North Carolina Agricultural and Technical State University

D.O.E. Project DE-FE0031747

Alloy for Enhancement of Operational Flexibility of Powerplants

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Outline

Heat Transfer Coefficient vs. Steam Mass Flow

Heat Transfer Coefficient vs. Pressure Drop

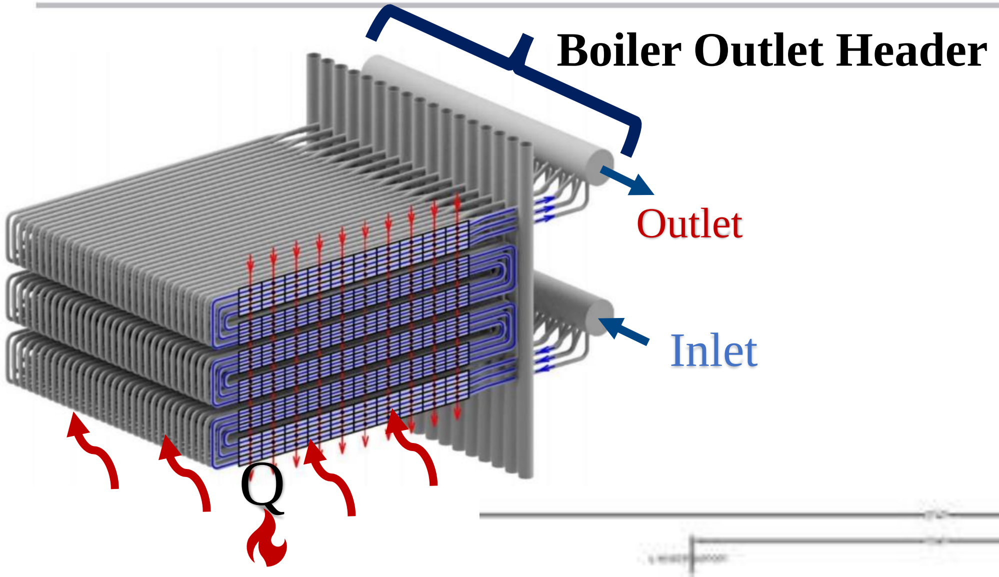
Steam Design Header

North Carolina A&T State University

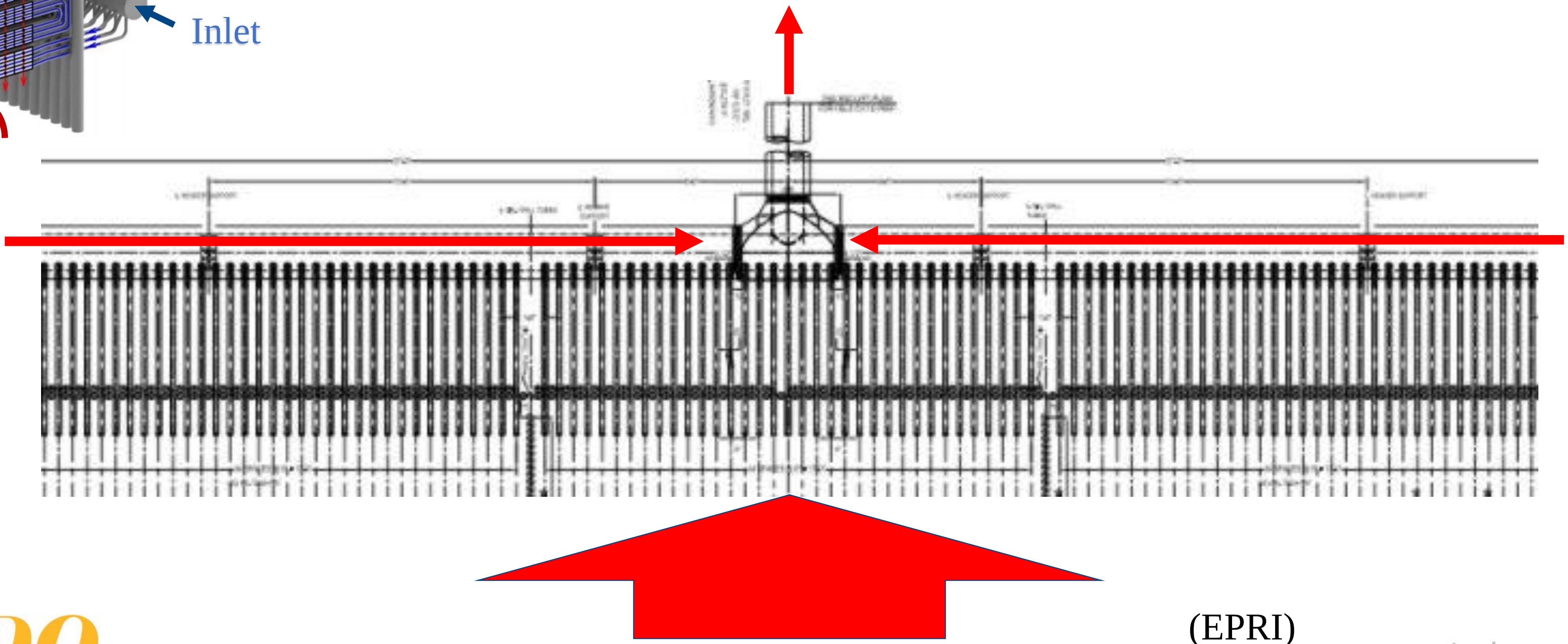
UNC Charlotte

PART I: HEAT TRANSFER COEFFICIENT VS. STEAM MASS FLOW

PREDICTION OF HEAT TRANSFER COEFFICIENT USING MACHINE LEARNING



320MW Outlet Header



(EPRI)

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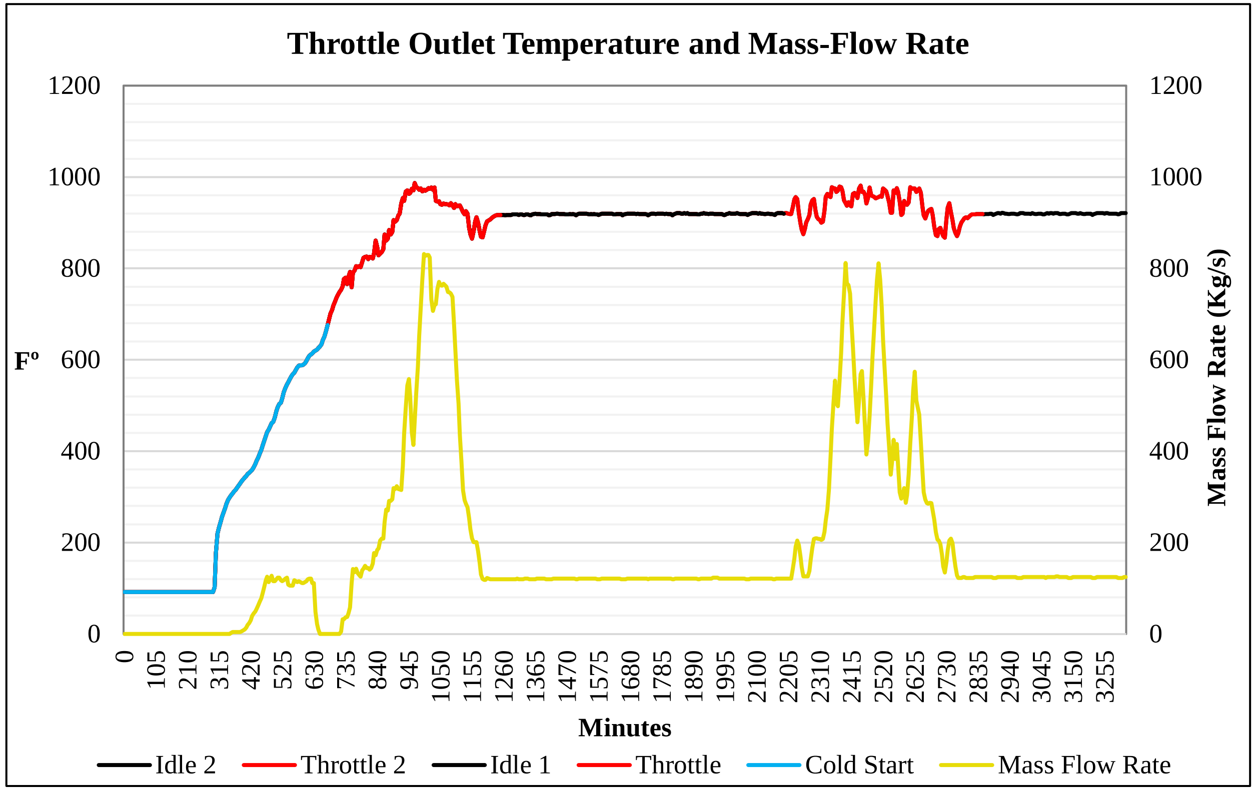

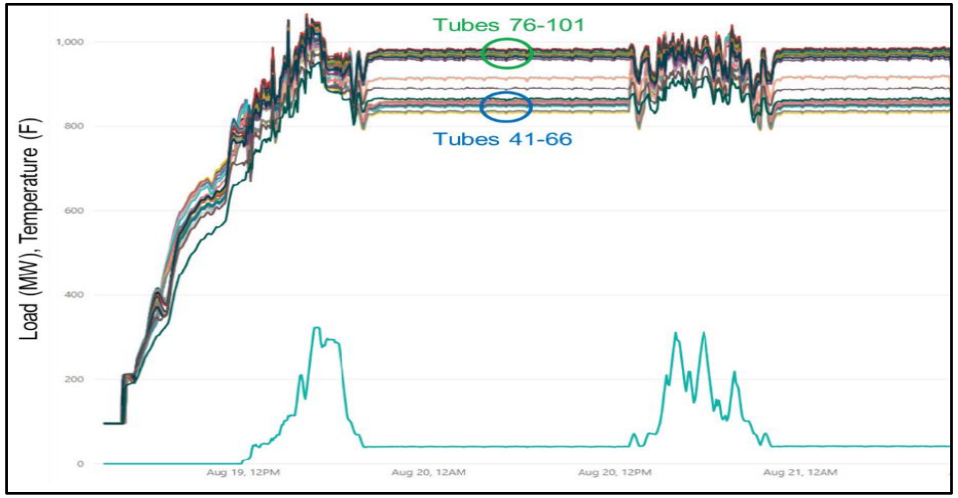

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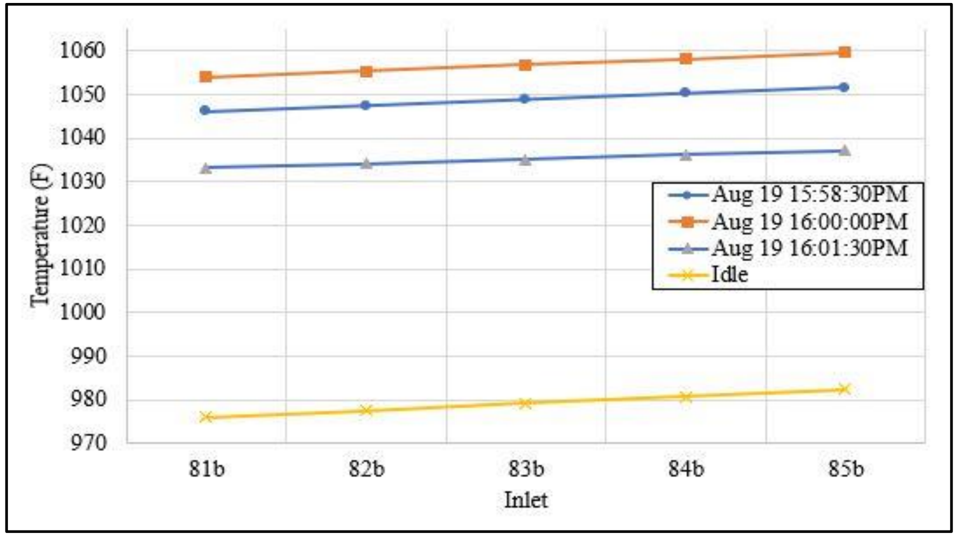

Givens

- Startup cycle of a 320MW powerplant was recorded over 53 hours.
- Temperature was recorded at each branch inlet.
- Temperature and total Mass flow rate was recorded at the throttle outlet.
- Data sampling frequency: 5 minutes.

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Powerplant Operation

First Set of Experimental Data

- Data from a real Power Plant
- Pressure, temperature, mass flow (no heat transfer is measured).
- Measurement over time (10 days measurement)
- Transient State ANSYS simulation

Methodology

Begin

Inlet Properties: Pressure, Temperature and Phase

Inlet Mass Flow

Inlet Calculation: Sp. Enthalpy, Sp. Entropy & Energy Flow

(for each Inlet)

Header Calculation: Total Inlet Energy Flow, Total Inlet Mass Flow, and Sp. Enthalpy

Header Properties: Specific Enthalpy and Temperature, Energy Flow

Begin

Experimental Data: Power Plant Data

Relationship between Energy flow and Mass flow (using data mining & machine learning)

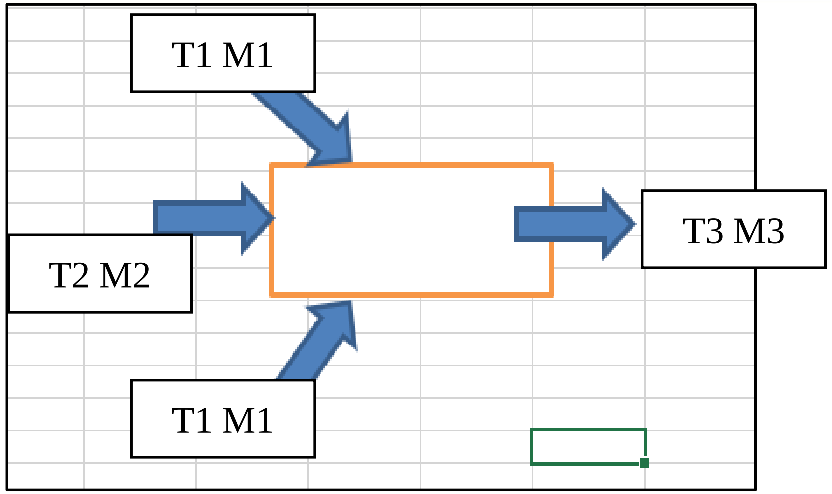
Database: ANSYS simulation to predict heat transfer coefficient as a function of the mass flow: (1) Velocity profile; (2) Reynolds Number; (3) Nusselt Number,

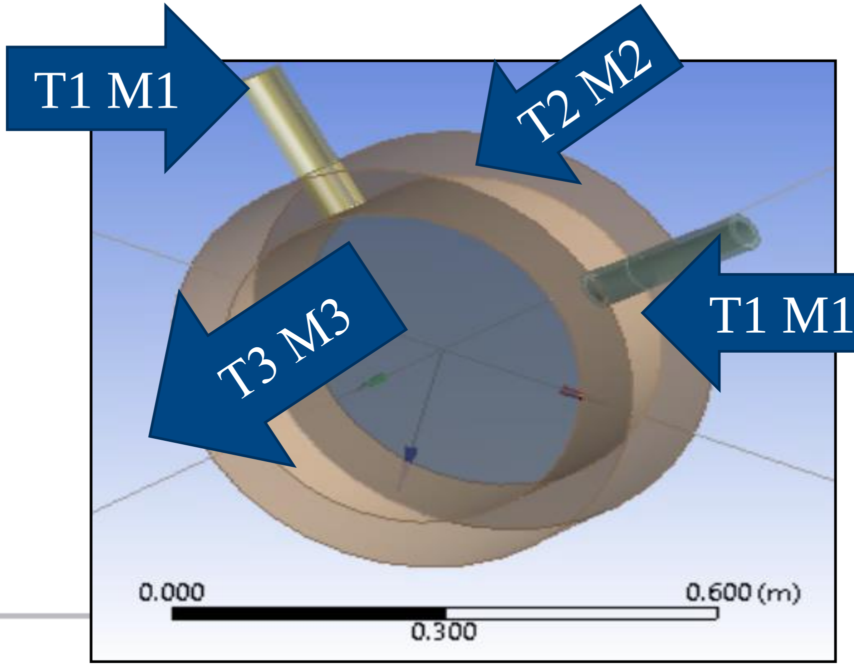
Predict heat transfer coefficient, using machine learning tools for any mass flow

END

Assumptions

- Steady-state
- Ideal Gas
  - Using **Pressure** based formulation to calculate density from pressure and temperature .
- Reference Density
  - Low **Mach** number flow
  - Introduced to improve stability of the system.
- Compressible
- Operating Pressure of 1 Atm





- Input:
  - Temperatures: T1, T2, T3
  - Steam mass flow: F1, F2, F3
- Output:
  - Heat Transfer Coefficient

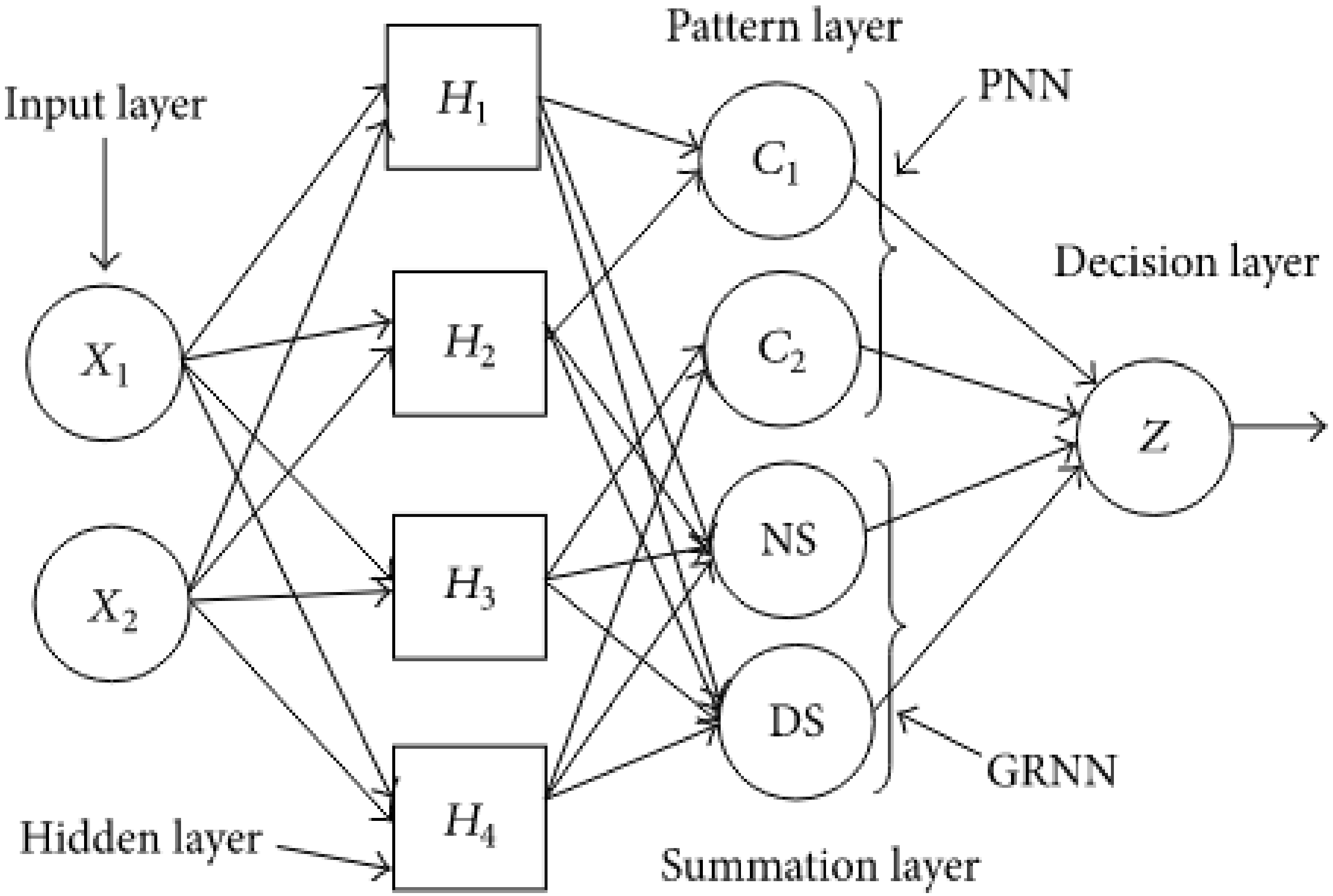
Predictive Models

- Simulation Data (Database)
- Develop the models (70% are for training & 30% are for Testing)
- Comparison between actual vs. model
  - (1) Prediction of Heat Transfer Coefficient as function of the main mass flow;
  - (2) Evaluation of the models using visualization techniques (gain & lift)

Methods

- Multilayer Perceptron
- PNN/GRNN Neural Network
- RBF Network
- GMDH Polynomial Network
- Cascade Correlation Network

Neural Network



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Simulation Parameters

Method	Number of layers	Number of Neurons	Other information related to inputs
Multilayer Perceptron	3 layers	6, 7, 1 Neurons	• 3 layers (1 hidden) • Automatic hidden layer neuron selection • Validation: Random 20% • Hidden layer activation function: Logistic • Output layer activation function: Logistic • Traditional conjugate gradient
PNN/GRNN Neural Network		79	• Sigma for each variable • Constrain minimum sigma values • Model optimization and simplification: remove unnecessary neurons (Minimize error) • Random: 20% • Type of kernel function: Gaussian
RBD Network		9	• Validation: Random 20%
GMDH polynomial network	20	20	• Validation: Random 20% • Layer connection: connect only to previous layer • Overfitting protection control: Hold out sample percent: 20%
Cascade Correlation Network	3	6, 4, 1	• Hidden layer kernel functions: Sigmoid & Gaussian • Model testing and validation: Random 20%

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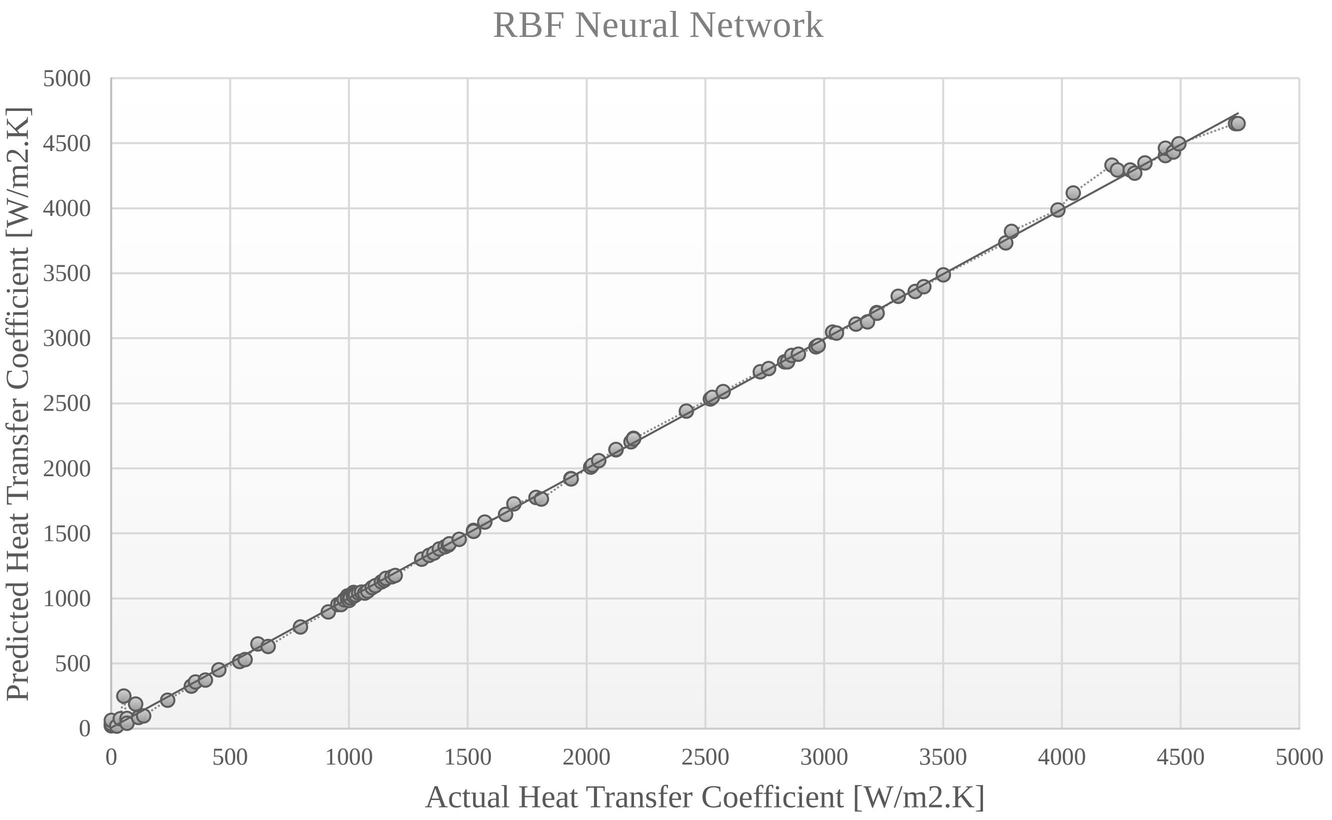
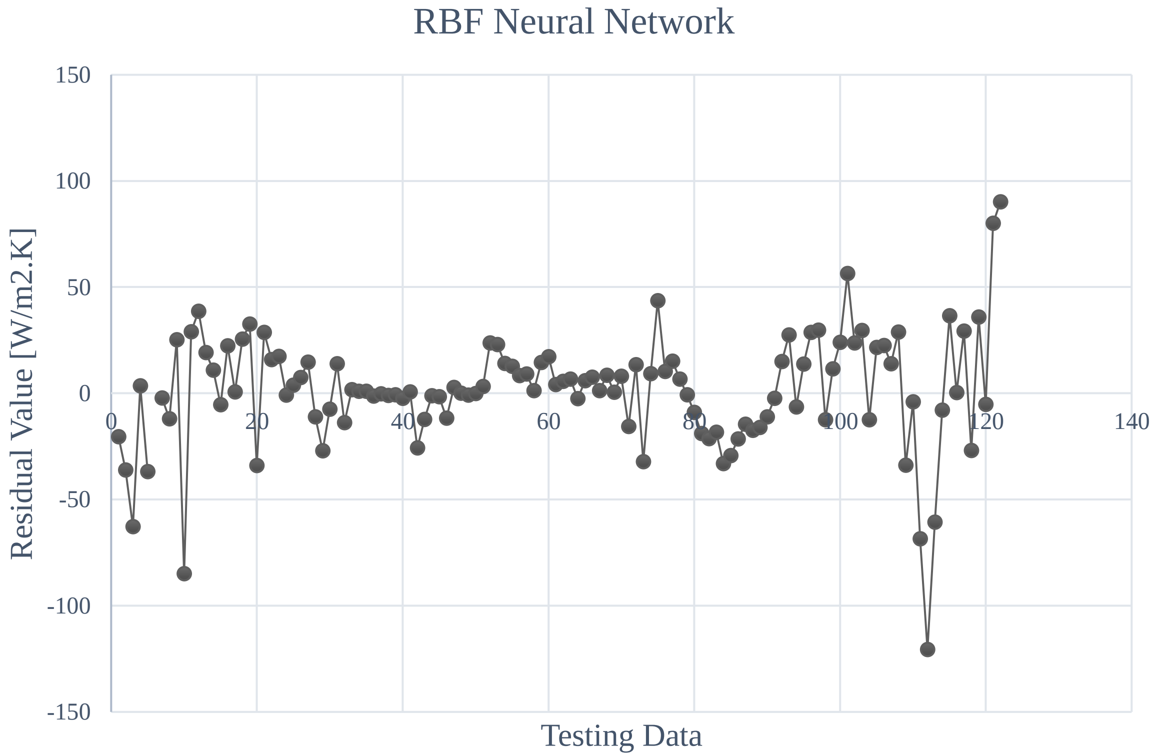
RBF Neural Network





Analysis of Variance

Method	R^2 (%)	CV	NMSE	Correlation	RMSE	MSE	MAE	MAPE
Multilayer Perceptron	99.902	0.023519	0.000980	0.999567	42.326272	1791.5133	27.994853	12057.24
PNN/GRNN Neural Network	99.958	0.015314	0.000416	0.999801	27.561308	759.6257	20.393533	4018.8622
RBD Network	99.851	0.029026	0.001493	0.999356	52.238191	2728.8286	30.969718	9530.1242
GMDH Polynomial Network	99.989	0.007760	0.000107	0.999949	13.965366	195.03145	10.78587	6662.6184
Cascade Correlation Network	99.917	0.021708	0.000835	0.999657	39.067047	1526.2341	29.394567	4160.4599

Data Normalization

R^2 (%)	CV	NMSE	Correlation	RMSE	MSE	MAE	MAPE	BEST METHOD
0.99913	3.030799	9.158879	0.999618	3.030804	9.185769	2.595512	3.000163	M4: Multilayer Perceptron
0.99969	1.973454	3.88785	0.999852	1.973548	3.894889	1.890764	1	M2: PNN/GRNN Neural Network
0.99862	3.740464	13.95327	0.999407	3.740555	13.99174	2.871323	2.371349	M5: RBD Network
1	1	1	1	1	1	1	1.657837	M1: GMDH Polynomial Network
0.99928	2.797423	7.803738	0.999708	2.797425	7.825581	2.725285	1.035233	M3: Cascade Correlation Network

Variable Importance

Method	T1	T2	T3	F1	F2	F3	Most important variable
Multilayer Perceptron	3.668	5.416	0.375	89.157	80.949	100.00	F3
PNN/GRNN Neural Network				95.301	90.688	100.00	F3
RBD Network	0.347	0.192	0.108	0.078	25.139	100.00	F3
GMDH polynomial network					100.00		F2
Cascade Correlation Network	5.103	1.906	0.187	5.086	6.006	100.00	F3

Heat Transfer Coefficient as function of Steam Mass Flow

- In this case the only Input is the Steam mass flow at the main pipe
- The variable importance analysis leads us to such assumption
- The output is the heat transfer coefficient

Analysis of Variance

Method	R^2 (%)	CV	NMSE	Correlation	RMSE	MSE	MAE	MAPE
Multilayer Perceptron	99.975	0.011245	0.000253	0.999878	22.560377	508.97063	14.837764	13314.713
PNN/GRNN Neural Network	99.925	0.019371	0.000750	0.999638	38.863604	1510.3797	26.997166	11408.283
RBD Network	99.730	0.036759	0.002702	0.998794	73.750907	5439.1963	44.793472	8957.221
GMDH polynomial network	99.987	0.007992	0.000128	0.999938	16.033898	257.0859	11.020228	9985.6856
Cascade Correlation Network	99.988	0.007702	0.000119	0.999946	15.452697	238.78583	12.06805	6460.1994

PART II: HEAT TRANSFER COEFFICIENT VS. PRESSURE DROP

PREDICTION OF PRESSURE DROP AND HEAT TRANSFER OF DEVELOPING AND FULLY DEVELOPED FLOW, USING MACHINE LEARNING TECHNIQUES

The purpose

- To establish the relationship between pressure drop and heat transfer in different flow regime.
- To use machine learning and experimental data to investigate in order to predict the heat transfer coefficient.

Second Set of Experimental Data

- A smooth circular test section with an inner diameter of 11.5 mm, and maximum length-to-diameter ratio of 872.
- Measurement:
  - Pressure drop and heat transfer measurements were taken at Reynolds numbers between 500 and 10,000 at different heat fluxes.
  - Water was used as the test fluid and the Prandtl number ranged between 3 and 7.
  - A total of 317 mass flow rate measurements, 34,553 temperature measurements and 2536 pressure drop measurements were taken.
  - Pressure drop and heat transfer measurements were taken simultaneously.

Development of Predictive Models

- Using machine learning techniques, the relationship between pressure drop and heat transfer was investigated.
- Correlations were developed to determine the relationship between heat transfer and pressure drop, as well as the average Nusselt numbers, in the laminar, transitional, quasi-turbulent and turbulent flow regimes, for both developing and fully developed flow in mixed convection conditions.

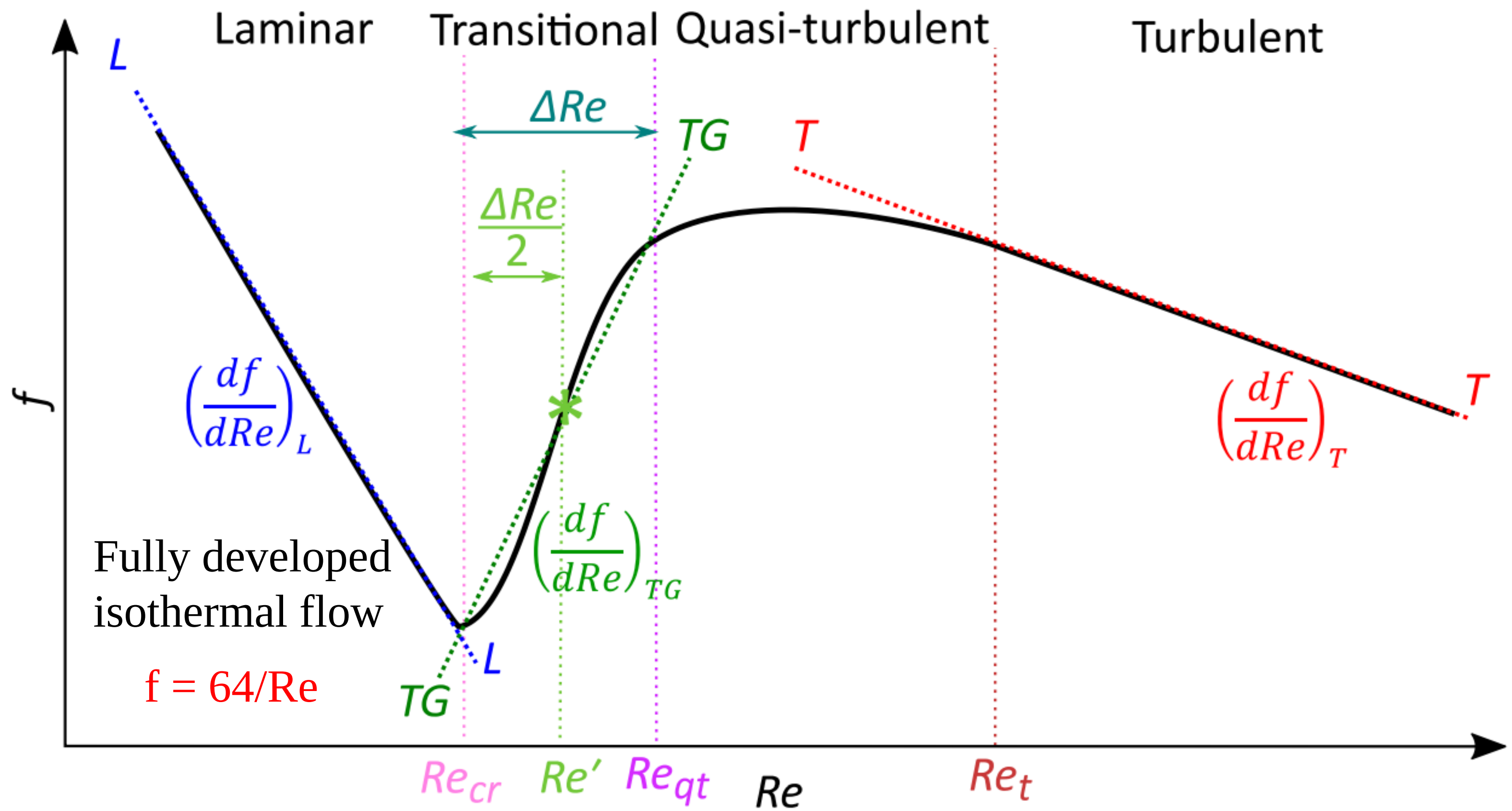
Predictive Methods

1. Gene Expression Programming
2. Multilayer perceptron neural network (*MLP*)
3. Generalized regression neural network (GRNN)
4. Radial basis function network
5. Cascade Correlation Neural Network with Deterministic Weight
6. GMDH (Group Method of Data Handling) Polynomial Neural Network
7. LSTM (Long Short-Term Memory)

The relationships between the friction factors and Reynolds Number [1]

$$f = \frac{2\Delta P D}{L(x)\rho V^2} = \frac{\Delta P \rho D^5 \pi^2}{8\dot{m}^2 L(x)}$$

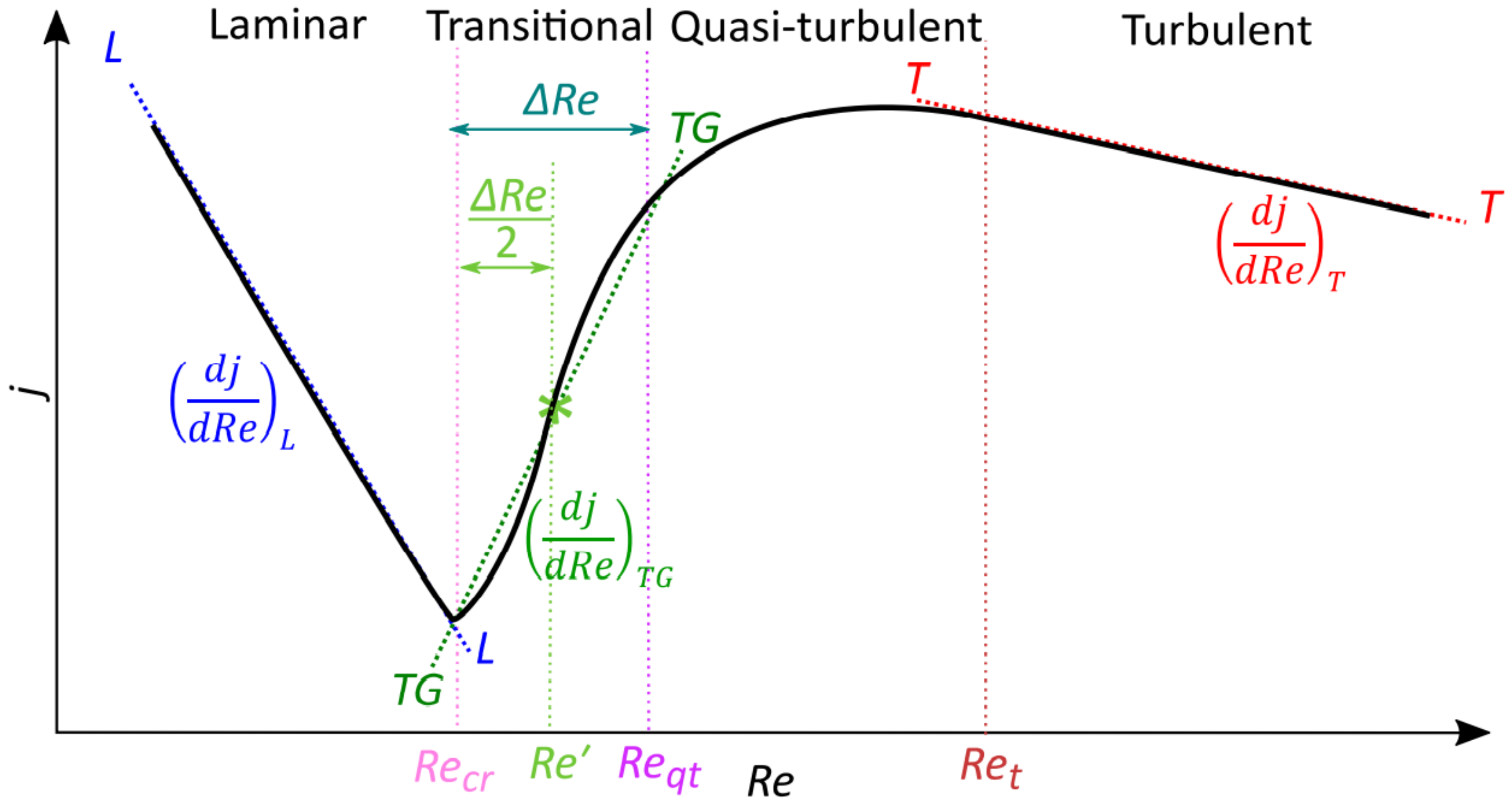
The friction factor (f) is representing the loss of pressure of a fluid in a pipe due to the interactions in between the fluid and the pipe.



[1] M. Everts, J.P. Meyer, Heat transfer of developing and fully developed flow in smooth horizontal tubes in the transitional flow regime, Int. J. Heat Mass Transf. 117 (2018) 1331–1351.

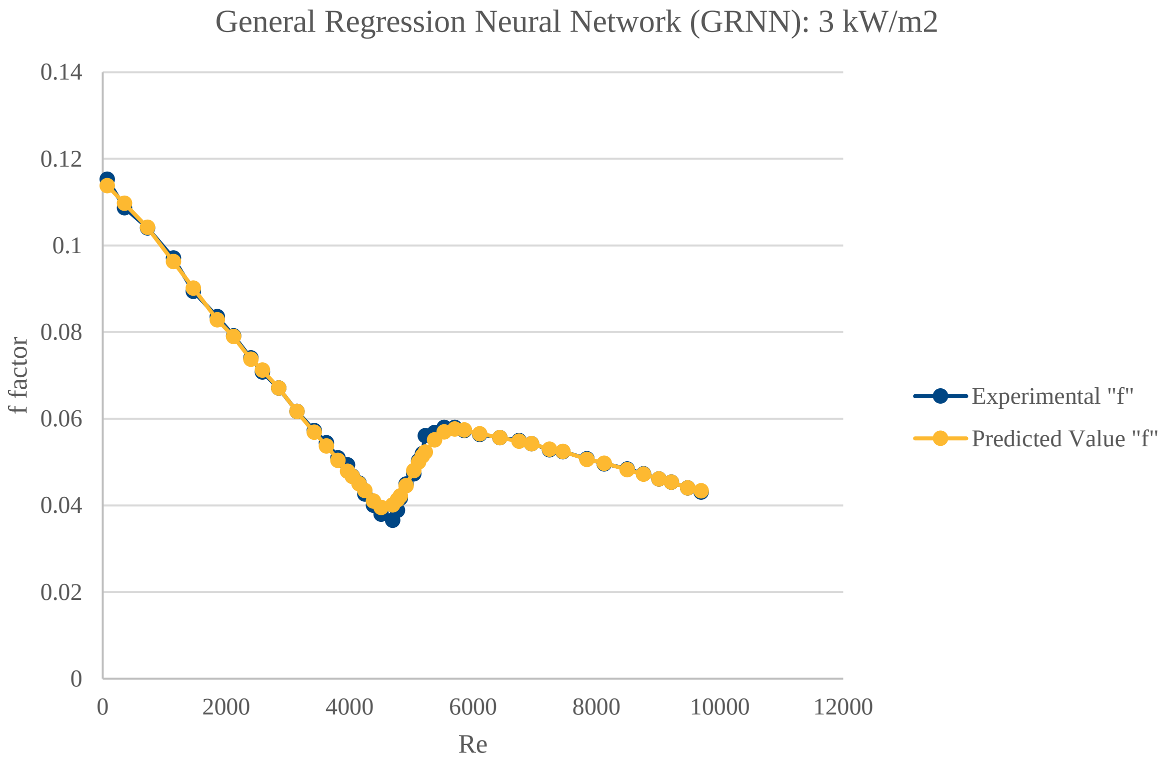
The relationships between the Colburn j-factors and Reynolds Number [3]

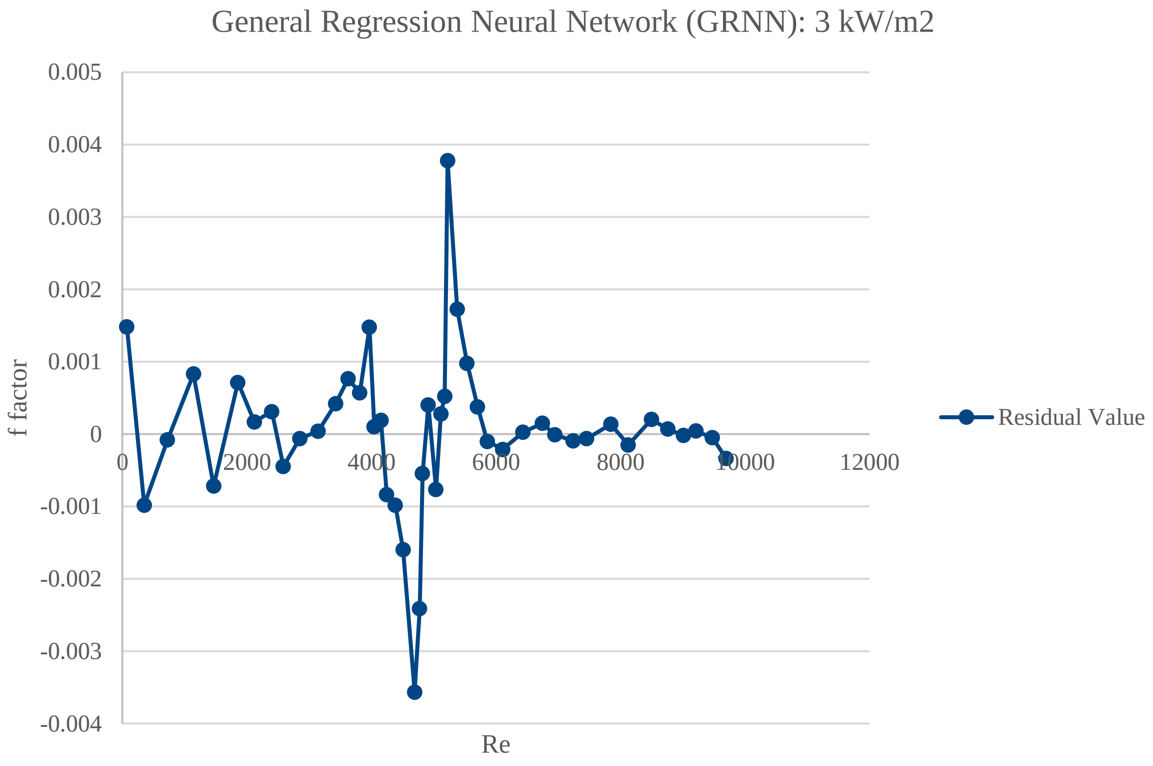
J Factor is **A dimensionless factor for heat transfer coefficient for calculating the heat transfer coefficient**



General Regression Neural Network (GRNN): 3 kW/m2

$0 \text{ m} \leq L \leq 2 \text{ m},$





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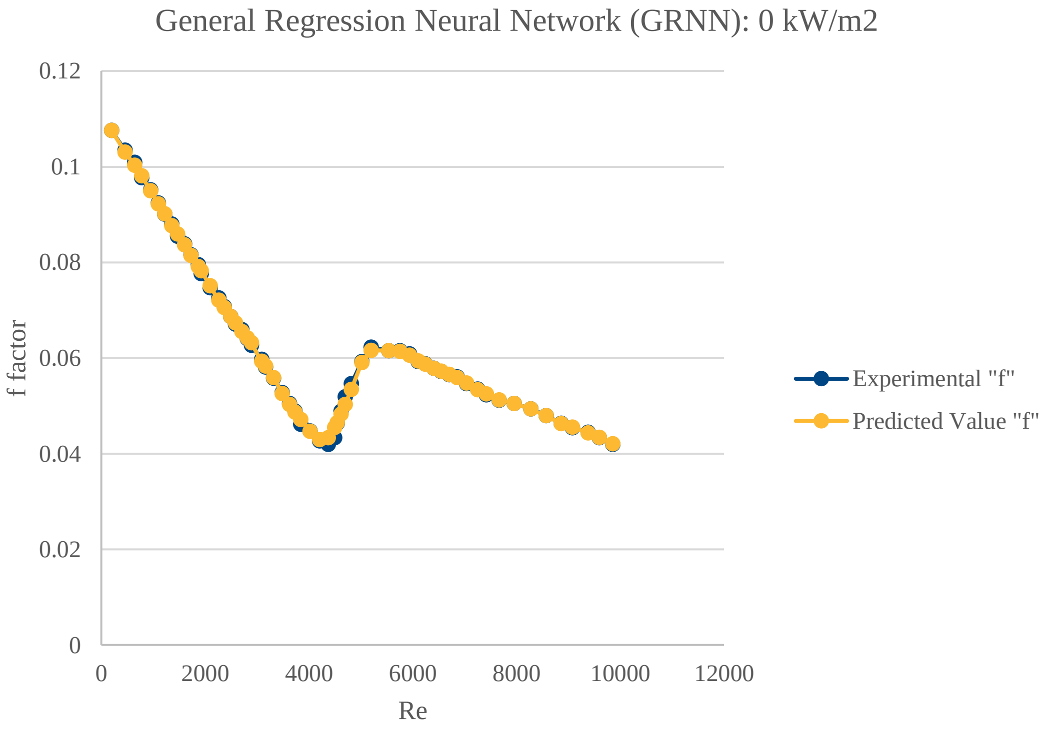


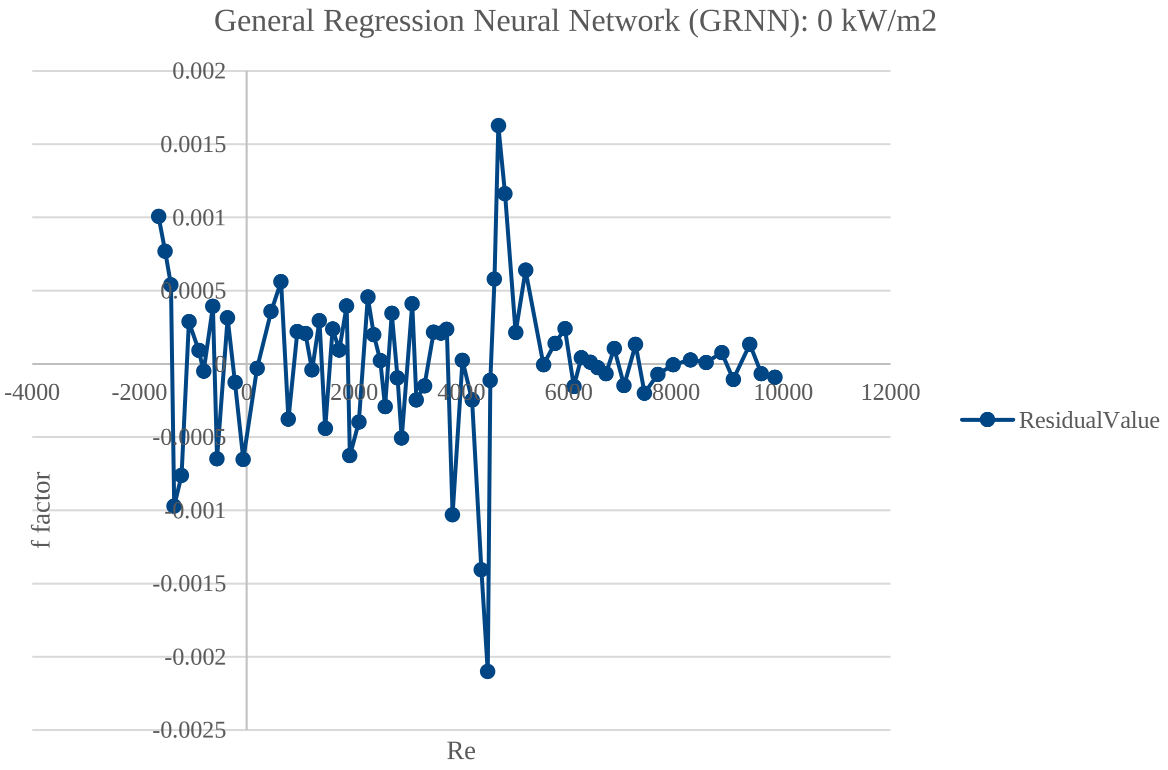
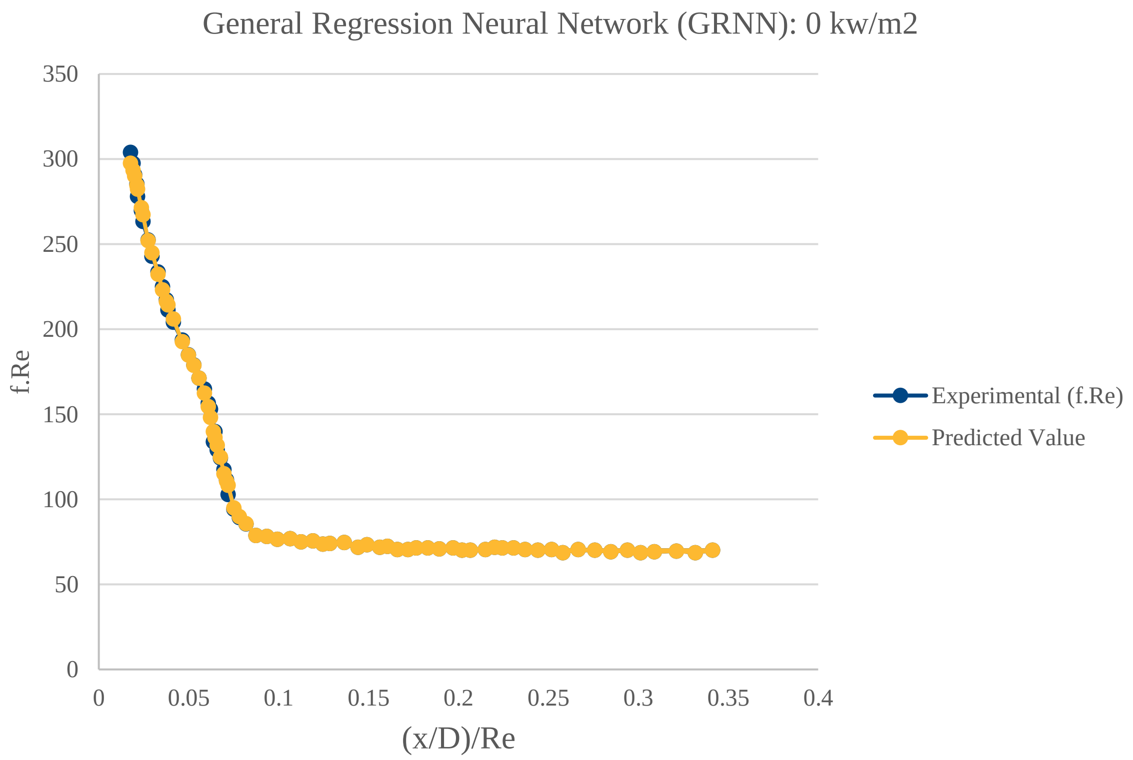
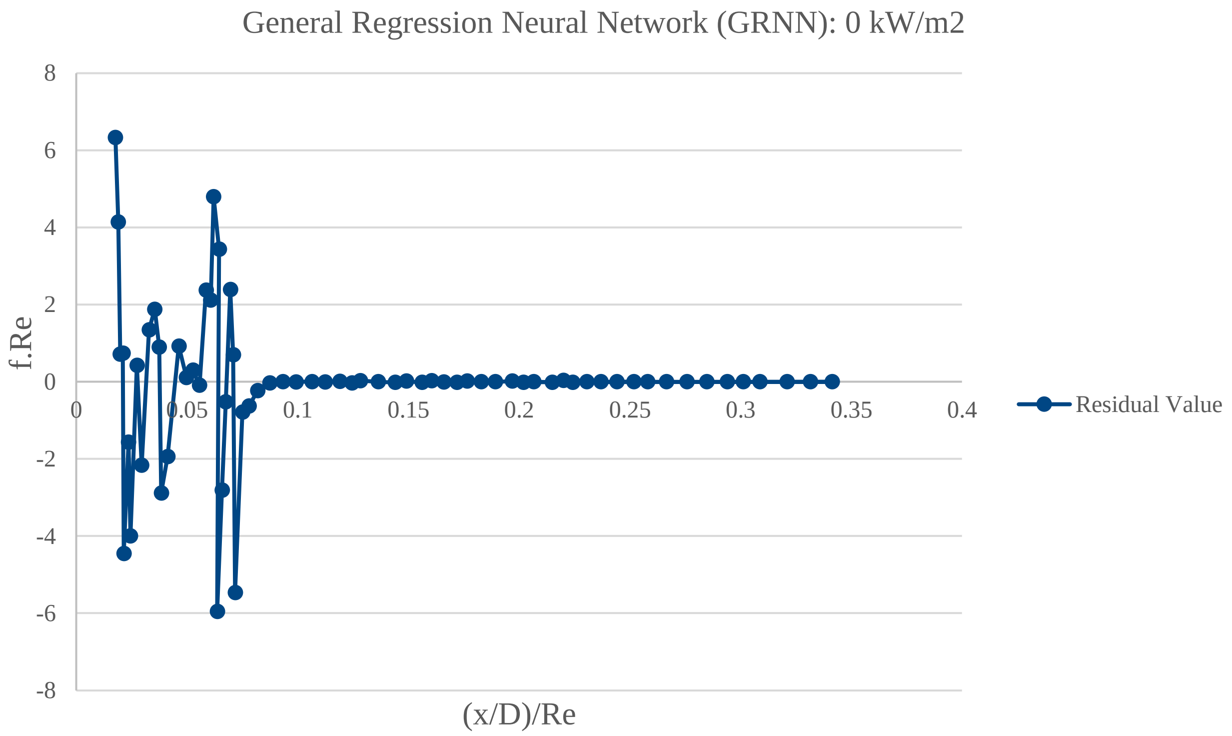


*Fig 6: Comparison of the product of the friction factor and Reynolds number (f*Re) as a function of dimensionless axial distance*





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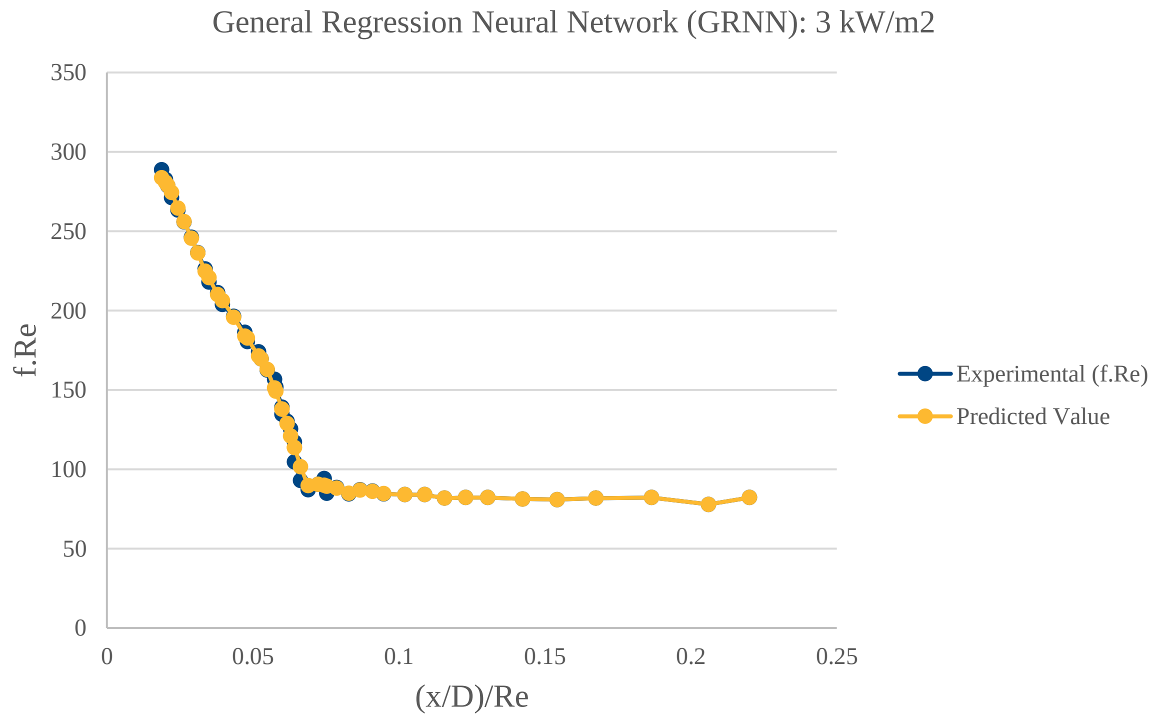


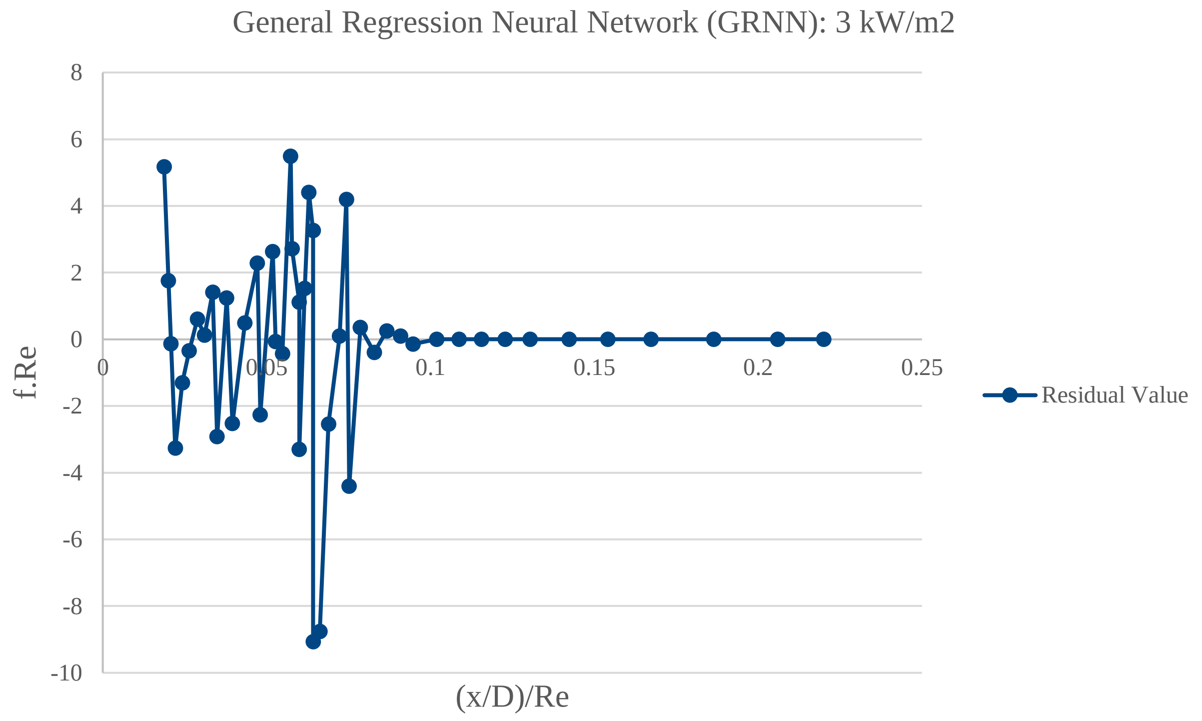
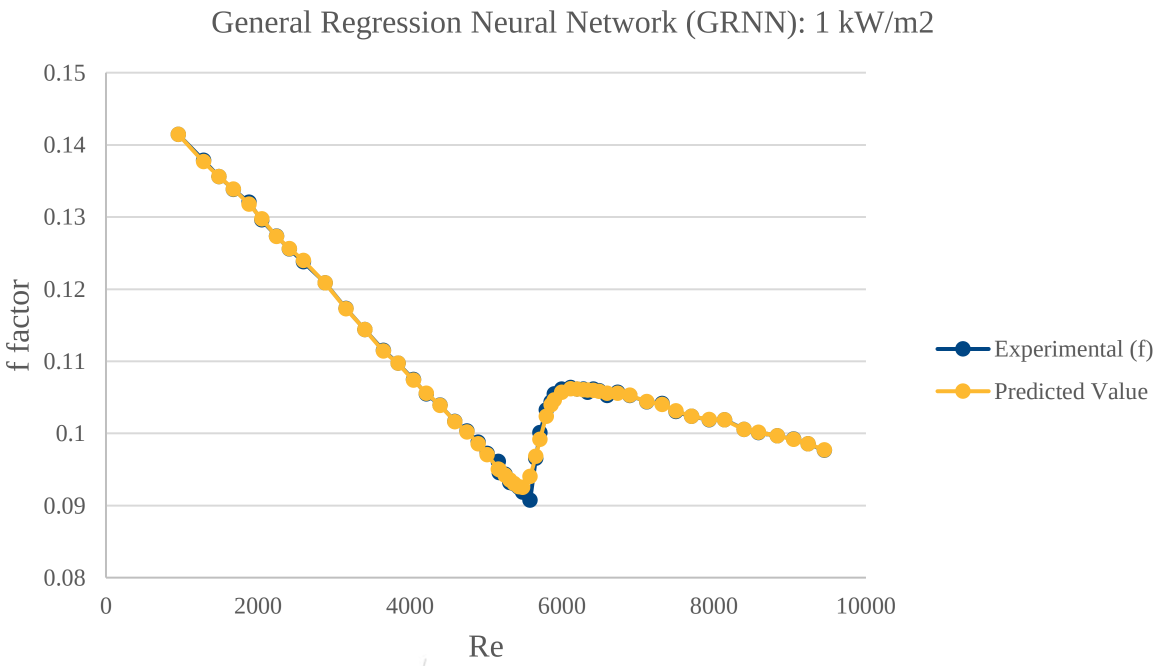
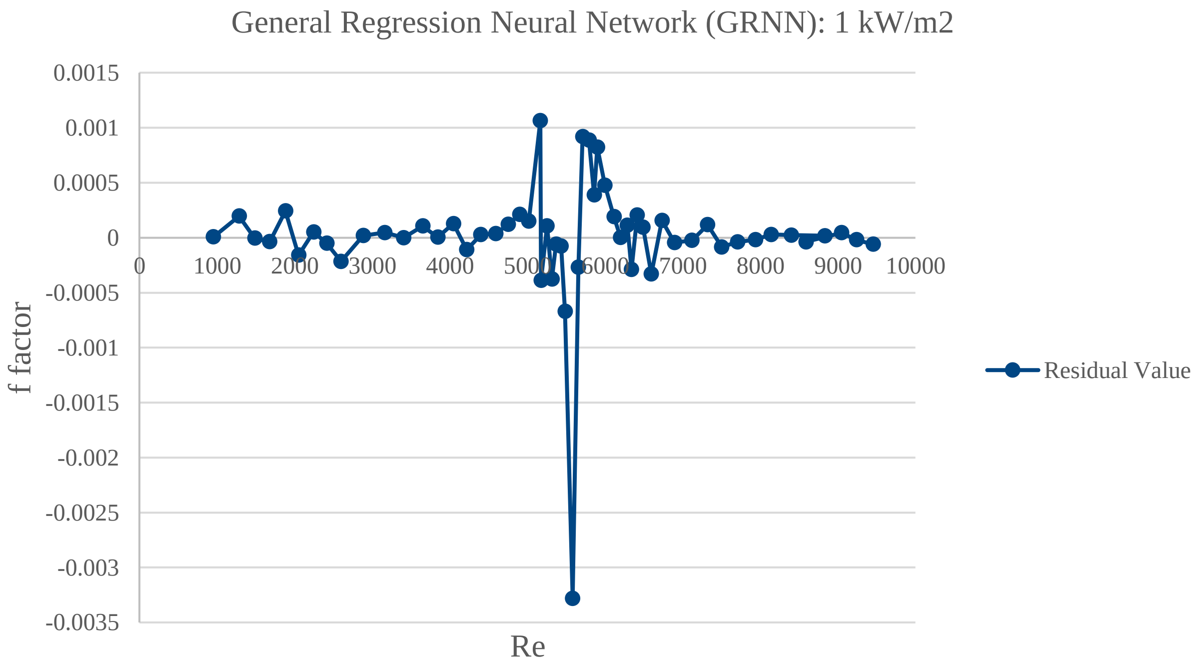
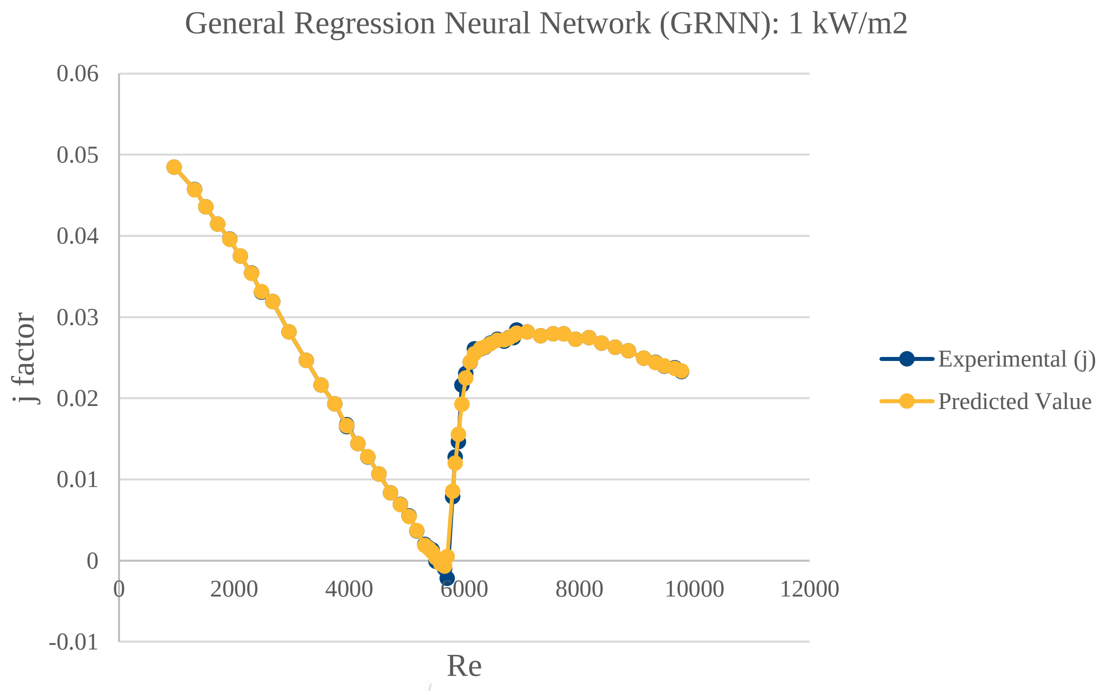


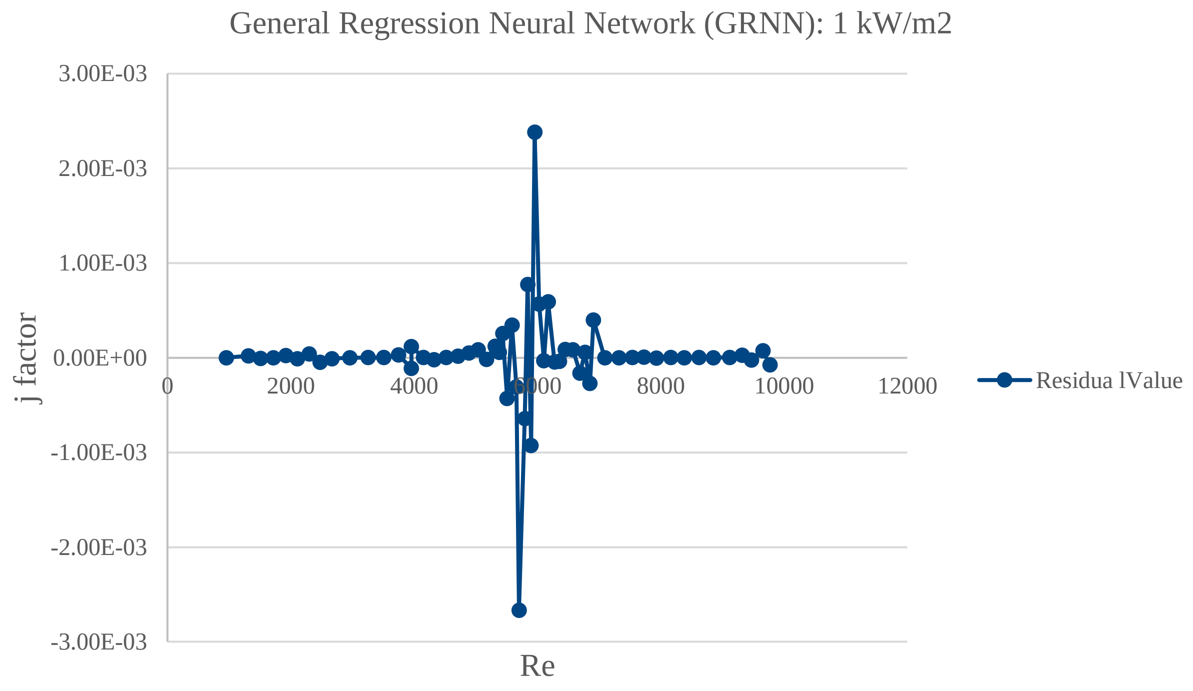
Fig. 8. Comparison of the pressure drop and heat transfer results in terms of the friction factors for 0 m < L < 8 m as a function of Reynolds number, at heat fluxes of 1 kW/m2



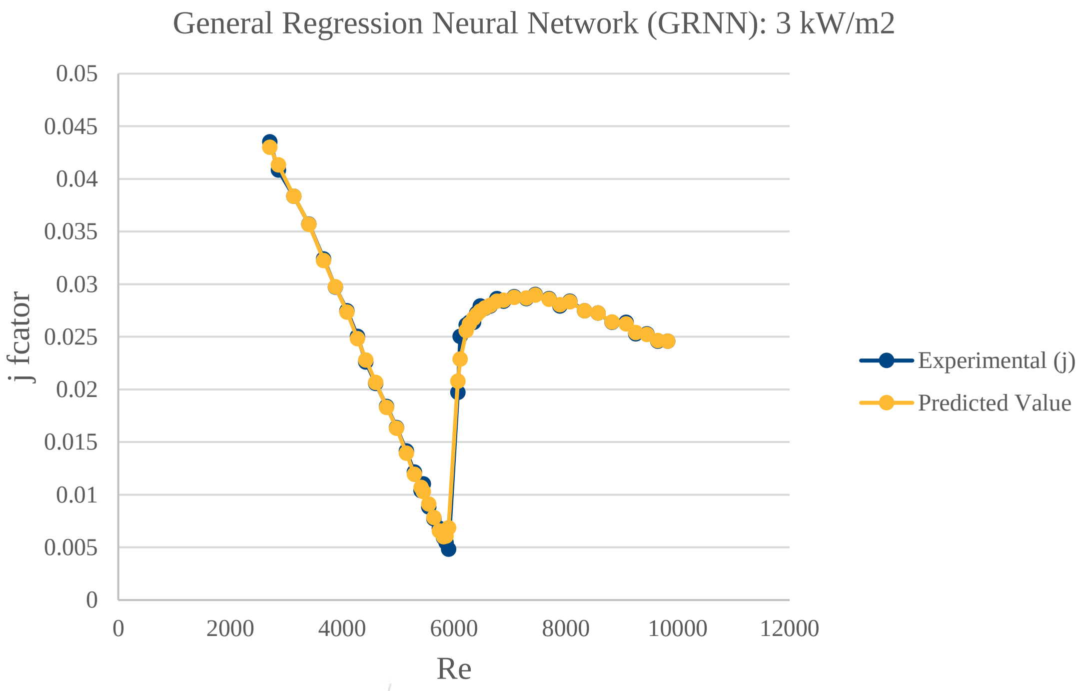


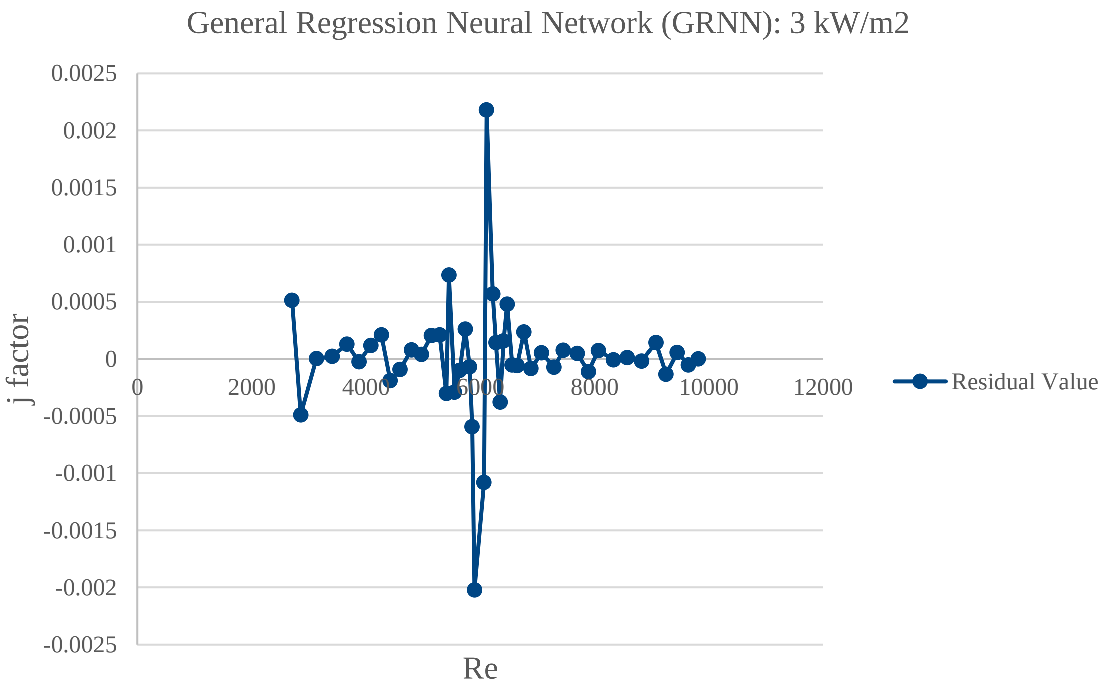
Comparison of the pressure drop and heat transfer results in terms of the average Colburn j-factors for 0 m < L < 8 m as a function of Reynolds number, at heat fluxes of 1 kW/m2



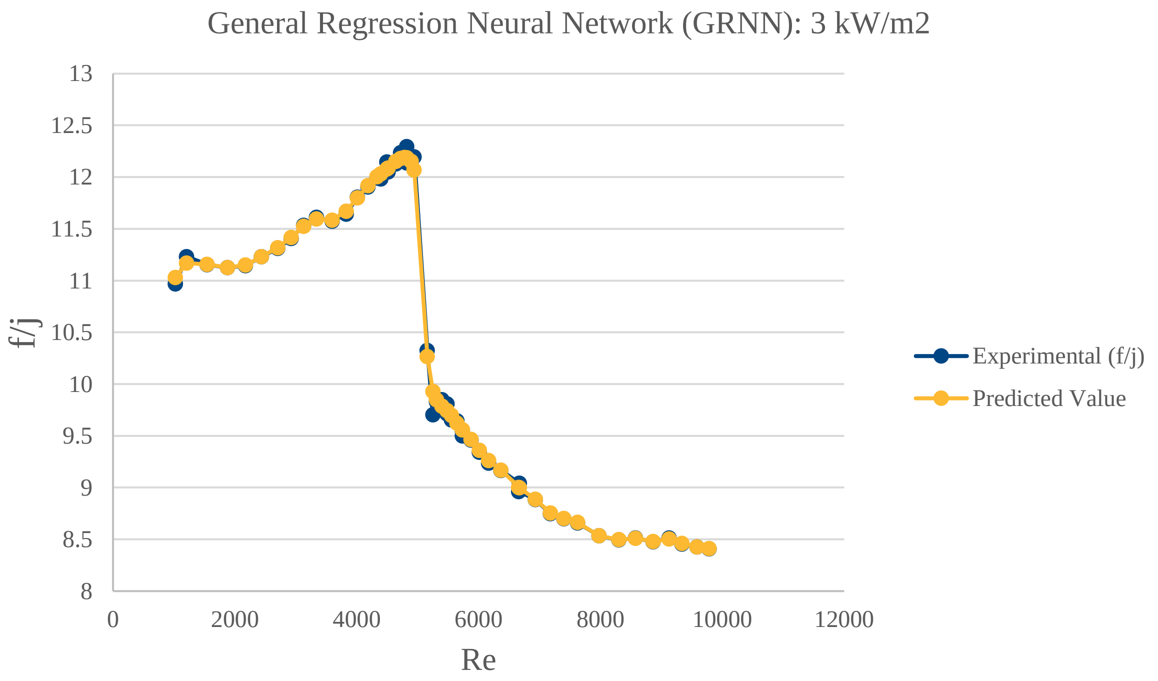


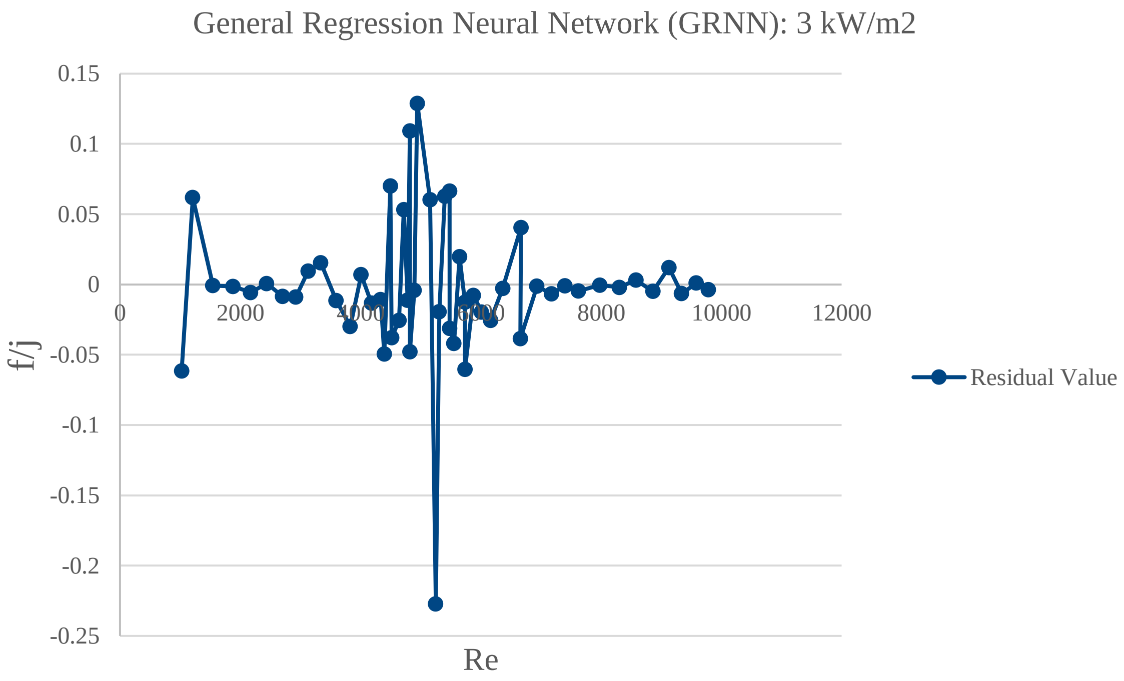
Comparison of the pressure drop and heat transfer results in terms of the average Colburn j-factors for 0 m < L < 8 m as a function of Reynolds number, at heat fluxes of 3 kW/m2



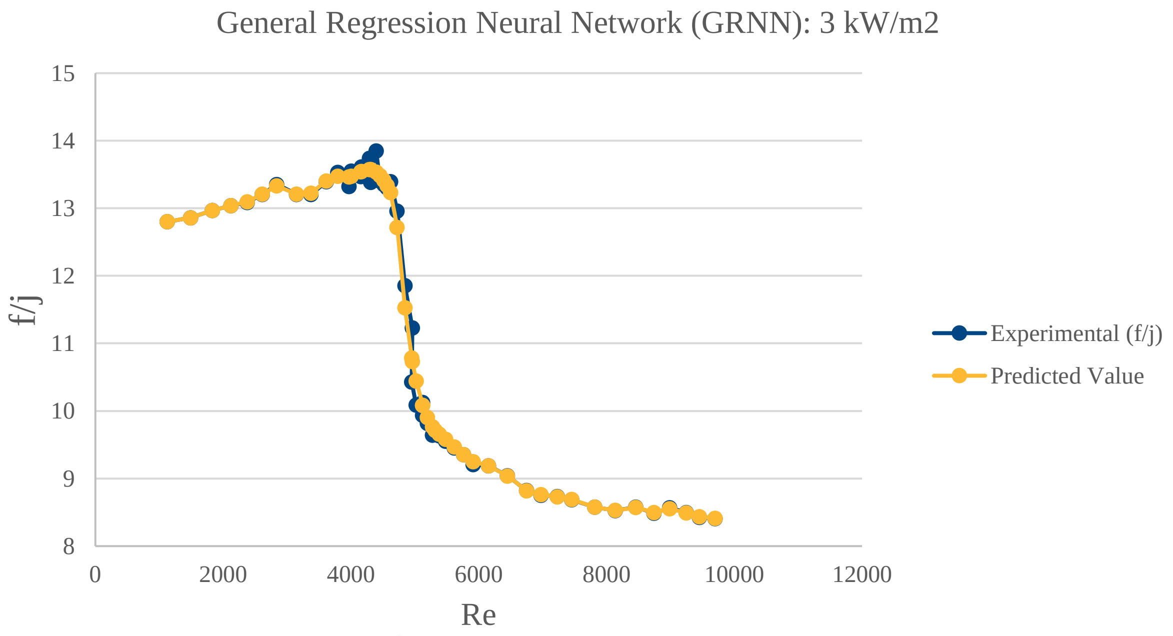


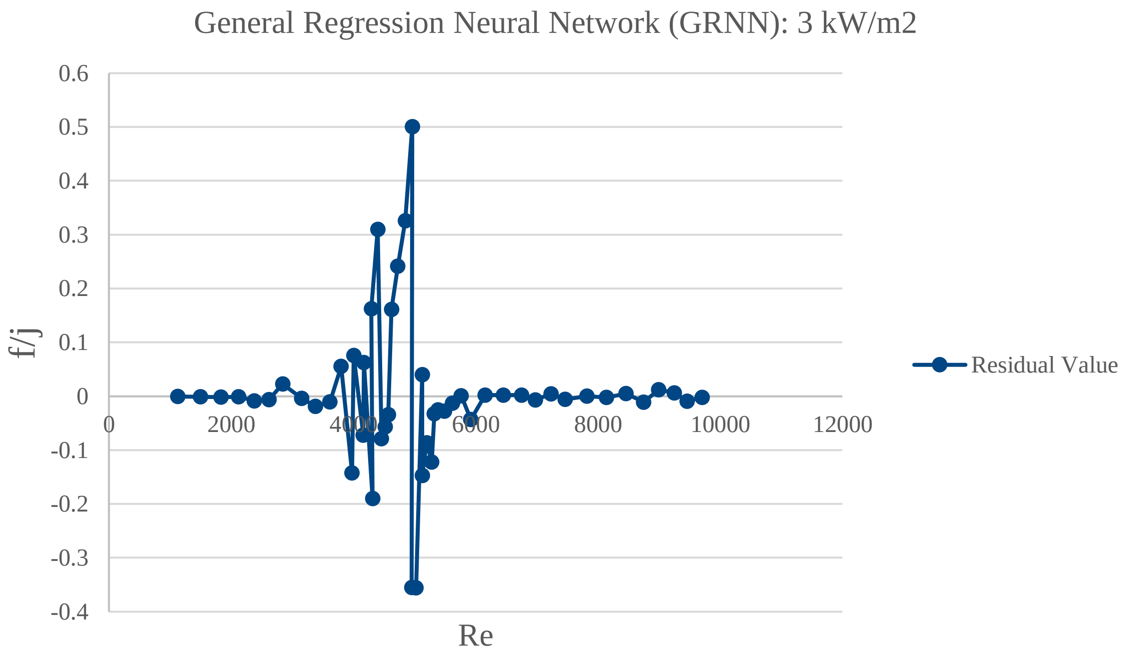
Comparison of the friction factors divided by the average Colburn j-factors as a function of Reynolds number for 0 m < L < 8 m at a heat flux of 3 kW/m2





Comparison of the friction factors divided by the average Colburn j-factors as a function of Reynolds number for 0 m < L < 2 m at a heat flux of 3 kW/m2





Analysis of Variance

	Figure 5: 0 kW/m2	Fig 5: 3 kW/m2	Fig6a_B0.csv	Fig6a_Y3.csv	Fig8_f_1.csv
Proportion of variance explained by model (R^2) %	99.968%	99.682	99.935	99.838	99.815
Coefficient of variation (CV)	0.007094	0.018168	0.015090	0.018976	0.004997
Normalized mean square error (NMSE)	0.000323	0.003183	0.000645	0.001616	0.001855
Correlation between actual and predicted	0.999840	0.998468	0.999679	0.999201	0.999083
Maximum error	0.0021012	0.0037786	6.3281898	9.0706368	0.0032808
RMSE (Root Mean Squared Error)	0.0005277	0.0010562	1.8890273	2.7823118	0.0005358
MSE (Mean Squared Error)	0.0000003	0.0000011	3.568424	7.7412589	0.0000003
MAE (Mean Absolute Error)	0.0003513	0.0006473	0.9776852	1.7255757	0.0002439
MAPE (Mean Absolute Percentage Error)	0.5314583	1.2717376	0.5700633	1.3014959	0.2448627

METHODOLOGY Developed

Laminar:

$48 \leq Re \leq 3217,\ 2.9 \leq Pr \leq 282,\ 5.5 \leq Gr \leq 4.5 \times 10^4,\ 41 \leq Gr^* \leq 7.3 \times 10^6$

Transitional:

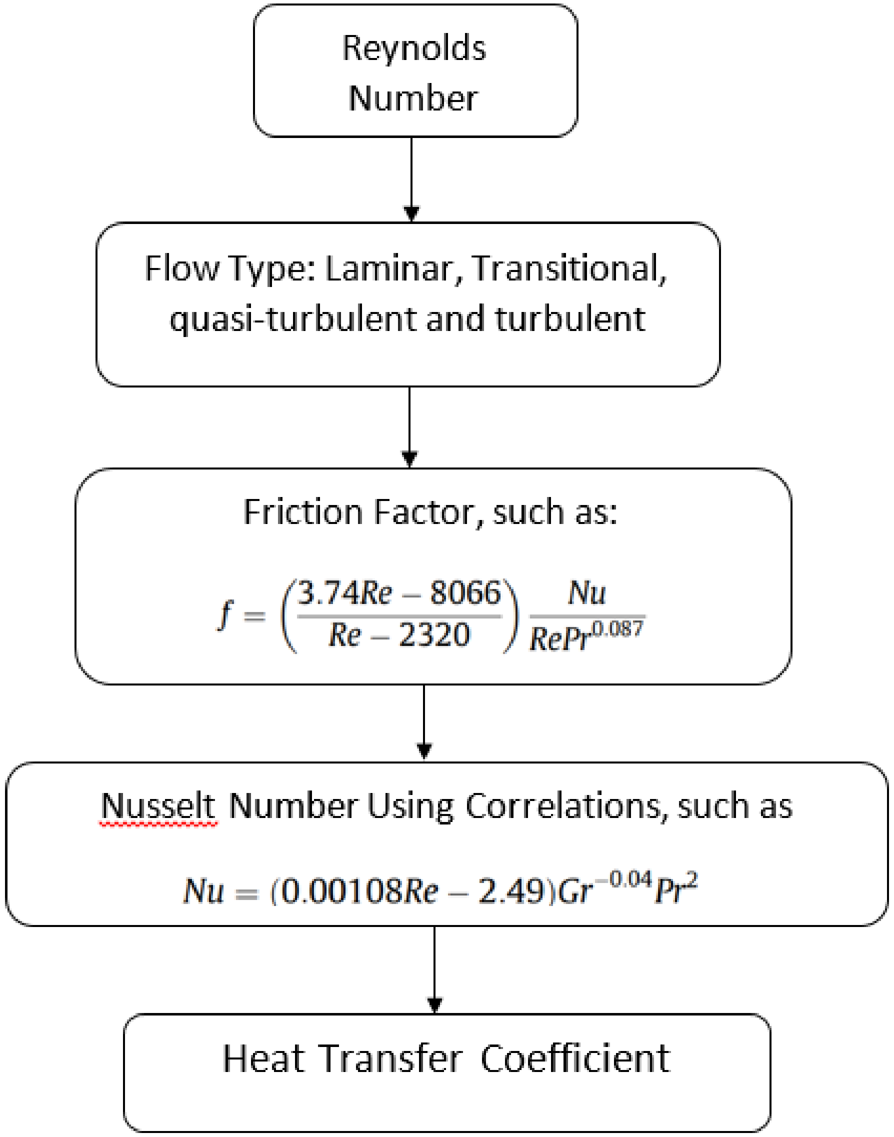
$2520 \leq Re \leq 3361,\ 5.4 \leq Pr \leq 6.8,\ 2.8 \times 10^4 \leq Gr \leq 3.2 \times 10^4,$
$6.1 \times 10^4 \leq Gr^* \leq 3.7 \times 10^5$

Quasi-turbulent and turbulent:

$2804 \leq Re \leq 9787,\ 5.5 \leq Pr \leq 6.9,\ 8.9 \times 10^2 \leq Gr \leq 1.4 \times 10^4,$
$5.9 \times 10^4 \leq Gr^* \leq 3.6 \times 10^5$

The average Colburn j-factors of the different tube lengths as a function of Reynolds number at different heat fluxes

$$Nu = \frac{h\ L}{\lambda}$$



Conclusions and Future Work

Conclusions

- The heat transfer coefficient depends mainly on the mass flow of steam. Temperature and pressure are secondary.

- Machine learning techniques: GMDH polynomial network and PNN/GRNN neural network are the best in predicting heat transfer coefficient.

- For both sets of experimental data, a methodology is developed to predict the heat transfer coefficient

- Our next goal is to predict the heat transfer coefficient using dynamic CFD modeling of an Inconel 740H alloy boiler outlet header.

Part III: Steam Header Design Progress

UNC CHARLOTTE

The WILLIAM STATES LEE COLLEGE of ENGINEERING

April 2022

Michael Zimnoch

Designing Headers

- Header is designed using three materials: P22, P91, IN740.
- Each header will be designed in accordance with a series of ASME BPVC Codes
  - Section I: General Design Requirements
  - Section II: Material Properties
  - Section III-NH: Evaluation of Components in Elevated Temperature Service
  - Section VIII-2: Alternative Rules – Design Fatigue Curves
- IN740 material properties will be taken from Special Metals
- The life expectancy of each header will be evaluated using
  - ASME BPVC Section VIII-2
  - STP-PT-070
  - ASME FFS-1/ API 579-1

https://www.indiamart.com/proddetail/boiler-headers-4962339955.html

Geometry Design

- The wall thickness of the header and tubes were found using the processes outlined in subsection PG-27.2.1

Tube thickness

$$t = \frac{Pd_o}{2S + P} + 0.005d_o$$

d_o = OD Tube = 2.0”

P = Maximum allowable working pressure (2450 psi)

S = Maximum Allowable Stress at Design Temperature

S_{P22} = 53.57 MPa at 541°C

S_{P91} = 108.4 MPa at 541°C

S_{IN740} = 276 MPa at 541°C

t_{P22} = 0.282”

t_{P91} = 0.155”

t_{IN740} = 0.070”

Geometry Design - Header

Header thickness ← $t = \frac{PD}{2SE + 2yP} + C$

D = Outer Diameter

- P22 - 22.25”
- P91 – 19.07”
- IN740 – 16.87”

ID = 15.25 for all models

P = Maximum allowable working pressure = 2450 psi

C = Minimum allowance for threading stability = 0

f = 0, tubes will be welded in.

E = Efficiency = 0.797

$$E = \frac{p - d}{p}$$

p = Pitch = 6”

d = Diameter of opening = 1.219”

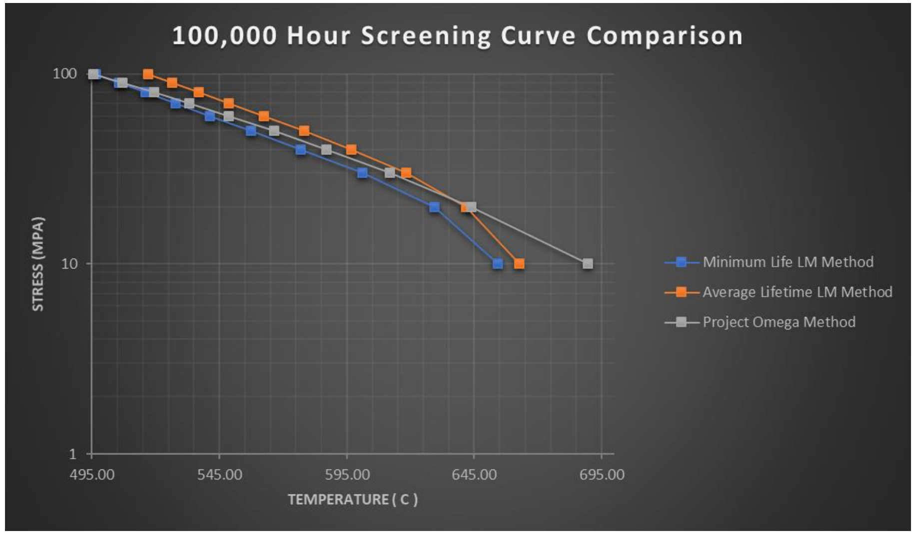
S = Maximum Allowable Stress at Design Temperature

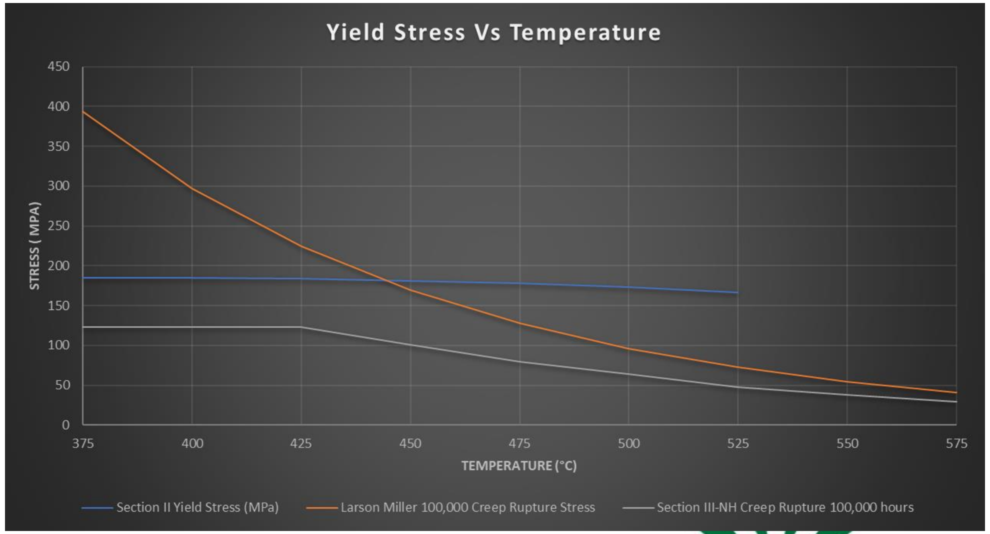
t = Wall Thickness

- P22 - 3.45”
- P91 – 1.91”
- IN740 – 0.81”

Creep Rupture

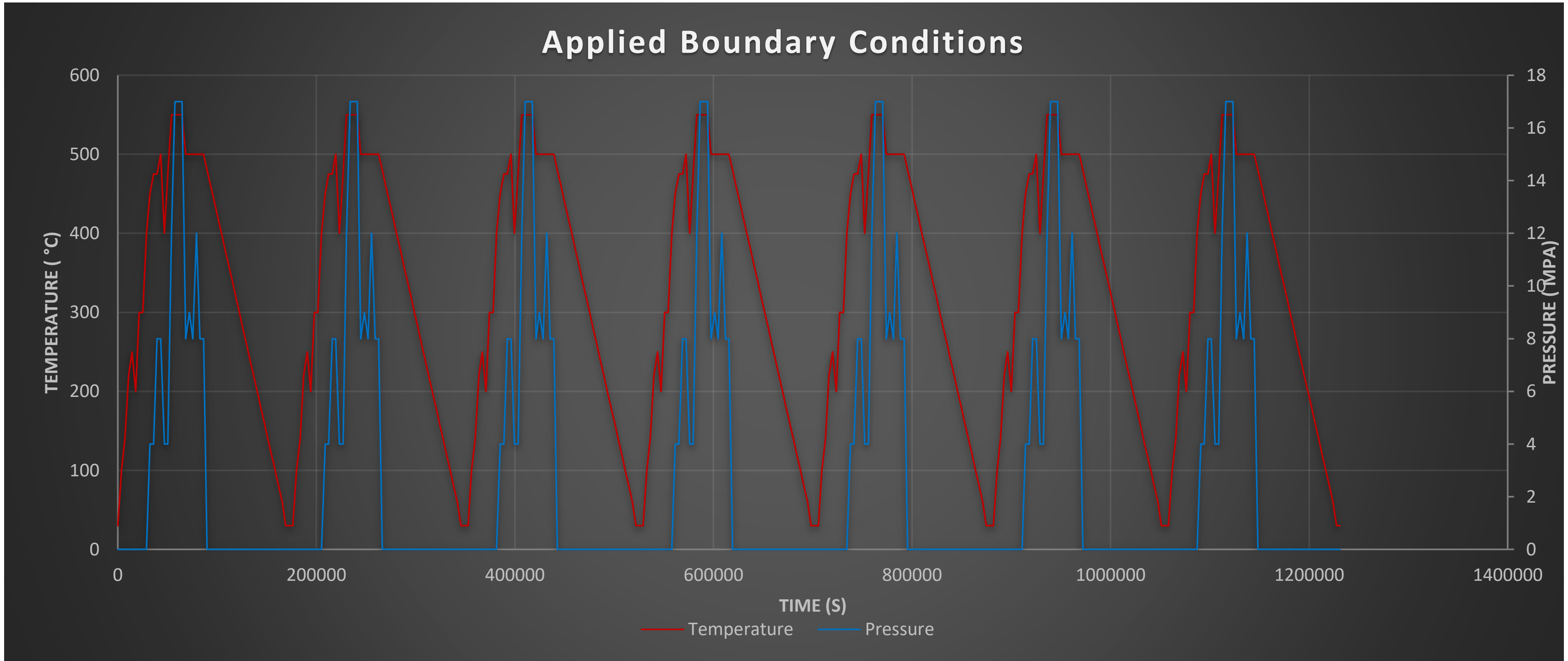
- API 579-1/ASME FFS-1 provides 3 options to determine the creep rupture at a given time.
  - Project Omega Method
  - Larson Miller Method – Average Lifetime
  - Larson Miller Method – Minimum Lifetime
- The Larson Miller Minimum Lifetime method was chosen to reflect the most conservative case.
- The lower value of the yield stress of the material or the stress to cause creep rupture at 100,000 hours was used to evaluate the model for shakedown.





Shakedown

- Idealized pressure and temperature profiles were generated from data provided by the power plant.
- The idealized cycle was ran 7 times to evaluate the model for shakedown.
- Peak Temperature: 550 °C
- Peak Pressure: 17 MPa



Geometry Design - Header

Header thickness ← $t = \frac{PD}{2SE + 2yP} + C$

D = Outer Diameter

P22 - 22.25”

P91 – 19.07”

IN740 – 16.87”

ID = 15.25 for all models

P = Maximum allowable working pressure = 2450 psi

C = Minimum allowance for threading stability = 0

f = 0, tubes will be welded in.

E = Efficiency = 0.797

$$E = \frac{p - d}{p}$$

p = Pitch = 6”

d = Diameter of opening = 1.219”

S = Maximum Allowable Stress at Design Temperature

t = Wall Thickness

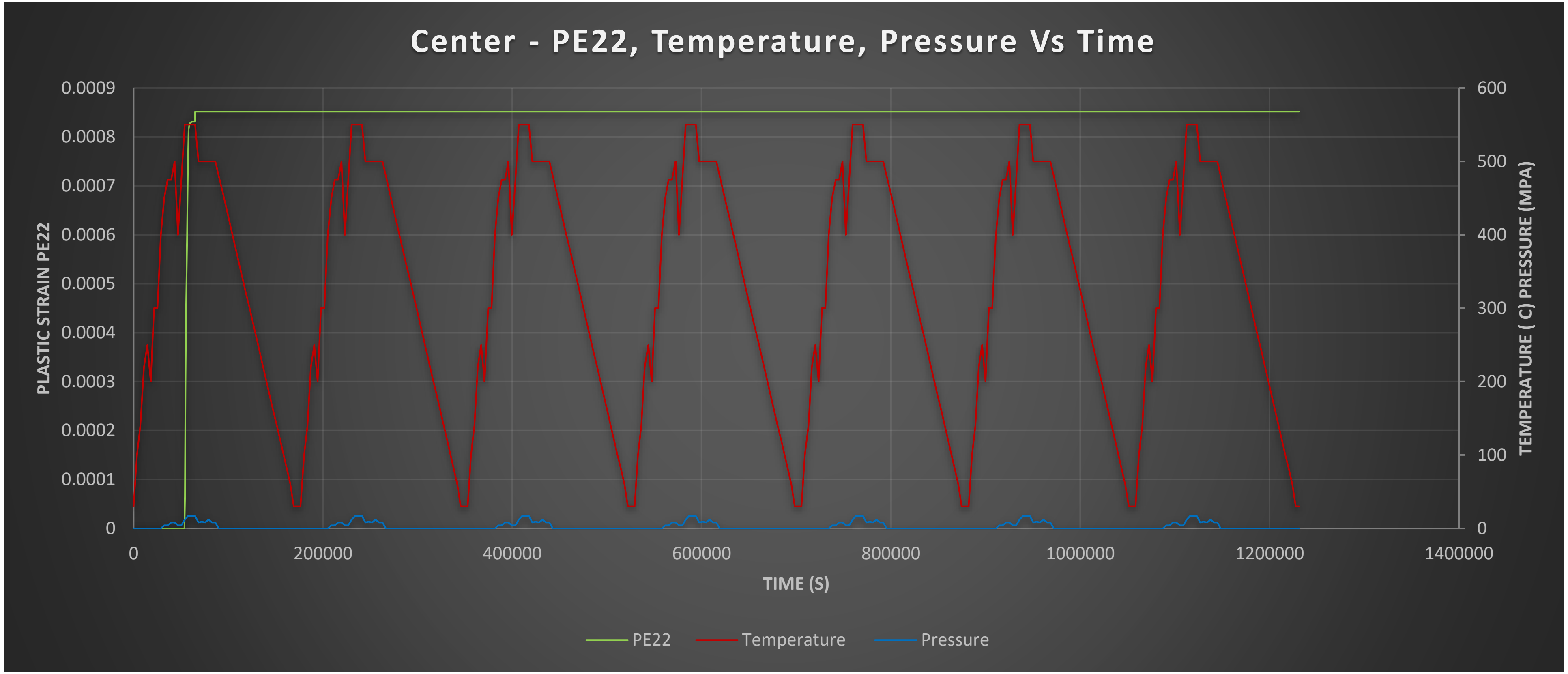
P22 - 3.45”

P91 – 1.91”

IN740 – 0.81”

Shakedown

- The P22 model was found to shakedown during the first cycle.



Material Model Verification

- Steps were also taken to validate the application of the material model in Abaqus.
- A paper evaluating a P91 header was recreated [1].
- The material used was a P91 Two-Layer Visco-Plastic model.

- $\varepsilon_p^{el} = \frac{1+v}{K_p}\boldsymbol{\sigma}_p - \frac{v}{K_p}tr(\boldsymbol{\sigma}_p)\mathrm{I}$
- $\varepsilon_v^{el} = \frac{1+v}{K_v}\boldsymbol{\sigma}_v - \frac{v}{K_v}tr(\boldsymbol{\sigma}_v)\mathrm{I}$
- $\boldsymbol{\sigma}_v = \boldsymbol{K}_v : (\varepsilon - \varepsilon_v)$
- $\boldsymbol{\sigma}_p = \boldsymbol{K}_p : (\varepsilon - \varepsilon_p)$
- $\boldsymbol{\sigma} = \boldsymbol{\sigma}_p + \boldsymbol{\sigma}_v$

- $\sigma^0 = k + Q_\infty(1 - \exp(-bp))$
- $\dot{\boldsymbol{\alpha}}_i = C_i\dot{p}\frac{1}{\boldsymbol{\sigma}^0}(\boldsymbol{\sigma}_p - \boldsymbol{\alpha}_i) - \gamma_i\boldsymbol{\alpha}_i\dot{p} + \frac{1}{C_i}\boldsymbol{\alpha}_i\dot{C}_i$
- $\frac{\Delta\sigma}{2} - k = \frac{C_i}{\gamma_i}\tanh(\gamma_i\frac{\Delta\varepsilon_p}{2})$
- $\dot{\boldsymbol{\varepsilon}}_v = \frac{3}{2}A[f(\boldsymbol{\sigma}_v)]^n\frac{\boldsymbol{S}_v}{f(\boldsymbol{\sigma}_v)}$
- $B = \frac{K_v}{K_v+K_p}$

Material Model Verification

- The temperature and pressure profiles were provided by [1].
  - Maximum Operating Pressure: 17 MPa
  - Maximum Operating Temperature: 490 °C

The failure criteria was taken as the largest Ostergren parameter $\Delta\varepsilon_{in}\sigma_{max}$ shown in the following equation [1]:

$$N_F = C(\Delta\varepsilon_{in}\sigma_{max})^{\beta}$$

– C & β are material constants determined from [1] and taken as 4,500 and -1.6 respectively.

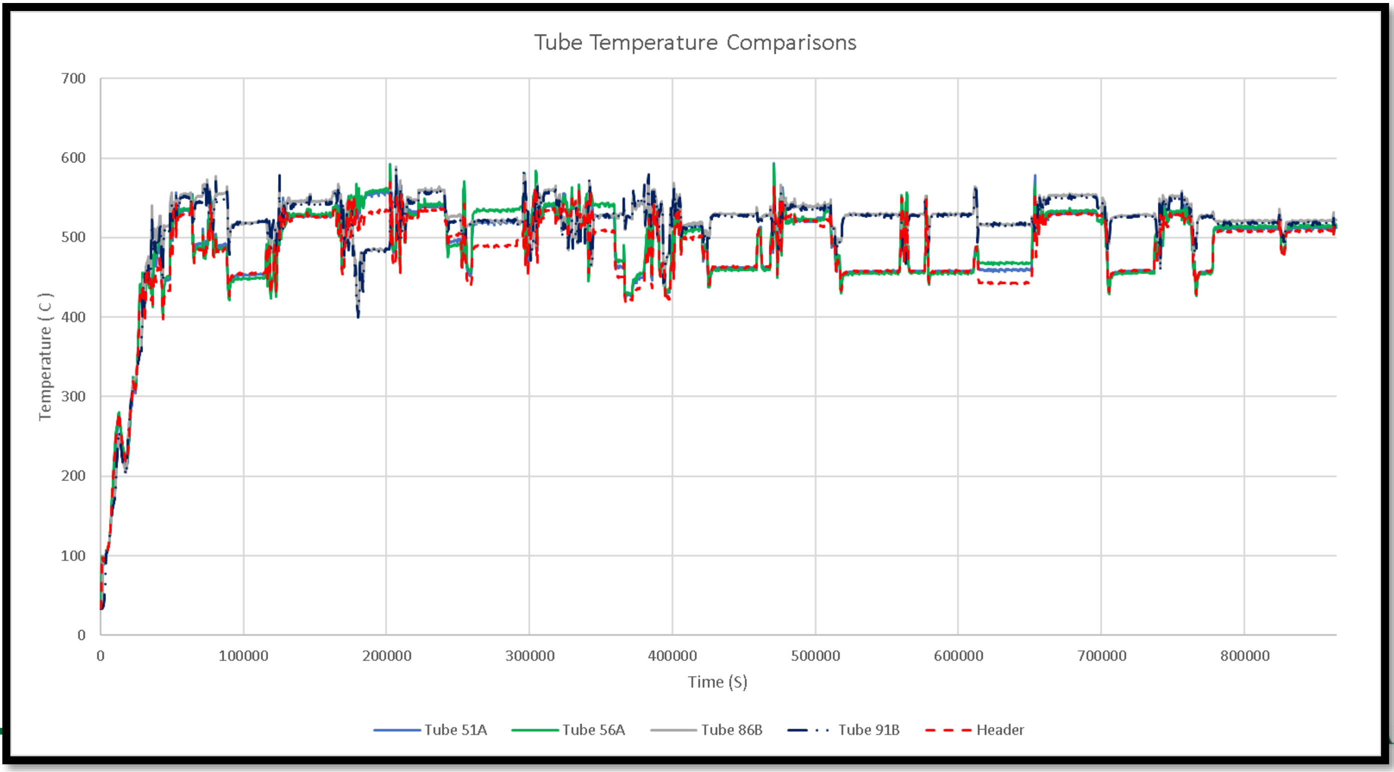
Model	Location	Cycles To Failure	Years To Failure
T.P. Farragher	Center	2,178	41.9
T.P. Farragher	Edge	1,954	37.6
M. Zimnoch	Center	2,211	42.5
M. Zimnoch	Edge	2,042	39.3

Material Model Verification

- The methodology was applied to the headers under normal loading scenarios and found an unrealistic lifespan on the order of >300 years for all materials.

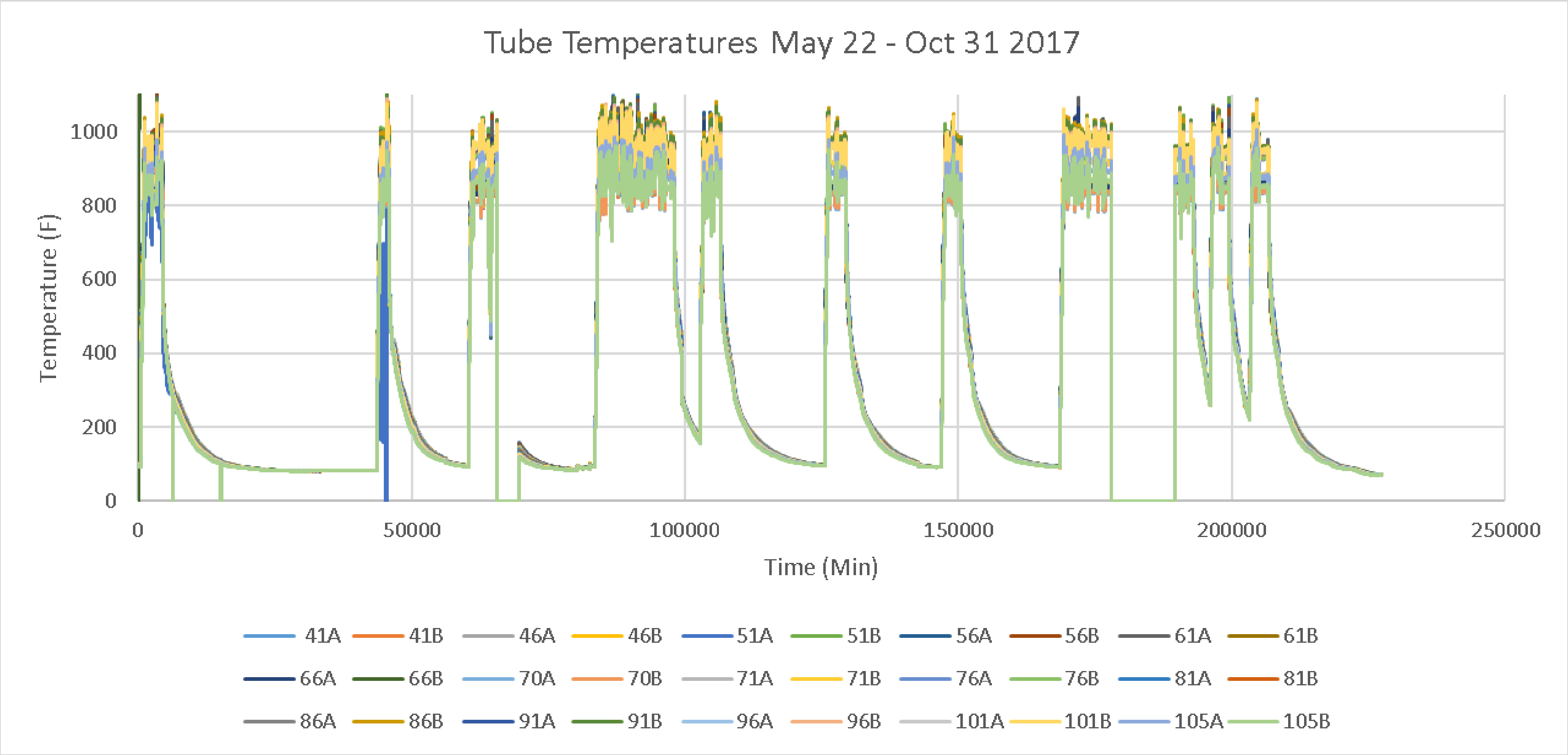
- Additional thermal data shows that the tube temperatures can significantly exceed the design temperature of the header.

- Some tubes have an average temperature 30 °C higher than the average header temperature.



Material Model Verification

- Additional thermal data shows that the tube temperatures can significantly exceed the design temperature of the header 1005 °F (540.6 °C) routinely throughout the year.



Material Model Verification

- The maximum tube temperatures exceed the design temperature of the header of 1005 °F (540.6 °C).
- The model was re-ran using the temperature data from the tubes expected to cause the most damage.

Summary of July 20-30 Tube Data															
Tube	Tube 41A	Tube 41B	Tube 46A	Tube 46B	Tube 51A	Tube 51B	Tube 56A	Tube 56B	Tube 61A	Tube 61B	Tube 66A	Tube 66B	Tube 70A	Tube 70B	Tube 71A
Average Temperature (F)	801	802	804	805	811	814	813	816	810	808	803	809	782	783	804
Maximum Temperature (F)	1057	1059	1090	1085	1100	1099	1096	1086	1089	1086	1075	1074	1030	1027	999
Tube	Tube 71B	Tube 76A	Tube 76B	Tube 81A	Tube 81B	Tube 86A	Tube 86B	Tube 91A	Tube 91B	Tube 96A	Tube 96B	Tube 101A	Tube 101B	Tube 105A	Tube 105B
Average Temperature (F)	804	832	835	845	842	850	853	844	848	837	836	830	833	783	762
Maximum Temperature (F)	1001	1054	1063	1074	1071	1085	1092	1074	1090	1073	1074	1065	1072	984	962

Summary of September 20-26 Tube Data															
Tube	Tube 41A	Tube 41B	Tube 46A	Tube 46B	Tube 51A	Tube 51B	Tube 56A	Tube 56B	Tube 61A	Tube 61B	Tube 66A	Tube 66B	Tube 70A	Tube 70B	Tube 71A
Average Temperature (F)	847	849	849	850	853	858	853	857	852	852	851	858	828	831	866
Maximum Temperature (F)	1026	1028	1047	1043	1067	1065	1090	1077	1091	1089	1066	1065	996	989	984
Tube	Tube 71B	Tube 76A	Tube 76B	Tube 81A	Tube 81B	Tube 86A	Tube 86B	Tube 91A	Tube 91B	Tube 96A	Tube 96B	Tube 101A	Tube 101B	Tube 105A	Tube 105B
Average Temperature (F)	866	902	906	914	913	919	923	911	919	905	905	899	904	846	822
Maximum Temperature (F)	984	1041	1043	1048	1047	1047	1052	1037	1048	1043	1043	1053	1063	993	936

P22 Lifetime Evaluation: Tube 56A

- Number of fatigue cycles in 10 days: 456
  - Let 456 Cycles equal one ten day block.

- ASME BPVC VIII-2 Annex 3F Table 3-F.1: 434 Blocks
  - 11.9 Years until failure
  - Peak Alternating Stress: 203 MPa

- Updated life expectancy represents the minimum known failure time of 10-20 years.

- Possible discrepancy in material model not accurately matching in service component.

P22 Material

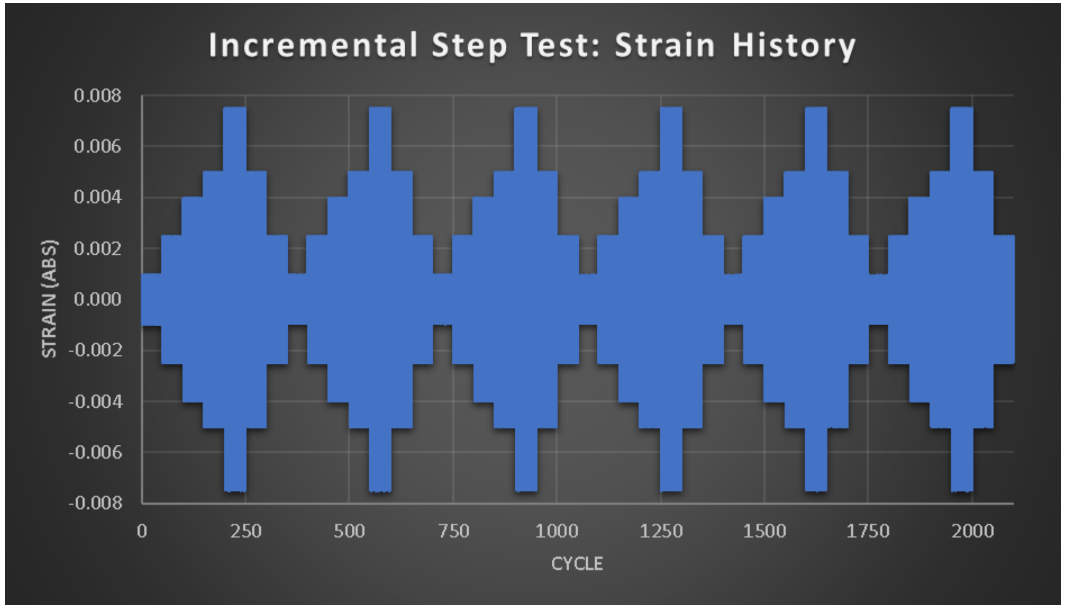
- To validate the material model, data from samples taken from a retired steam header will be evaluated.

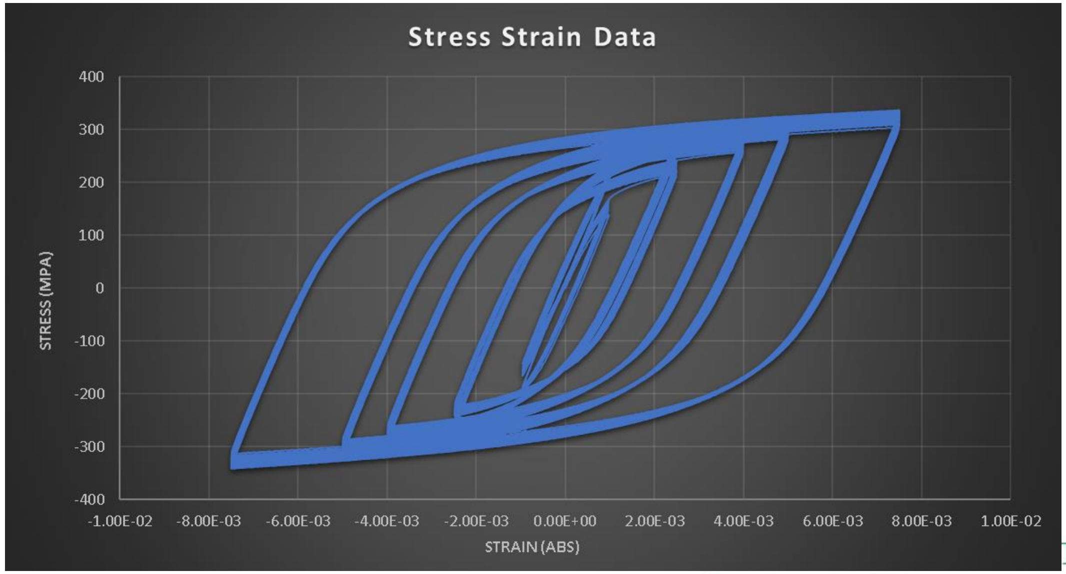
- The samples were evaluated at 3 temperatures.
  - 20 °C
  - 300 °C
  - 500 °C

- Each sample was subjected to 50 cycles at the following strains
  - 0.1%, 0.25%, 0.4%, 0.5%, 0.75%, 0.5%, 0.25%

New Material Model Constants

- Stress-Strain data was provided for serviced P22 samples at 3 temperatures.
  - 20 °C
  - 300 °C
  - 500 °C
- Each sample was subjected to 50 cycles at the following strain blocks
  - 0.1%, 0.25%, 0.4%, 0.5%, 0.75%, 0.5%, 0.25%
  - 50 Cycles per block
  - 6 Blocks per sample





New Material Model Constants

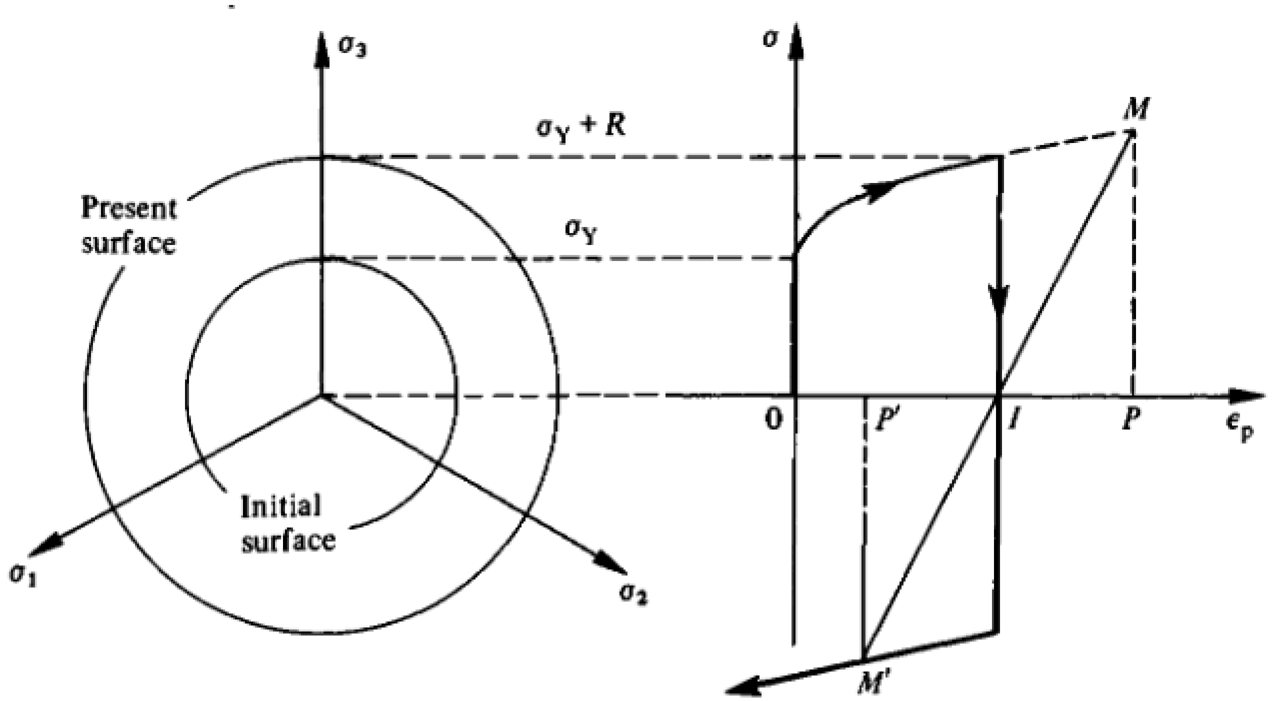
- The desired material model will be a Non-Linear Kinematic Hardening, NLKH, model.
  - The model will not incorporate Isotropic Hardening or Creep effects.
- The provided samples are from a retired unit with an unknown strain history needed to determine Isotropic Hardening material parameters.
- The data provided does not include rate effects required to obtain the Creep material parameters.
- The NLKH constants were found following the procedure outlined in Lemaitre &Chaboche, “Mechanics of Solid Materials ,” 1994.

New Material Model Constants

- Material hardening is generally broken into two categories.
  - Isotropic Hardening
  - Kinematic Hardening
    - Linear
    - Nonlinear
- Isotropic Hardening is used to reflect symmetric increases of the yield surface.
- Kinematic Hardening is used to reflect translations of the yield surface.

New Material Model Constants

- Isotropic Hardening: Increases yield strength equally in tension and compression.
- The yield function, f, has the form of $f = \sigma_{eq} - R - \sigma_y$



Adapted from [2]

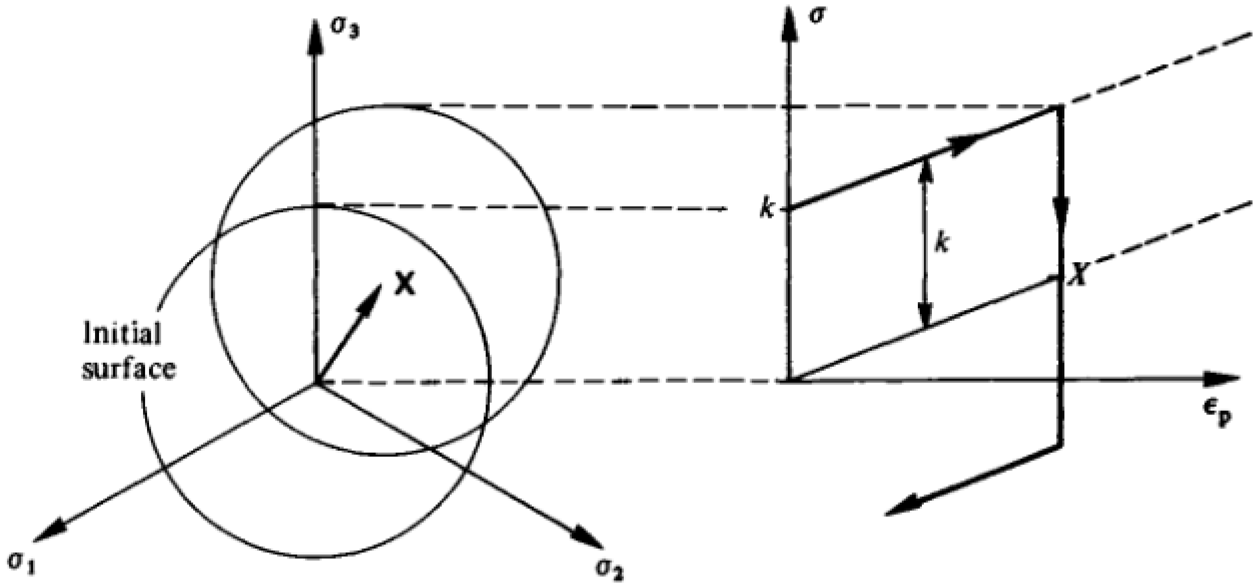
New Material Model Constants

- Under symmetric strain cycles, Isotropic Hardening stabilizes to a set value as the mean stress approaches zero.
- The level of Isotropic Hardening depends on the strain amplitude.
- Therefore, only Kinematic hardening effects are considered when evaluating a stabilized state.
- This can be seen by the definition of the evolution of R.

$$dR = b(Q - R)dp$$

New Material Model Constants

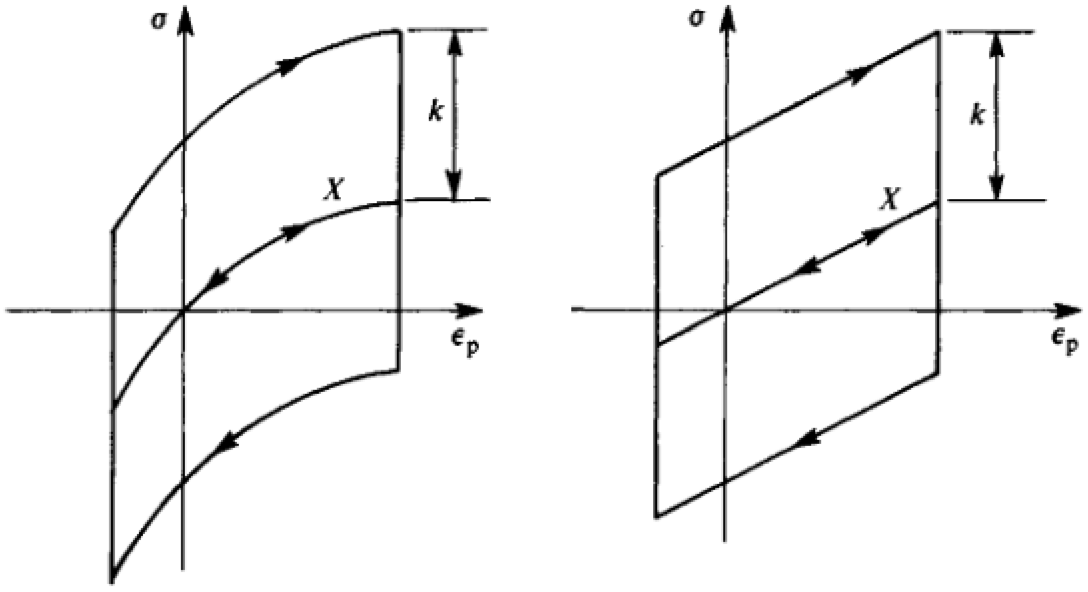
- Kinematic Hardening: An increase in tensile yield strength reduces the compressive yield strength.
- For Kinematic Hardening, the yield function, f, has the form of $f = J_2(\sigma - \chi) - k$



Adapted from [2]

New Material Model Constants

- Kinematic Hardening can be represented as linear and nonlinear hardening.
- For linear hardening $\mathrm{d}\chi = C_0 d\varepsilon^p$
- For nonlinear hardening $\mathrm{d}\chi = \frac{2}{3} C d\varepsilon^p - \gamma \chi dp$



(a) (b)

Adapted from [2]

New Material Model Constants

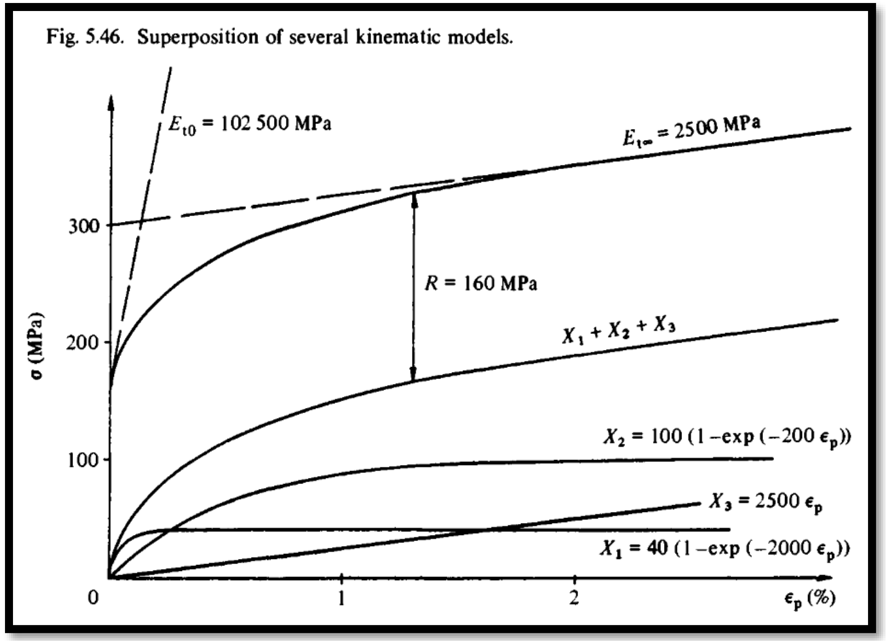
- Initial constants were found using a single set of coefficients for the NLKH model.
  1. Determine the initial yield stress of the first cycle
  2. Determine the $\frac{C}{\gamma}$ value as an asymptotic value of $\Delta\sigma - k$ plotted against $\Delta\varepsilon$.
  3. Determine the constants C, γ by fitting the relationship of

$$\frac{\Delta\sigma}{2} - k = \frac{C}{\gamma}\tanh\left(\gamma\ \frac{\Delta\varepsilon_p}{2}\right)$$

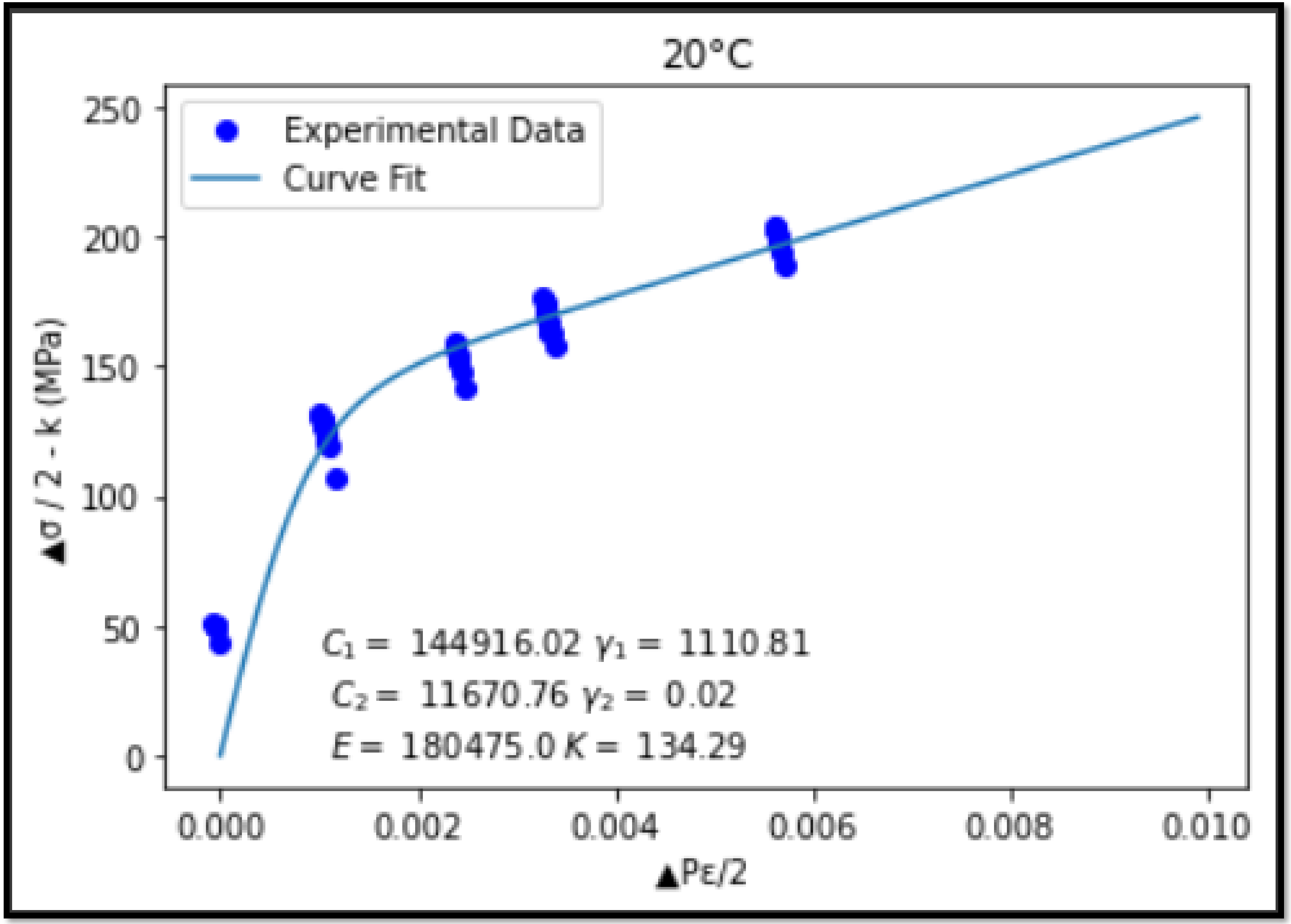
- Note: The modulus was taken as a linear fit of the first 0.00095 strain. The initial yield stress was found as the intersection of the stress strain data and the 0.2% offset modulus.

New Material Model Constants

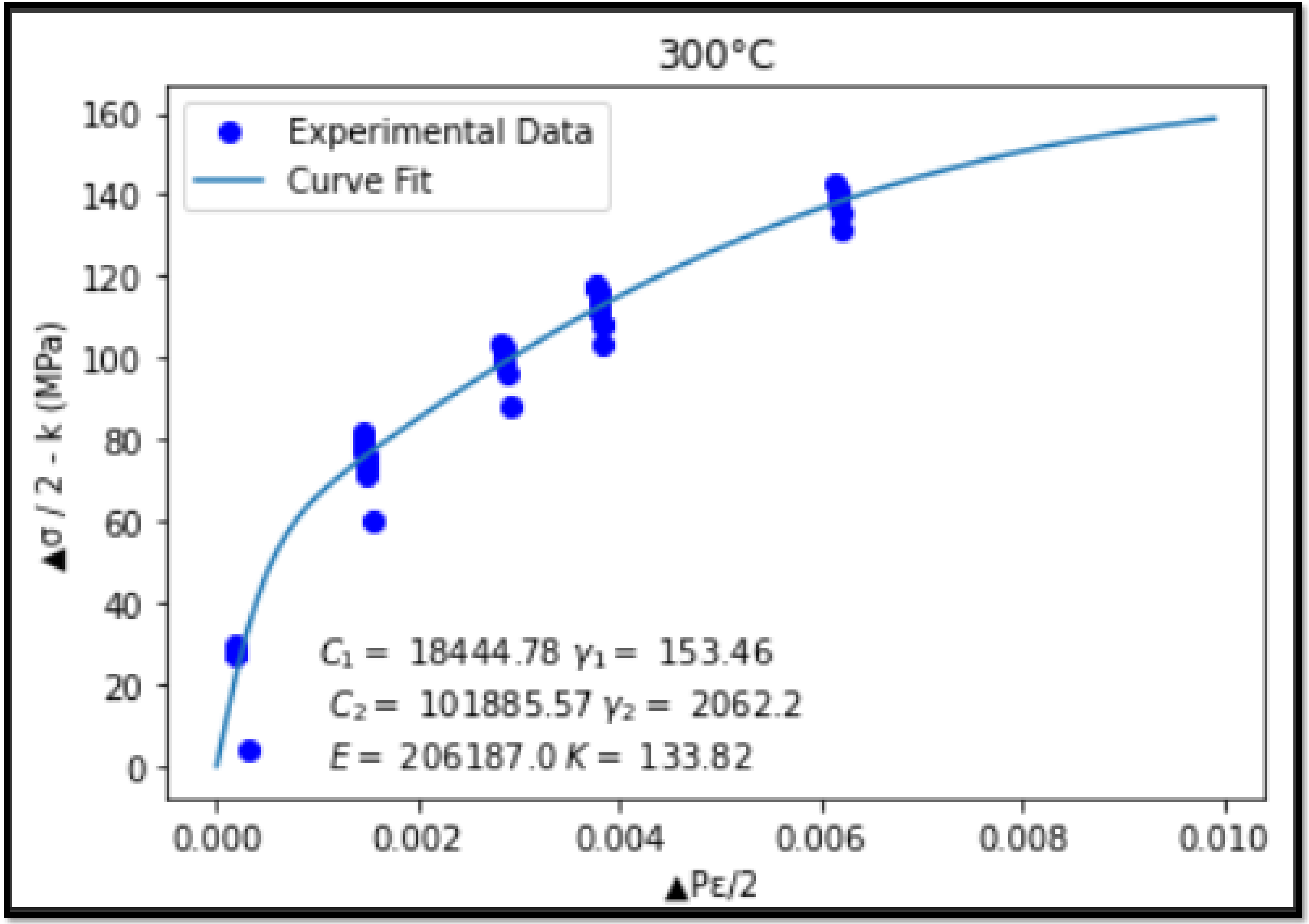
- The model was updated to reflect the superposition of multiple NLKH models.
- A python script using the scipy.optimize.curve_fit() functionality was used to determine the coefficients C, γ
  - The model uses Least Square Minimization

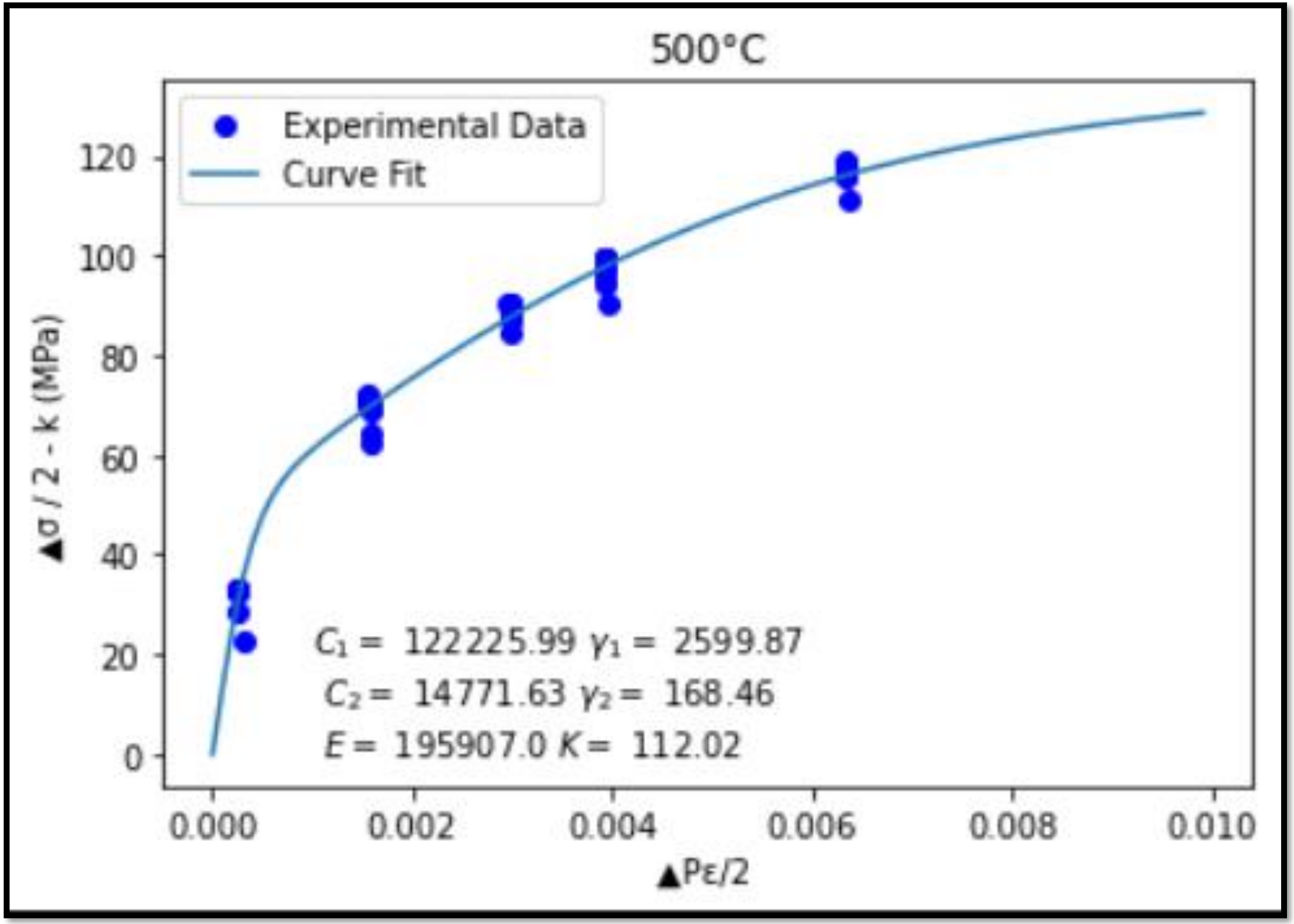


Adapted from [1]



20°C
Experimental Data
Curve Fit
250
200
150
100
50
0
0.000
0.002
0.004
0.006
0.008
0.010
Δσ / 2 - k (MPa)
ΔPε/2
C₁ = 144916.02 γ₁ = 1110.81
C₂ = 11670.76 γ₂ = 0.02
E = 180475.0 K = 134.29


300°C
Experimental Data
Curve Fit
$C_1 = 18444.78\ \gamma_1 = 153.46$
$C_2 = 101885.57\ \gamma_2 = 2062.2$
$E = 206187.0\ K = 133.82$
▲σ / 2 - k (MPa)
▲Pε/2
0
20
40
60
80
100
120
140
160
0.000
0.002
0.004
0.006
0.008
0.010



500°C
Experimental Data
Curve Fit
$C_1 = 122225.99$ $\gamma_1 = 2599.87$
$C_2 = 14771.63$ $\gamma_2 = 168.46$
$E = 195907.0$ $K = 112.02$
▲σ / 2 - k (MPa)
▲Pε/2
0
20
40
60
80
100
120
0.000
0.002
0.004
0.006
0.008
0.010

New Material Model Constants

- The updated constants for the NLKH model are shown below.

$$\frac{\Delta\sigma}{2} - k = \frac{C}{\gamma}\tanh\left(\gamma \frac{\Delta\varepsilon_p}{2}\right)$$

Temperature	E (MPa)	K (MPa)	C_1	γ_1	C_2	γ_2
20°C	180,475	134.29	144916.02	1,110.81	11,670.76	0.02
300°C	206,187	133.82	18,444.78	153.46	101,885.57	2062.2
500°C	195,907	112.02	122,225.99	2,599.87	14,771.63	168.46

References

- [1] Farragher, T.P., Scully, S., O'Dowd, N.P. and Leen, S.B., 2013. Development of life assessment procedures for power plant headers operated under flexible loading scenarios. *International Journal of Fatigue*, *49*, pp.50-61.
- [2] Lemaitre, J. and Chaboche, J.L., 1994. *Mechanics of solid materials*. Cambridge university press.

Thank you for your participation.

Questions?

D.O.E. Project
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Alloy for Enhancement of Operational Flexibility of Powerplants