Process of building AI models for predicting engine performance and emissions

MATLAB EXPO 2023

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Public

About Cummins

- Corporate Headquarters: Columbus, Indiana
- Founded: 1919
- Cummins Inc., a global power leader, is a corporation of complementary business segments that design, manufacture, distribute and service a broad portfolio of power solutions.
- The company's products range from diesel, natural gas, electric and hybrid powertrains and powertrain-related components including filtration, aftertreatment, turbochargers, fuel systems, controls systems, air handling systems, automated transmissions, electric power generation systems, batteries, electrified power systems, hydrogen generation and fuel cell products.

Content

- ❑ Background
- ❑ Methodology
- ❑ Results
- ❑ Summary

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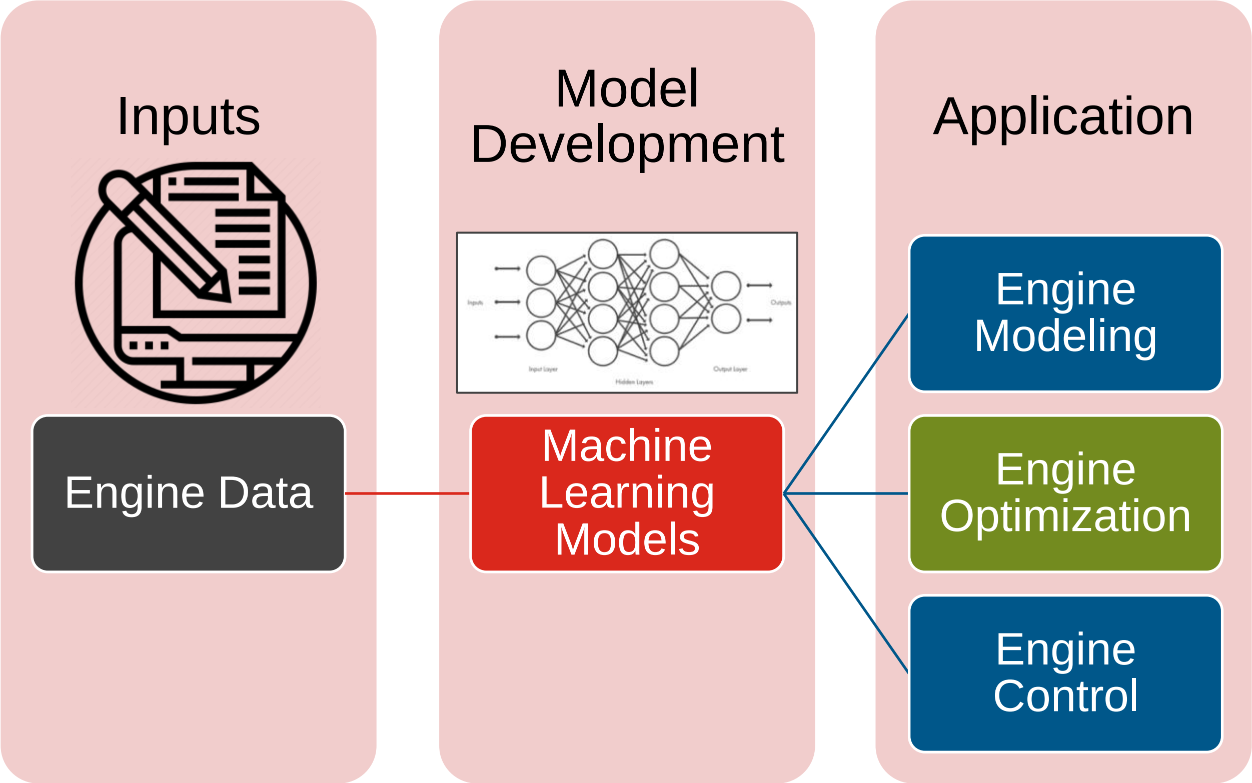
Machine Learning for Engine Cycle Simulation

- Investigation was done to find a low fidelity model or algorithm which could predict engine performance and emissions responses* with good accuracy and model run time close to real time.
- The robustness of AI models to learn from the data encouraged us to try several machine learning models.
- A detailed approach was taken to build LSTM based deep neural network models that allowed these models to achieve target model accuracy with a model run time ~ 1/8 of real time.



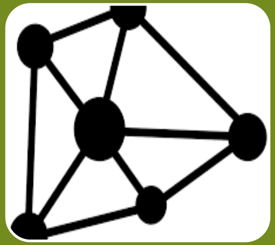
Some critical applications of trained machine learning models include Real Driving Emission (RDE) modeling and control, combustion knock detection and control, combustion mode transition in multi-mode engines, combustion noise modeling and Control, combustion instability, and cyclic variability control, costly and time-consuming engine calibration.

** Typical engine responses include flow, temperature, pressure, torques at different engine locations*

Motivation

Reducing model development time by automating the process

Faster model run time



Easy handling of multi-dimensional and multi-variety data

Wide Applications

Benefits of using MATLAB?

1. Low to no coding experience required
2. Spend more time on applying technical expertise than writing code
3. All workflow is app-based
4. Provide end to end solutions from data preprocessing till validation of the trained models
5. Documentation: domain-based shipping examples are available

Content

- ❑ Background
- ❑ Methodology
- ❑ Results
- ❑ Summary

Methodology

Iterative process

1. Neural Network Architecture definition (Scope of optimization)
2. Define initial values of hyperparameters*
3. Train model for one response*
4. Optimize hyper parameters (Scope of optimization)
5. Generate code of the process (Script version)
6. Automate process for training multiple responses

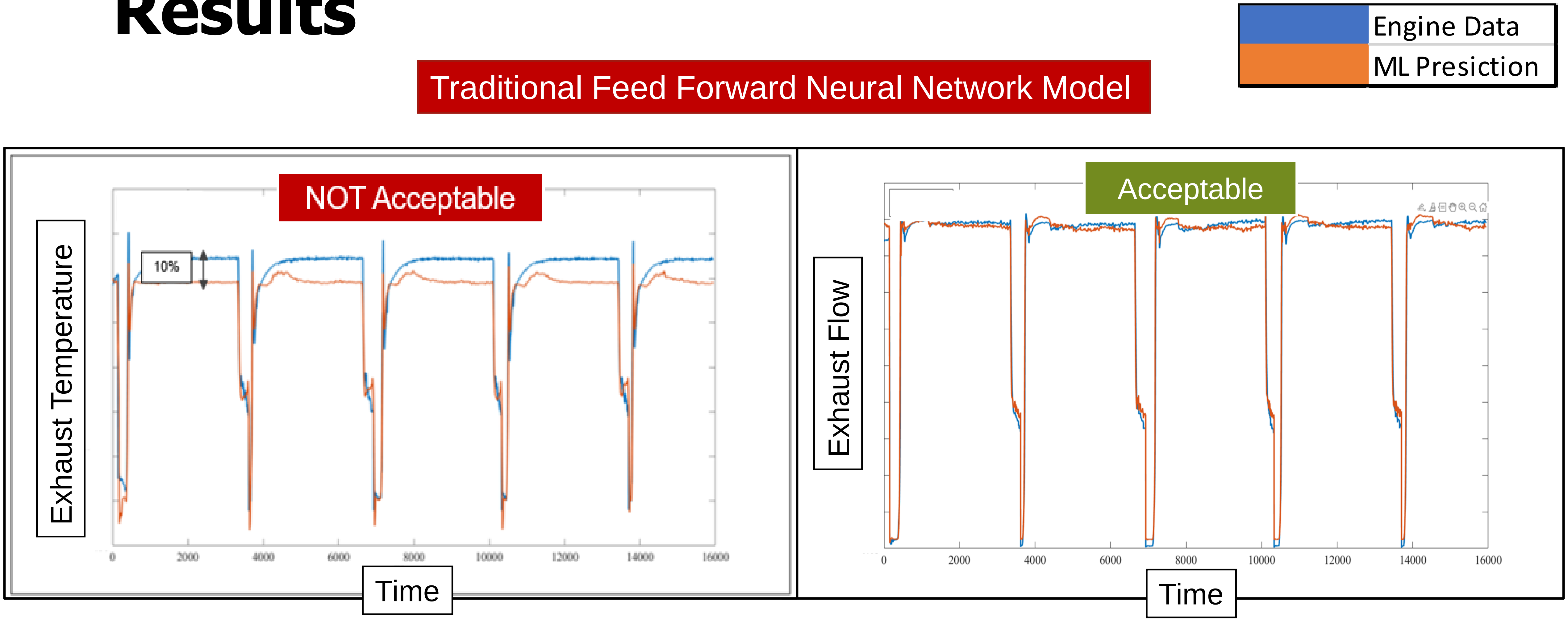
- *Typical engine responses include flow, temperature, pressure, and torques at different engine locations*
- *Hyperparameters in machine learning are those parameters that are explicitly defined by the user to control the learning process, and their values are set before starting the learning process of the model.*

Content

- ❑ Background
- ❑ Methodology
- ❑ Results
- ❑ Summary

Results

Traditional Feed Forward Neural Network Model



- With a traditional NN model of 6 hidden layers and 5 neurons within each layer acceptable prediction on exhaust flow was observed.

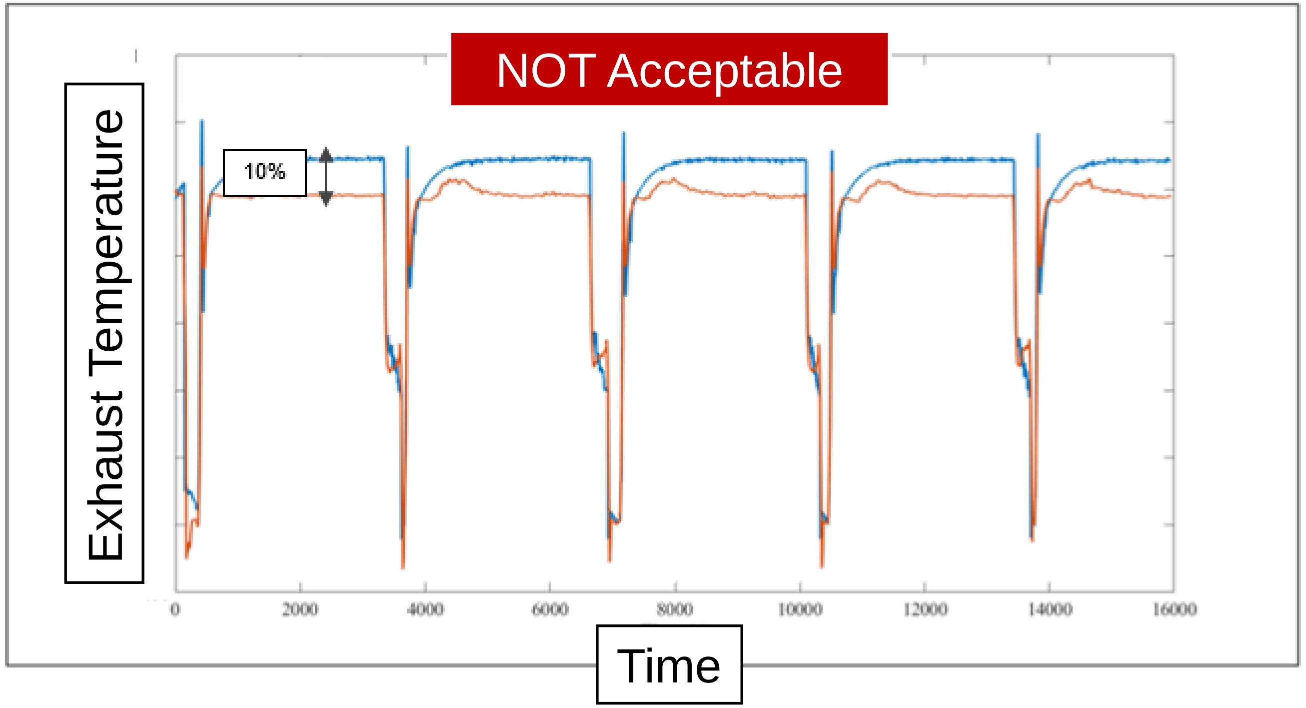
- After trying multiple architectures based on the number of hidden layers and neurons acceptable accuracy on temperature predictions was not observed. This motivated an LSTM-based detailed ML model development.

Results

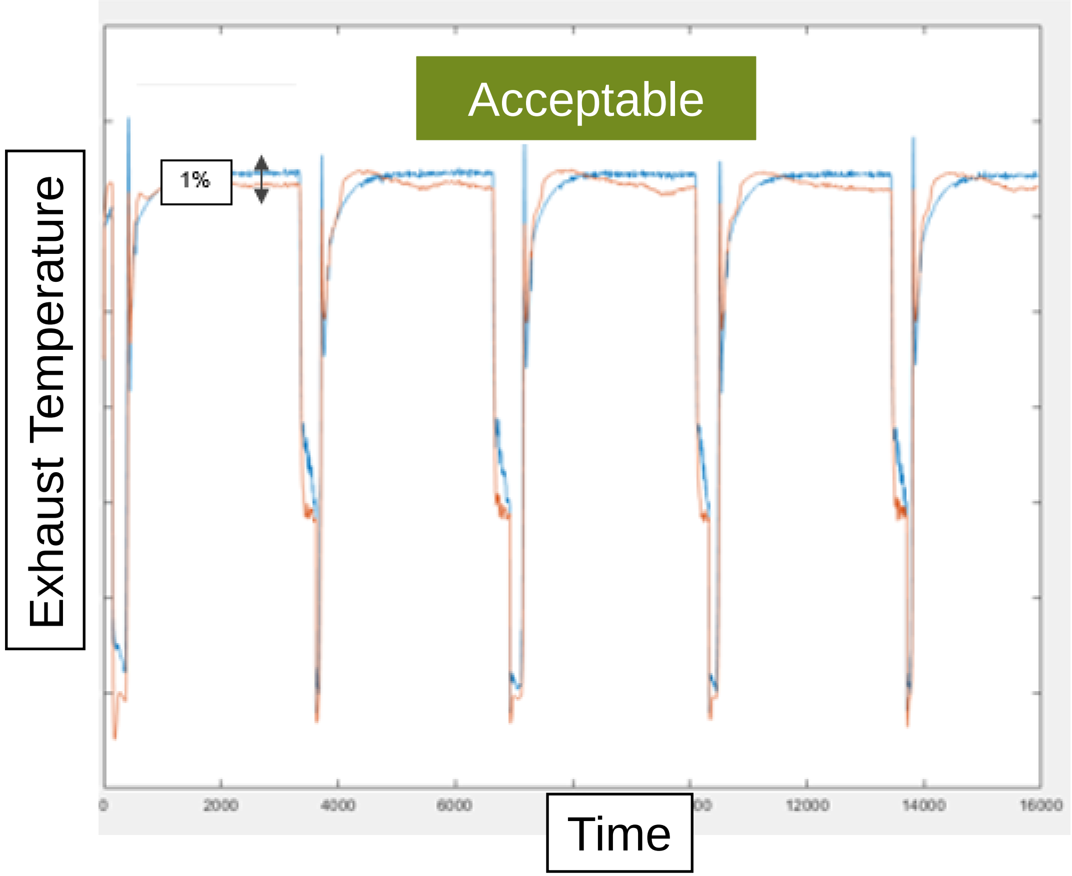
(blue)	Engine Data
(orange)	ML Presiction

➢ Exhaust Temperature

Traditional Feed forward neural network model (R-Square = 0.89)



Deep neural network with LSTM layer and optimized hyper parameters (R-Square = 0.95)



- With a detailed approach of modeling deep neural networks along with LSTM layers it is observed that temperature predictions improved compared to a traditional feed-forward deep neural network

- Optimized hyperparameters were solver options, number of training iterations, learn rate, and shuffle option.

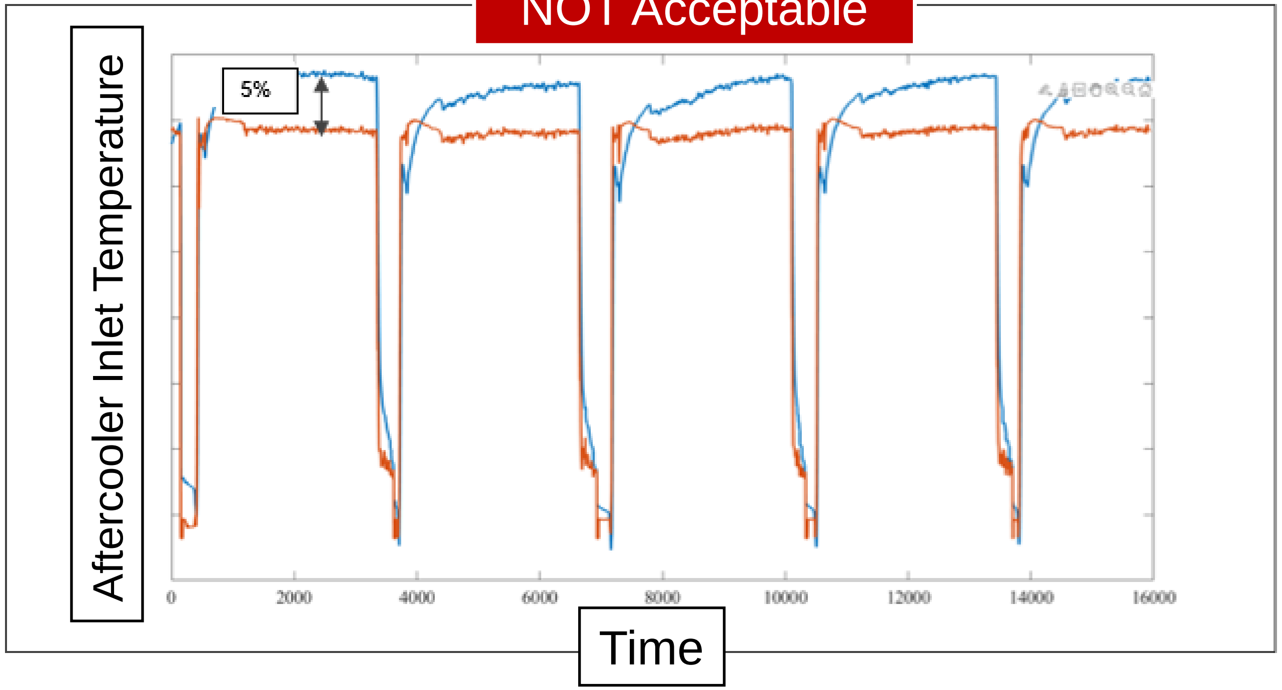
Results

(blue)	Engine Data
(orange)	ML Presiction

➢ Aftercooler Inlet Temperature

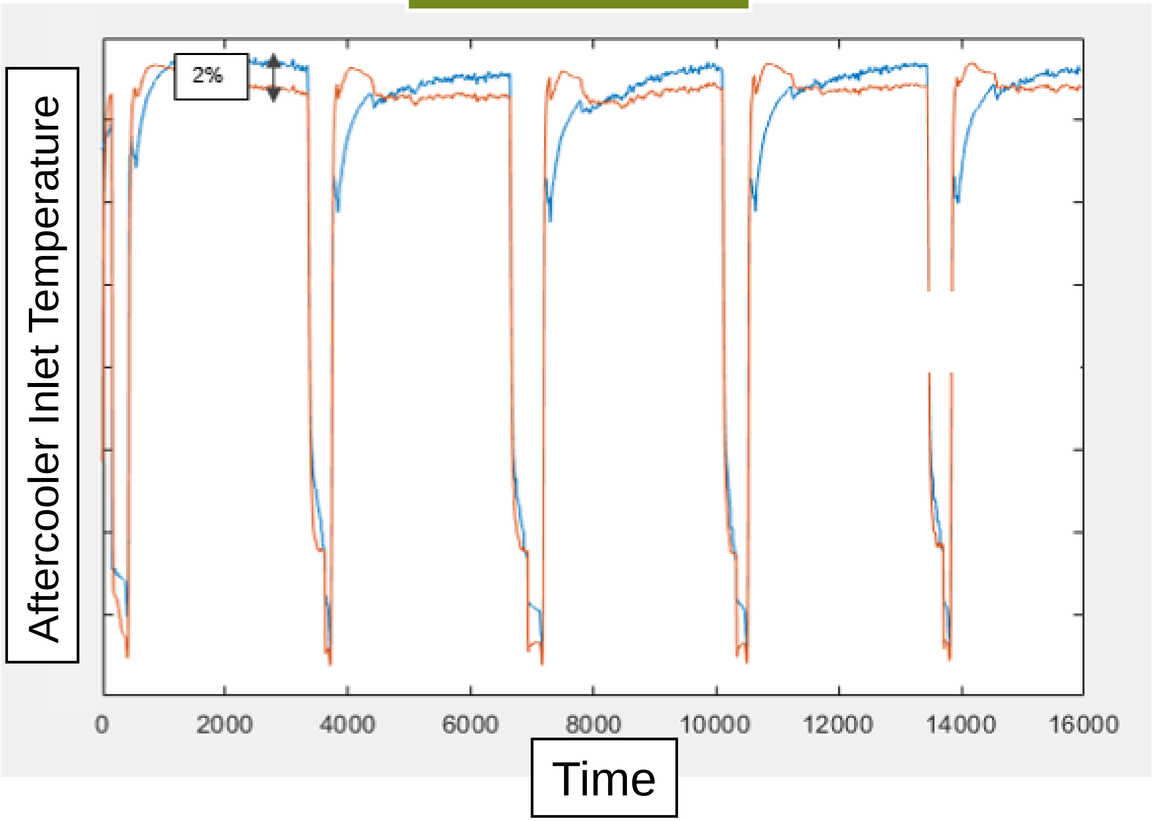
Traditional Feed forward neural network model (R-Square = 0.85)

NOT Acceptable



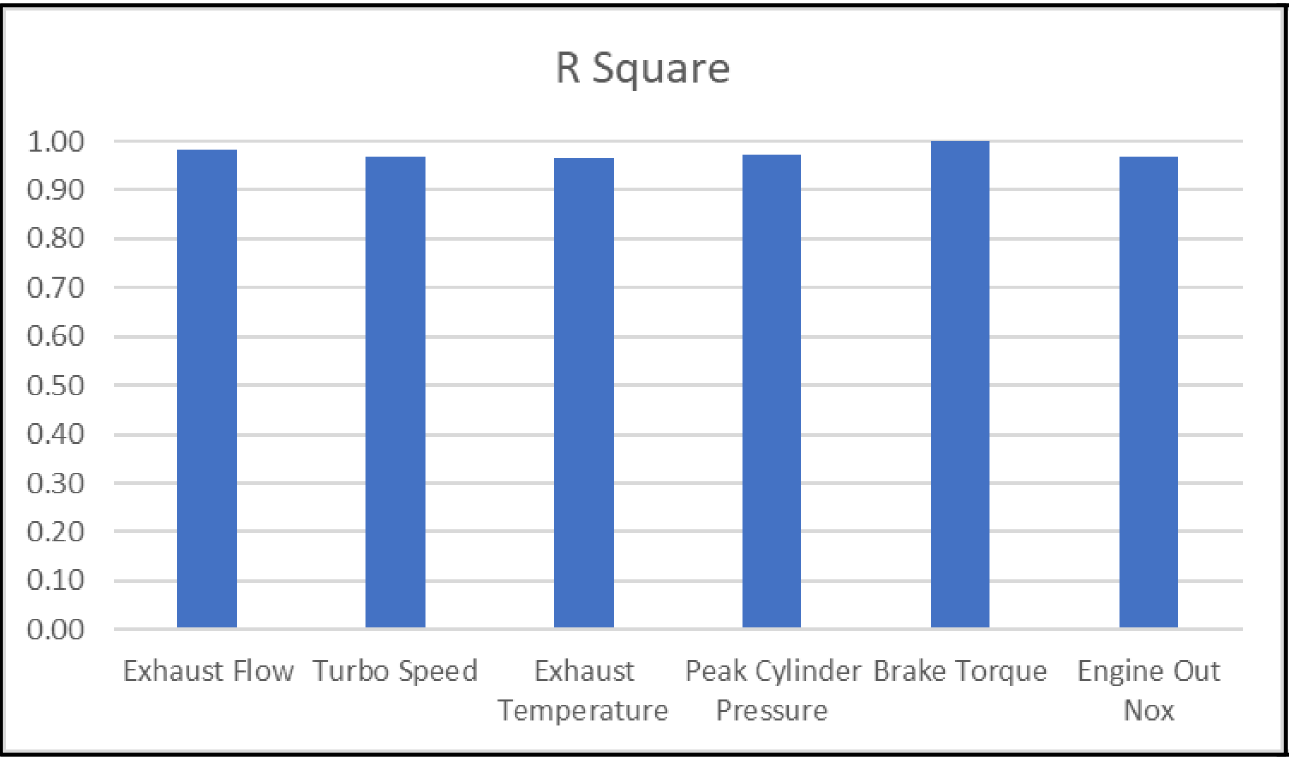
Deep neural network with LSTM layer and optimized hyper parameters (R-Square = 0.95)

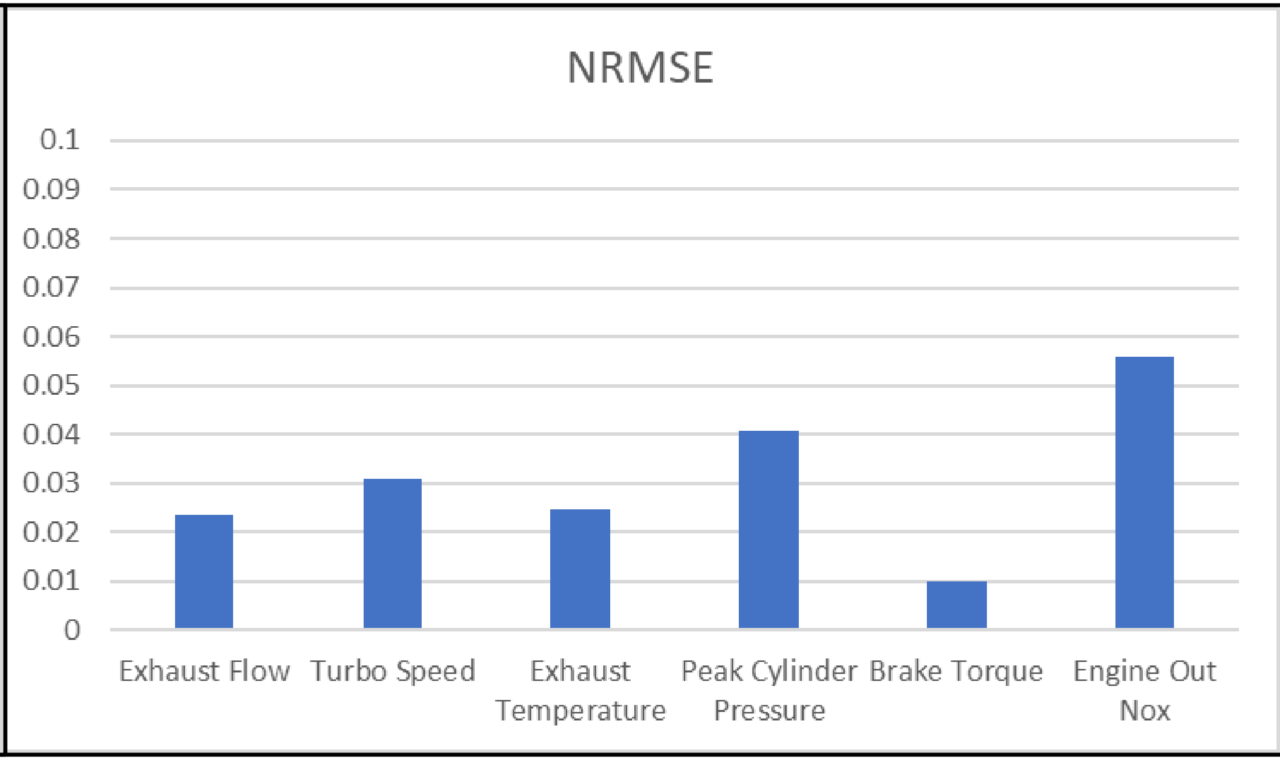
Acceptable



- Optimized hyperparameters were solver options, number of training iterations, learn rate, and shuffle option.
- Along with the LSTM layer and optimized hyperparameters an additional dropout layer was included to prevent the model from overfitting.

Results





- For all the responses machine learning models are capable to predict with accuracy close to or higher than r-square greater than 0.95.

Summary

- Machine learning models were developed to predict various engine performance and emissions parameters.
- Trained machine learning models were validated against new engine data and models predicted with accuracy greater than 0.95 r-square and low NRMSE for all the responses.
- Two approaches to developing machine learning models were evaluated:
  1. A traditional feed-forward NN model through which good accuracy on pressure, flow, and emission parameters was observed with FoRT ~ 1/1500 for predicting 26 responses in series.
  2. A detailed approach was taken to develop the models which include traditional feed-forward NN along with multiple LSTM layers, optimizing hyperparameters, and use of activation functions such as dropout layers through which good accuracy on temperature parameters was observed with FoRT ~ 1/800 for predicting 26 responses in series.
- Both approaches enabled us to build models much faster than real-time and acceptable prediction accuracy which aligns with the motivation of the project.
- Machine learning models provide the opportunity to optimize and control engine performance and emissions by accurate prediction and easy deployment capability.

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Thank You !