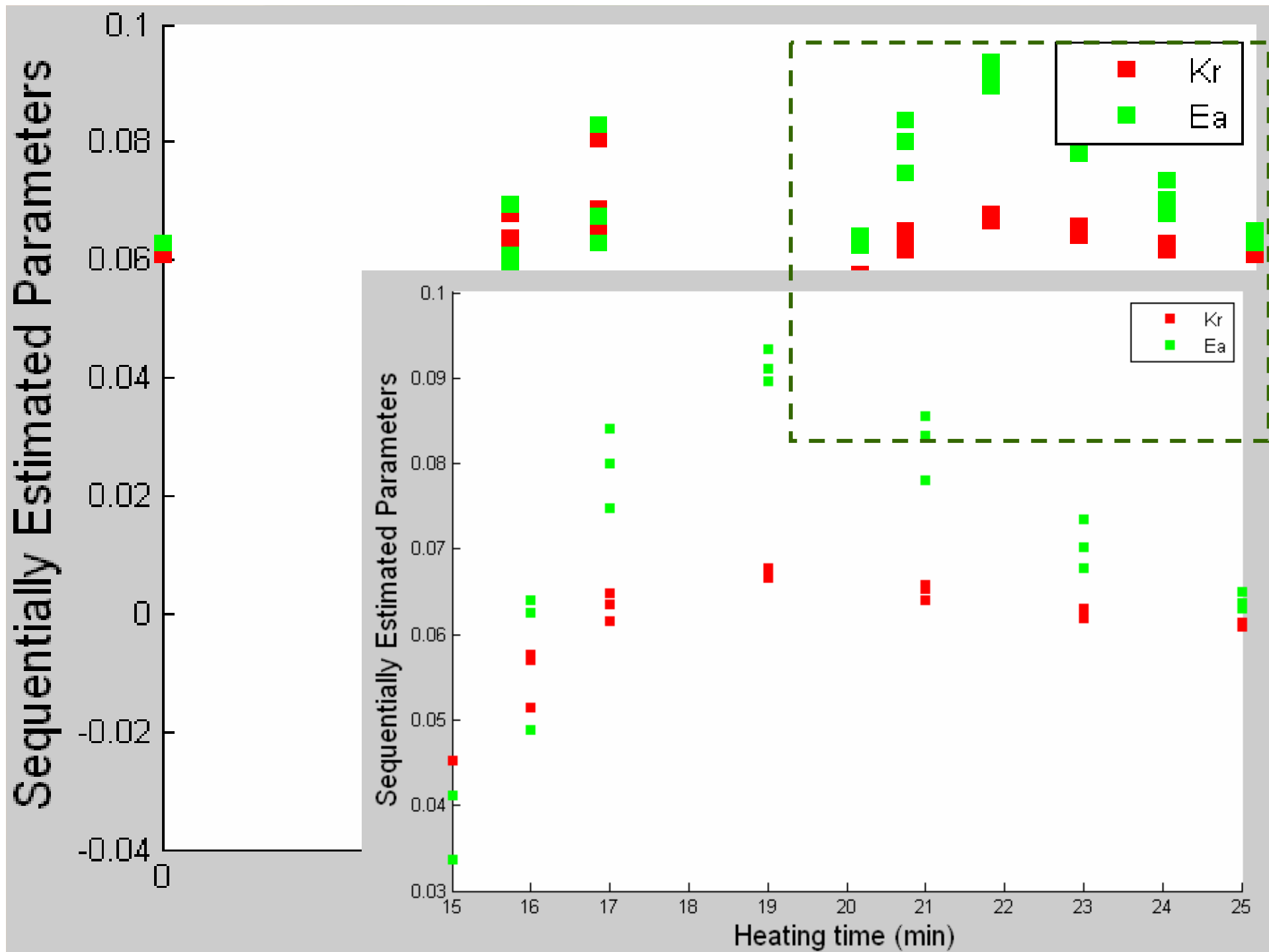


# Result - Kinetic Parameters

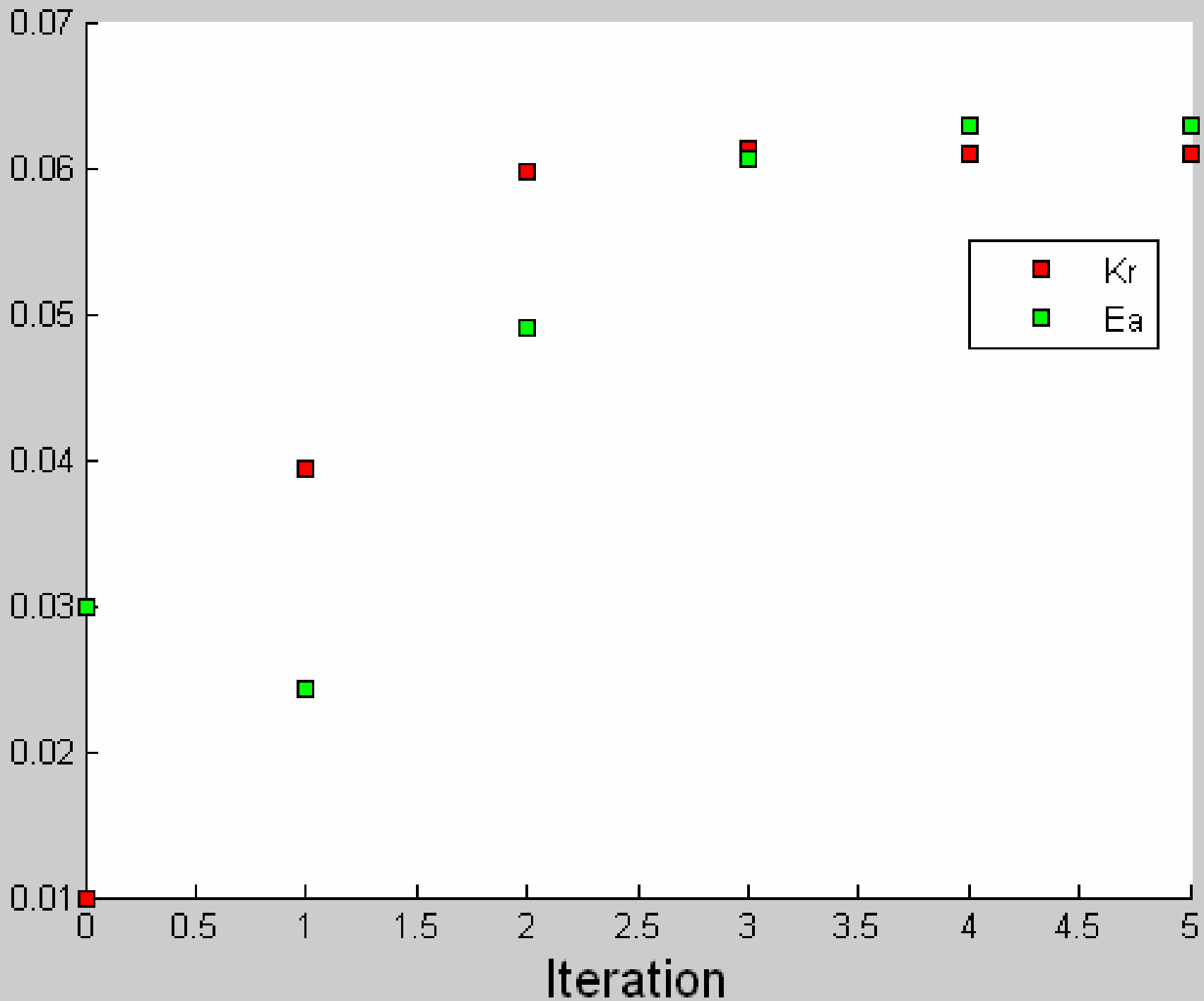
Parameter	No. of Data	Parameter Estimates	Standard Error	Correlation coefficient	95% asymptotic confidence interval	RMSE
$k_{113.9^{\circ}\text{C}}$	42	0.0611 min <sup>-1</sup>	0.0059	$\rho_{k_r, E_a} = 6.49\text{e-}5$ $\rho_{C_o, E_a} = -0.44$ $\rho_{k_r, C_o} = 0.66$	0.0515, 0.0707	4.136
$E_a$		62.23 kJ/g mol	22.16		17.40, 107.0	
$C_o$		37.63 μg/ml	1.361		34.88, 40.38	

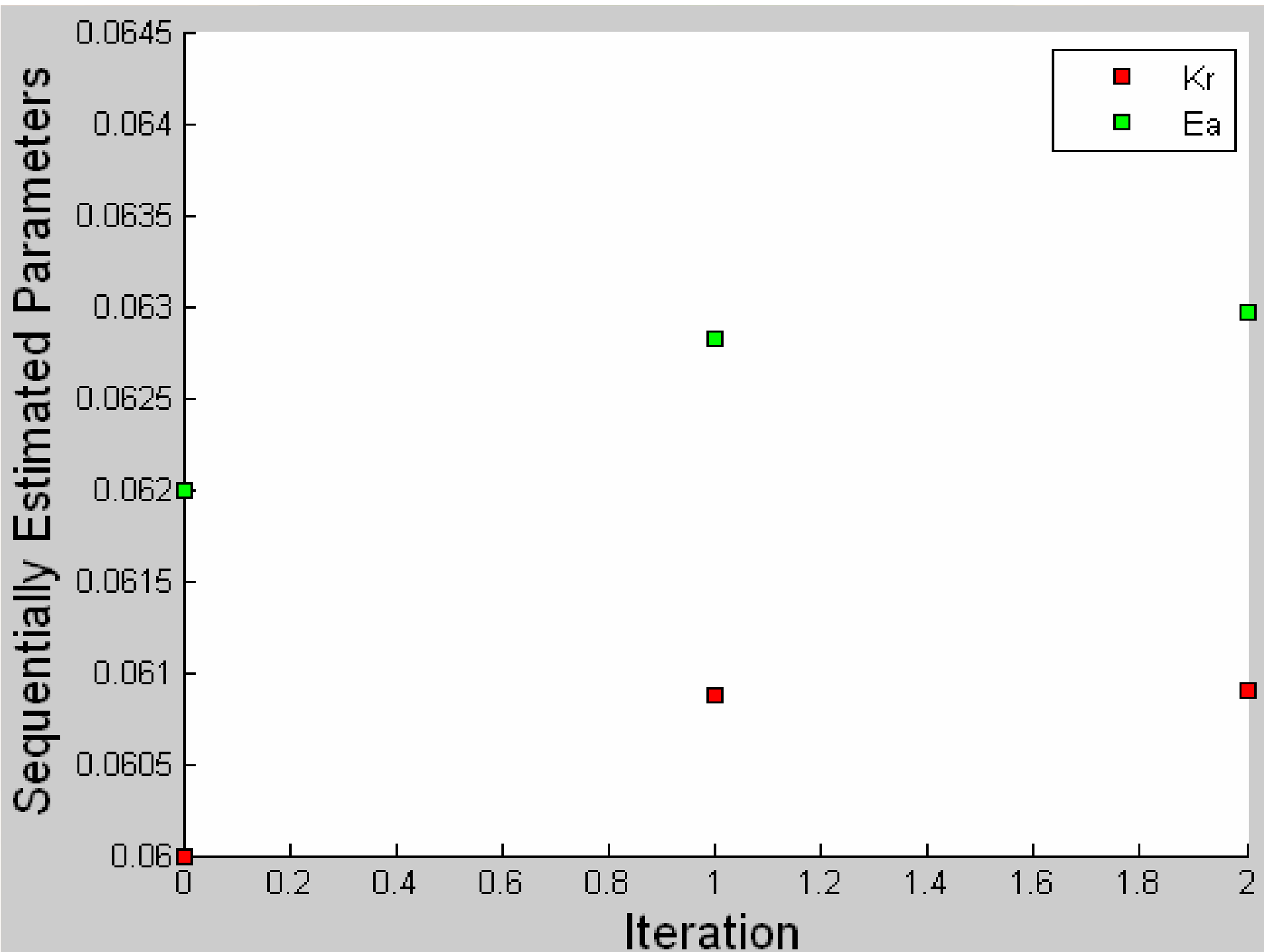
The estimated reference temperature was 113.9 °C (confidence interval 96.5, 129.6)





Sequentially Estimated Parameters





# Conclusions

Sensitivity coefficient analysis is helpful in determining whether all the parameters are estimable in the model

Sequential estimation provides insight into the parameter estimation process