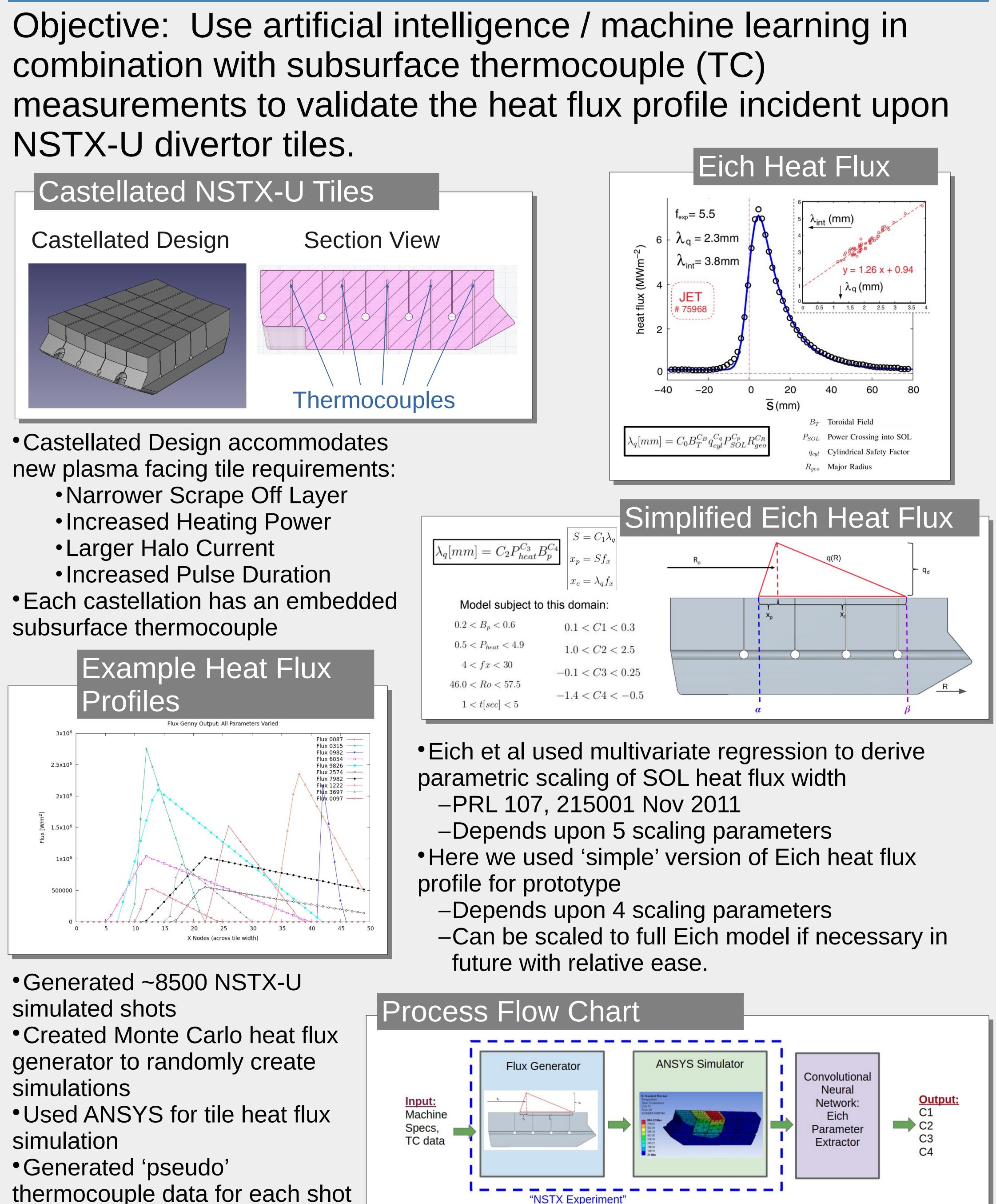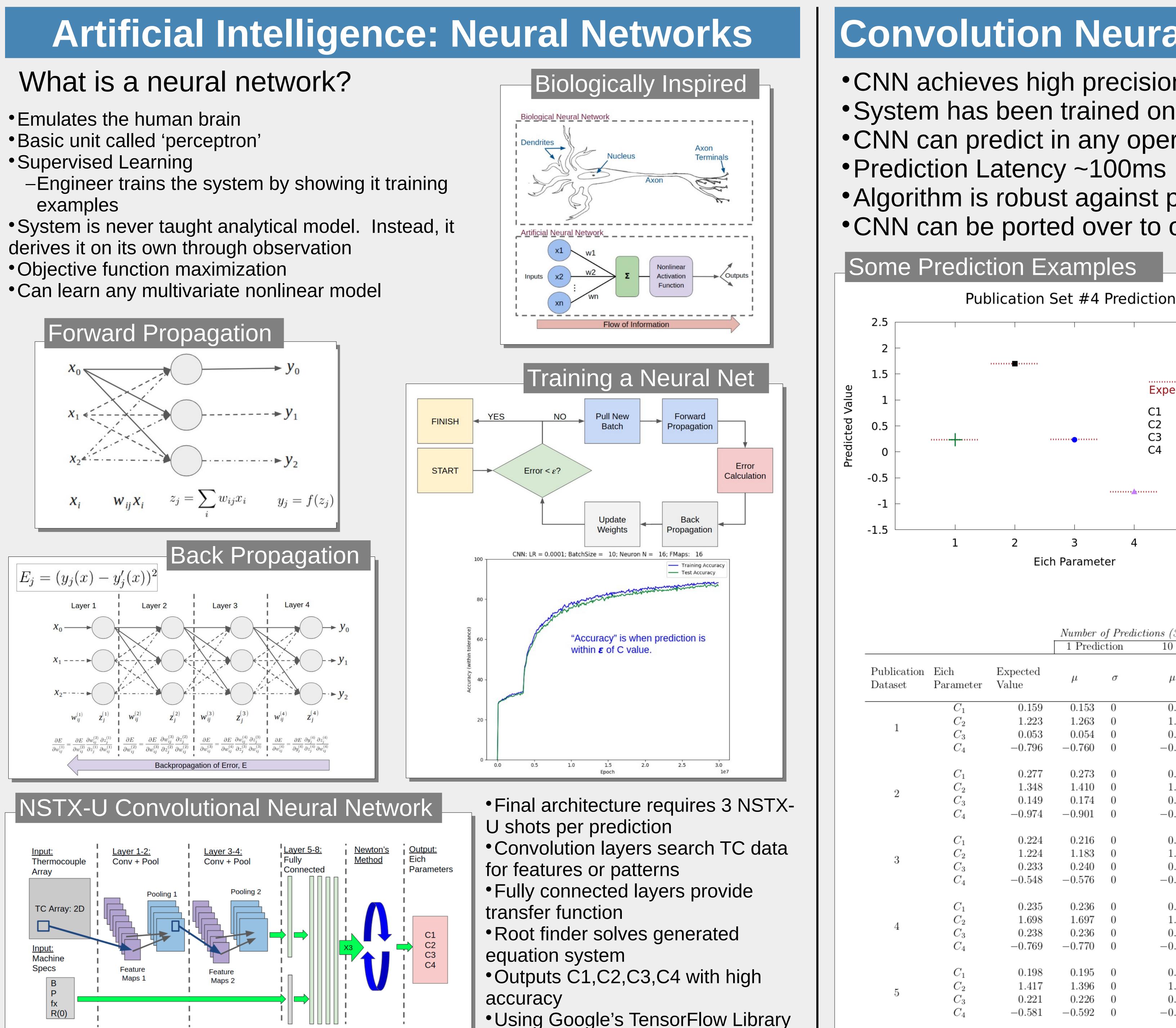# Heat Flux Model Validation Using Machine Learning and Sub-surface Thermocouples for NSTX-U Plasma Facing Components

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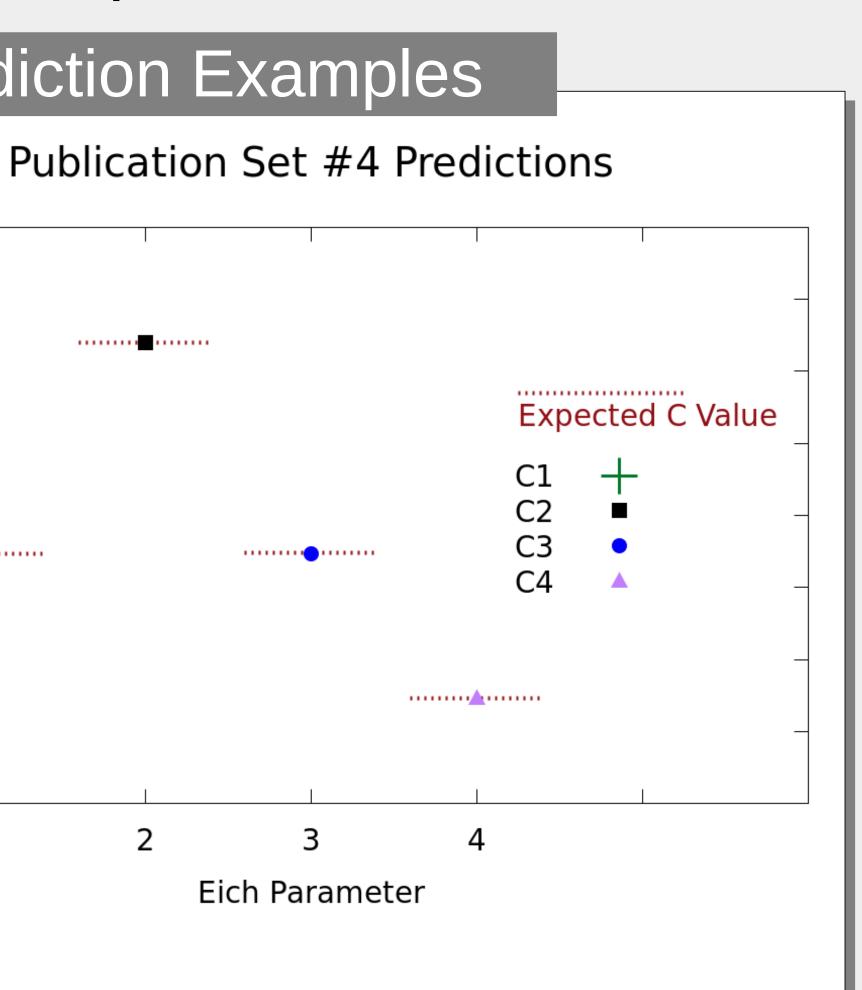
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NSTX-U

Objective / Background

Objective: Use artificial intelligence / machine learning in combination with subsurface thermocouple (TC) measurements to validate the heat flux profile incident upon NSTX-U divertor tiles.

Castellated NSTX-U Tiles

Castellated Design   Section View

Thermocouples

- Castellated Design accommodates new plasma facing tile requirements:
  - Narrower Scrape Off Layer
  - Increased Heating Power
  - Larger Halo Current
  - Increased Pulse Duration
- Each castellation has an embedded subsurface thermocouple

Eich Heat Flux

$f_{\text{exp}} = 5.5$
$\lambda_q = 2.3\text{mm}$
$\lambda_{\text{int}} = 3.8\text{mm}$

λ_{int} (mm)

$y = 1.26 x + 0.94$

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λ_q (mm)

$\lambda_q[mm] = C_0 B_T^{C_B} q_{cyl}^{C_q} P_{SOL}^{C_P} R_{geo}^{C_R}$

B_T — Toroidal Field
P_{SOL} — Power Crossing into SOL
q_{cyl} — Cylindrical Safety Factor
R_{geo} — Major Radius

Simplified Eich Heat Flux

$\lambda_q[mm] = C_2 P_{heat}^{C_3} B_p^{C_4}$

$S = C_1 \lambda_q$
$x_p = S f_x$
$x_c = \lambda_q f_x$

Model subject to this domain:
$0.2 < B_p < 0.6$ $0.1 < C_1 < 0.3$
$0.5 < P_{heat} < 4.9$ $1.0 < C_2 < 2.5$
$4 < f_x < 30$ $-0.1 < C_3 < 0.25$
$46.0 < R_0 < 57.5$ $-1.4 < C_4 < -0.5$
$1 < t[sec] < 5$

Example Heat Flux Profiles

Flux Geony Output: All Parameters Varied

- Generated ~8500 NSTX-U simulated shots
- Created Monte Carlo heat flux generator to randomly create simulations
- Used ANSYS for tile heat flux simulation
- Generated 'pseudo' thermocouple data for each shot

- Eich et al used multivariate regression to derive parametric scaling of SOL heat flux width
  - PRL 107, 215001 Nov 2011
  - Depends upon 5 scaling parameters
- Here we used 'simple' version of Eich heat flux profile for prototype
  - Depends upon 4 scaling parameters
  - Can be scaled to full Eich model if necessary in future with relative ease.

Process Flow Chart

Input: Machine Specs, TC data → Flux Generator → ANSYS Simulator → Convolutional Neural Network: Eich Parameter Extractor → Output: C1 C2 C3 C4

"NSTX Experiment"

Artificial Intelligence: Neural Networks

What is a neural network?

- Emulates the human brain
- Basic unit called 'perceptron'
- Supervised Learning
  - Engineer trains the system by showing it training examples
- System is never taught analytical model. Instead, it derives it on its own through observation
- Objective function maximization
- Can learn any multivariate nonlinear model

Biologically Inspired

Biological Neural Network
Dendrites — Nucleus — Axon — Axon Terminals

Artificial Neural Network
x_1 w_1
Inputs x_2 w_2 → Σ → Nonlinear Activation Function → Outputs
x_n w_n

Flow of Information

Forward Propagation

x_0 → y_0
x_1 → y_1
x_2 → y_2

x_i $w_{ij} x_i$ $z_j = \sum_i w_{ij} x_i$ $y_j = f(z_j)$

Back Propagation

$E_j = (y_j(x) - y_j'(x))^2$

Layer 1   Layer 2   Layer 3   Layer 4

Backpropagation of Error, E

Training a Neural Net

FINISH ← YES — NO — Pull New Batch → Forward Propagation
START → Error < ε? → Error Calculation
Update Weights ← Back Propagation

CNN: LR = 0.0001; BatchSize = 10; Neuron N = 16; FMaps: 16

"Accuracy" is when prediction is within ε of C value.

NSTX-U Convolutional Neural Network

Input: Thermocouple Array — TC Array: 2D
Input: Machine Specs — B, fx, R(0)

Layer 1-2: Conv + Pool — Pooling 1 — Feature Maps 1
Layer 3-4: Conv + Pool — Pooling 2 — Feature Maps 2
Layer 5-8: Fully Connected
Newton's Method
Output: Eich Parameters — C1 C2 C3 C4

- Final architecture requires 3 NSTX-U shots per prediction
- Convolution layers search TC data for features or patterns
- Fully connected layers provide transfer function
- Root finder solves generated equation system
- Outputs C1,C2,C3,C4 with high accuracy
- Using Google's TensorFlow Library

Convolution Neural Network (CNN) Results

- CNN achieves high precision heat flux profile predictions
- System has been trained on over 8500 simulated NSTX-U shots
- CNN can predict in any operational space of tokamak
- Prediction Latency ~100ms
- Algorithm is robust against potential noise sources
- CNN can be ported over to other diagnostics

Some Prediction Examples

Publication Set #4 Predictions

Expected C Value
C1 (+)
C2 (■)
C3 (●)
C4 (▲)

Predicted Value vs Eich Parameter

What About Noisy Data?

Original 'ideal' TC Data → Noise Function n(TC) → New 'noisy' TC Data

TC Noise Injection Yields C1 Prediction Error
TC Noise Injection Yields C2 Prediction Error
TC Noise Injection Yields C3 Prediction Error
TC Noise Injection Yields C4 Prediction Error

New Temp = (Old Temp)m + b

Noise Bias: b   Noise Multiplier: m   Percent Error (% of range)

Number of Predictions (3 shots each)

Publication Dataset	Eich Parameter	Expected Value	1 Prediction μ	1 Prediction σ	10 Predictions μ	10 Predictions σ
1	C_1	0.159	0.153	0	0.157	±0.0015
	C_2	1.223	1.263	0	1.241	±0.0515
	C_3	0.053	0.054	0	0.053	±0.0185
	C_4	−0.796	−0.760	0	−0.782	±0.0304
2	C_1	0.277	0.273	0	0.276	±0.0026
	C_2	1.348	1.410	0	1.318	±0.0660
	C_3	0.149	0.174	0	0.161	±0.0166
	C_4	−0.974	−0.901	0	−0.986	±0.0454
3	C_1	0.224	0.216	0	0.218	±0.0080
	C_2	1.224	1.183	0	1.254	±0.0639
	C_3	0.233	0.240	0	0.202	±0.0601
	C_4	−0.548	−0.576	0	−0.550	±0.0192
4	C_1	0.235	0.236	0	0.234	±0.0016
	C_2	1.698	1.697	0	1.689	±0.0486
	C_3	0.238	0.236	0	0.234	±0.0089
	C_4	−0.769	−0.770	0	−0.778	±0.0216
5	C_1	0.198	0.195	0	0.192	±0.0105
	C_2	1.417	1.396	0	1.452	±0.0913
	C_3	0.221	0.226	0	0.185	±0.0824
	C_4	−0.581	−0.592	0	−0.583	±0.0360