Weighted Loss GRU Network for Machine Failure Prediction

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Outline

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- Model Architecture
- Weighted Loss/Error Formulation
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Motivation and Background

- Mechanical systems require periodic maintenance
- Unanticipated system failure can be extremely expensive
- Accurate predictions of remaining useful life (RUL) can help a business save money
- Mechanical failures cost F500 companies $225 billion annually

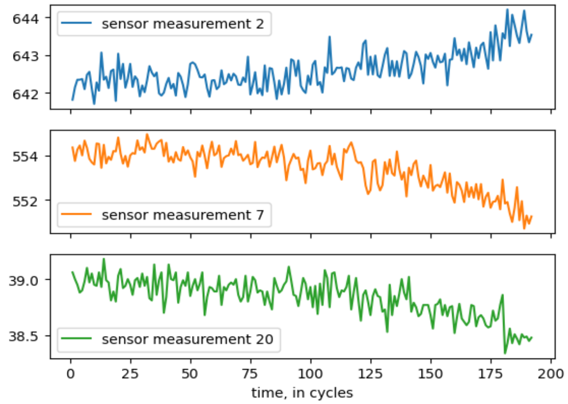
Cost of Maintenance

	True Working	True Failure
Predicted Working	No cost	Very high cost
Predicted Failure	Minor cost	Necessary cost

Dataset Overview

- CMAPPS - Jet Engine Simulated Dataset
- Simulated jet engine data from NASA
- 4 sets of training & testing data (FD001 through FD004)
  - Different combinations of operating and failure conditions
- Time signals for 3 operational settings and 21 sensor measurements
  - Temperature, pressure, speed measurements from various locations in engine
- Objective is to determine the RUL (Remaining Useful Life) of the engines in the test set

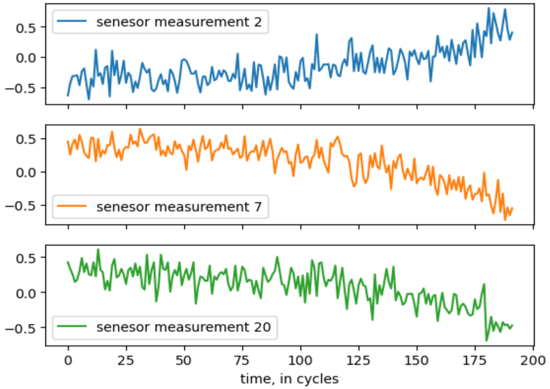
Dataset	FD001	FD002	FD003	FD004
Training Time Series	100	260	100	249
Testing Time Series	100	259	100	248
Operational Conditions	1	6	1	6
Failure Conditions	1	1	2	2



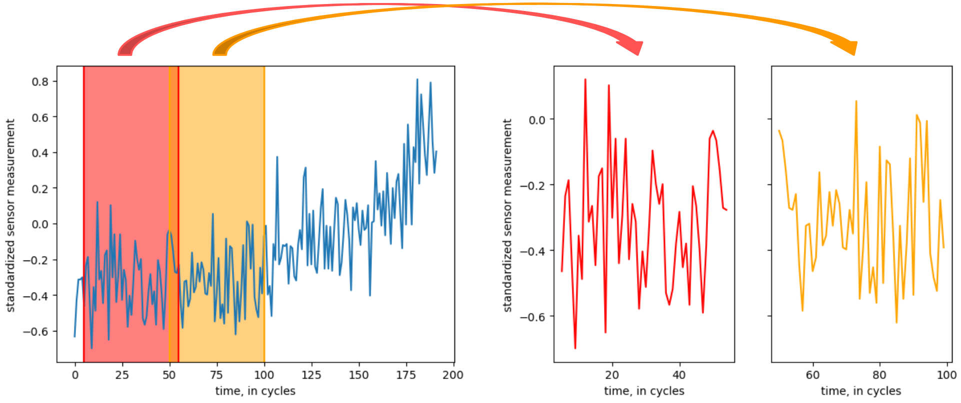
Example sensor signals

Data Preprocessing

- Min-max scaling onto the range [-1, 1]
- Data windowing to augment training time series
    - Subsample sections of training signals to turn one signal into multiple shorter
- Potential for future addition of feature extraction

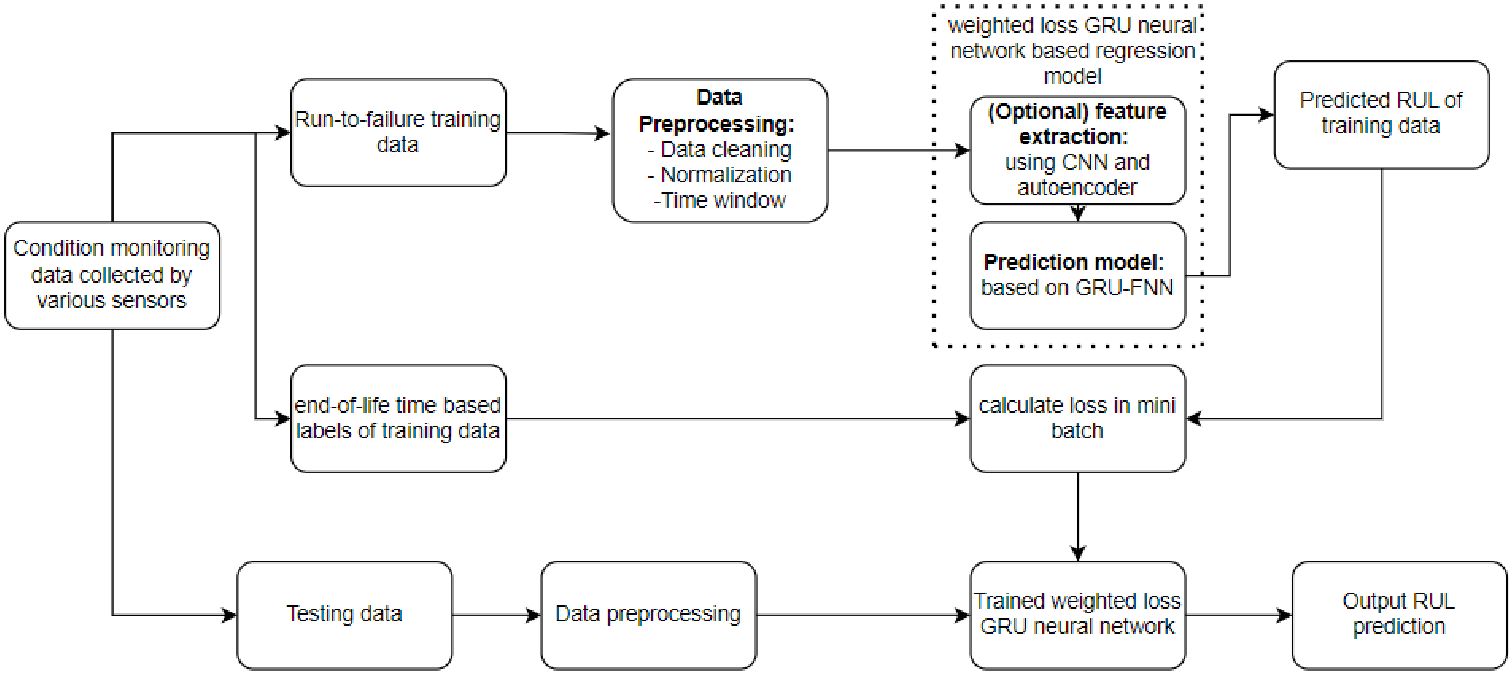


Example of standardized signals



Example of data windowing

Model Architecture



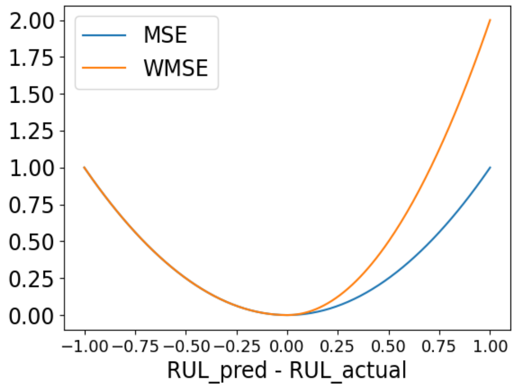
Weighted Loss/Error Formulation

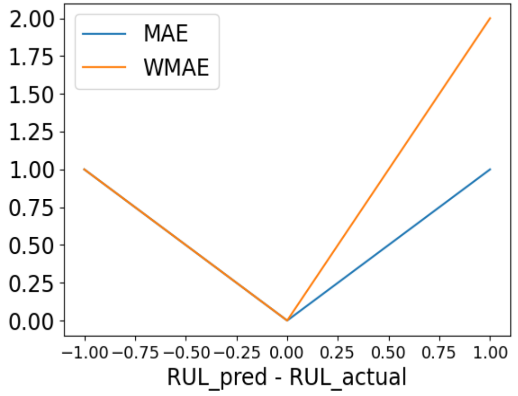
- Weighting of loss equation to penalize over predicting RUL
    - Weighted mean square error (WMSE)
- Weighting of error metric to better evaluate the model in the context of the problem's economics
    - Weighted mean absolute error (WMAE)
- Weighting factor *C* becomes a tunable parameter
    - Separate values for WMAE and WMSE

$$\mathrm{WMSE} = \frac{1}{n}\sum_{i=1}^{n} w_i \left(\hat{y}_i - y_i\right)^2$$

$$w_i = \begin{cases} C & \hat{y}_i - y_i > 0 \\ 1 & \hat{y}_i - y_i \leq 0 \end{cases}$$

$$\mathrm{WMAE} = \frac{1}{n}\sum_{i=1}^{n} w_i \left|\hat{y}_i - y_i\right|$$





Experiment Setup

- Test each dataset across a range of training weighting factors
    - Extract any trends in the results
- Benchmark performance against previous work
- Evaluate performance using WMAE to account for economic cost

Tested model structure

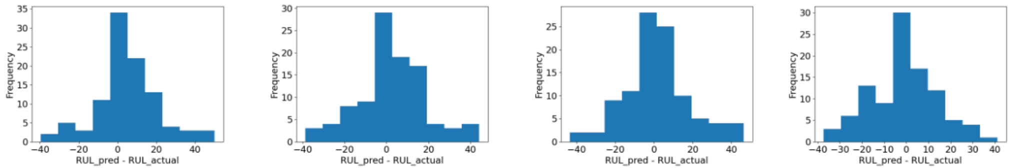
	Input Size	Num Layers	Output Size
Gated Recurrent Unit	24	2	256
ReLU Activation	256	-	256
Fully Connected Layer	256	1	1

Results

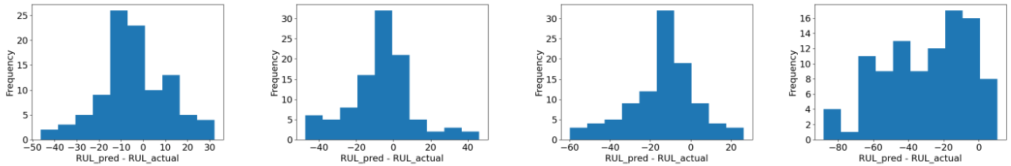
- Model performance on FD001 dataset
- Moderate weighting factor does not notably change MAE, R^2
  - Better performances in some cases
- Weighting shifts predictions to be more conservative

FD001 Results

Weighting Factor C	MAE	R^2	# Conservative Predictions
1	12.2	0.83	35
10	11.8	0.83	43
50	12.2	0.84	49
100	11.2	0.85	51
200	12.2	0.83	53
300	12.0	0.84	69
500	15.5	0.76	84
1000	32.3	0.22	97



(a) $C = 1$ (b) $C = 10$ (c) $C = 50$ (d) $C = 100$



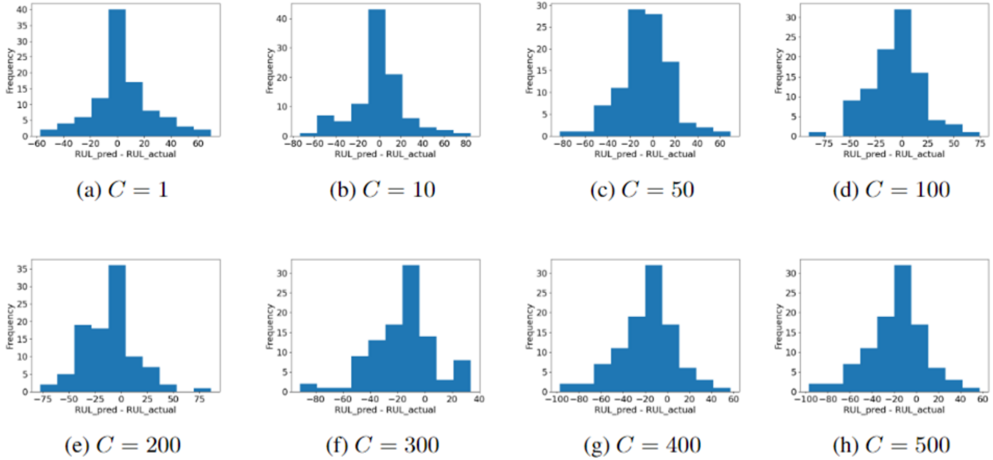
(e) $C = 300$ (f) $C = 500$ (g) $C = 750$ (h) $C = 1000$

Results

- Similar observations on the FD002, FD003, and FD004 datasets
- Higher error rates when trying to predict on more complex data
- Some trends not as clear
    - Stochastic training process

FD004 Results

Weighting Factor C	MAE	R^2	# Conservative Predictions
1	15.9	0.71	45
10	16.4	0.69	59
50	17.4	0.71	69
100	20.0	0.63	67
200	22.0	0.58	77
300	21.2	0.59	82
400	22.2	0.58	79
500	23.4	0.50	81



(a) $C = 1$ (b) $C = 10$ (c) $C = 50$ (d) $C = 100$

(e) $C = 200$ (f) $C = 300$ (g) $C = 400$ (h) $C = 500$

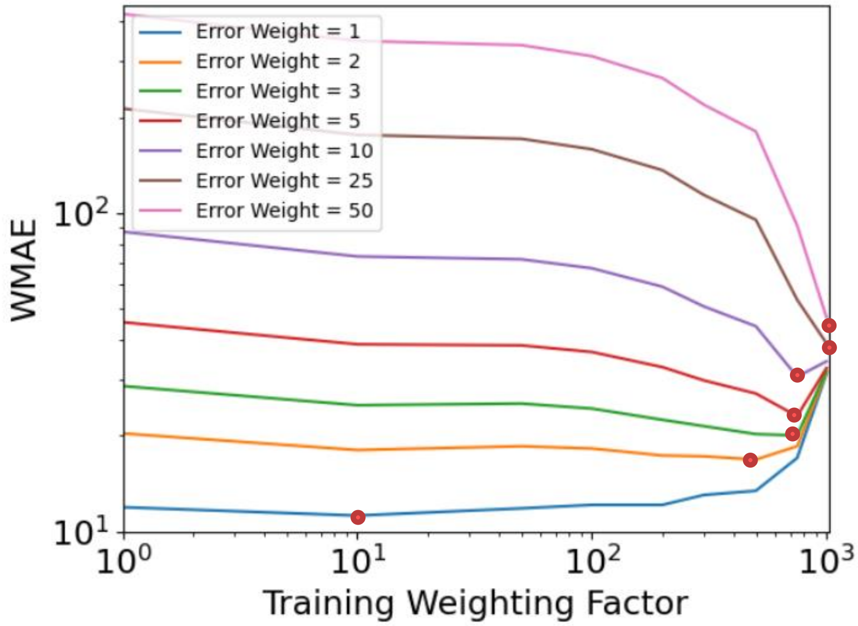
Results

- Benchmarking against previous work on this dataset
- Outperforms the models presented in Li et. al. (2020)

Dataset	Metrics	LSTM	Bi-LSTM	SAE-GRU	Weighted Loss GRU
FD001	MAE	13.6	14.4	13.5	**11.2**
	R^2	0.77	0.75	0.79	**0.85**
FD002	MAE	44.2	19.9	22.0	**13.6**
	R^2	-0.05	0.72	0.69	**0.78**
FD003	MAE	17.1	20.8	16.4	**11.7**
	R^2	0.51	0.25	0.57	**0.84**
FD004	MAE	47.9	28.1	25.4	**15.9**
	R^2	-0.20	0.53	0.56	**0.71**

Results

- Weighted error function (WMAE) to compare model performance considering problem economics
- Higher training weights lead to model that performs best under higher weighted/penalized MAE



Remarks

- Use of a weighted loss function helps promote RUL predictions to be better in the context of the economics of the problem
  - Tunable parameter to control how conservative predictions will be
- Constructed error metric can more effectively evaluate model performance
- Future work
  - Investigate using more complex loss formulations that may promote even more effective training of the model
  - Apply this approach to other datasets/problems in prognostics and health monitoring