Rank Reduction of LSTM Models for Online Vibration Signal Compensation on Edge Computing Devices

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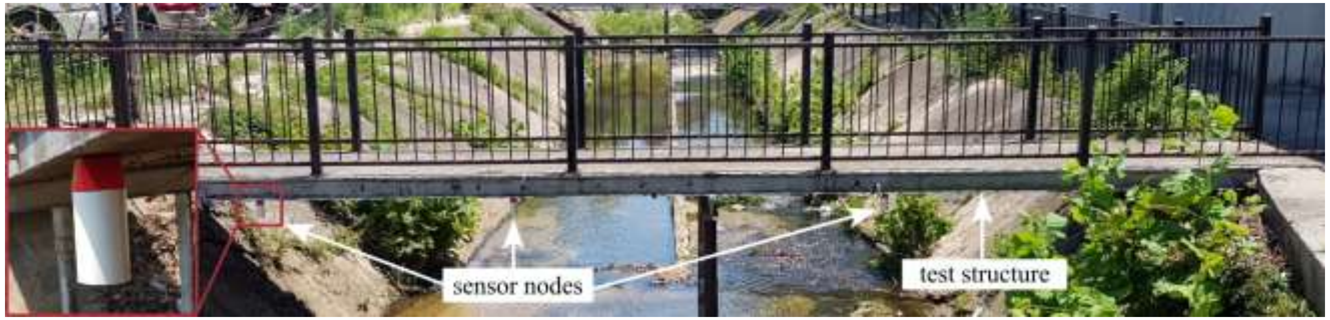
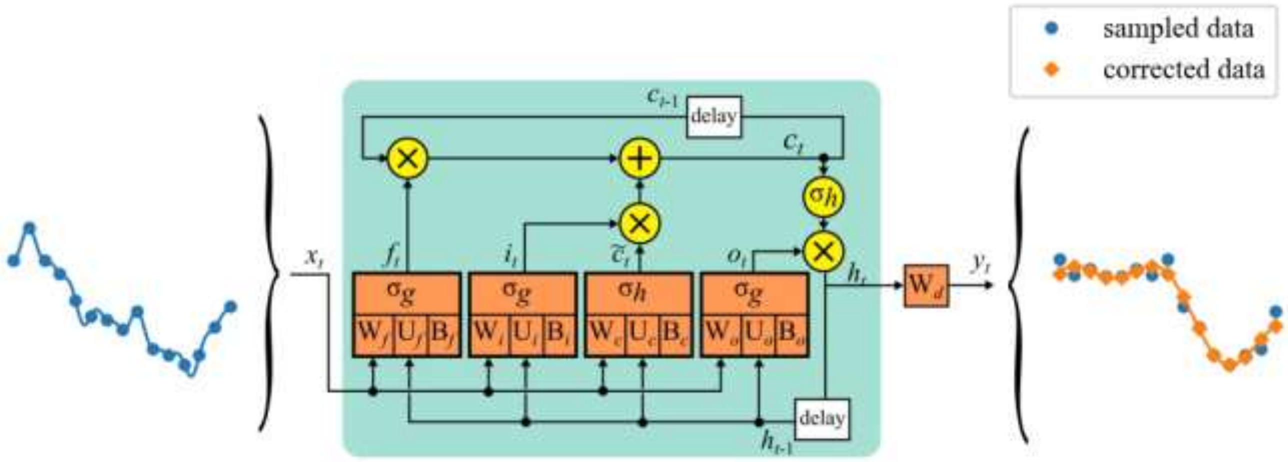
Outline

- Background
  - Structural health monitoring
  - UAV-deployable sensor package
  - Vibration signal compensation
  - Edge machine learning
  - Model compression
  - Long Short-Term Memory
- Methodology
  - Degrees-of-freedom decomposition
  - Collecting training data
  - Bench top experiment
  - Training the model
  - Rank reduction
- Results and discussion
  - Model performance
  - Future work





Background

Structural Health Monitoring

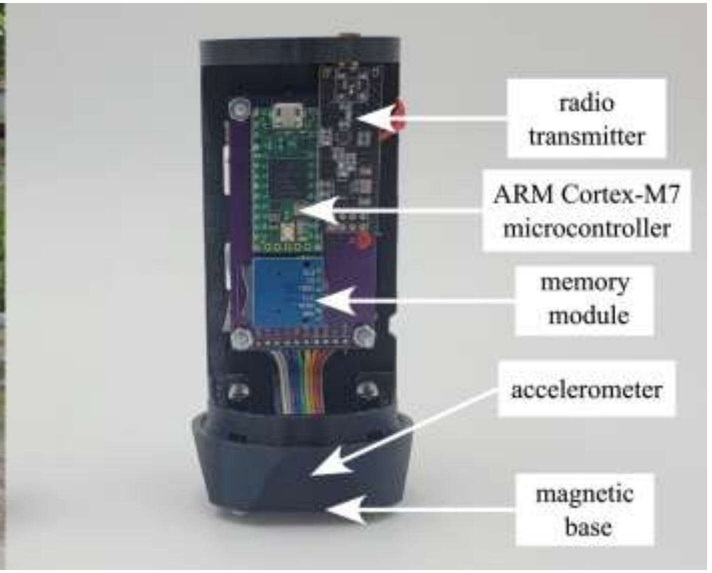
Structural Health Monitoring (SHM) is the process of assessing the integrity of structures in real time. It has the following benefits:

- Enables early warning for structural failure
- Provides insights into how the structure responds to changing conditions
- Collects data to inform future designs

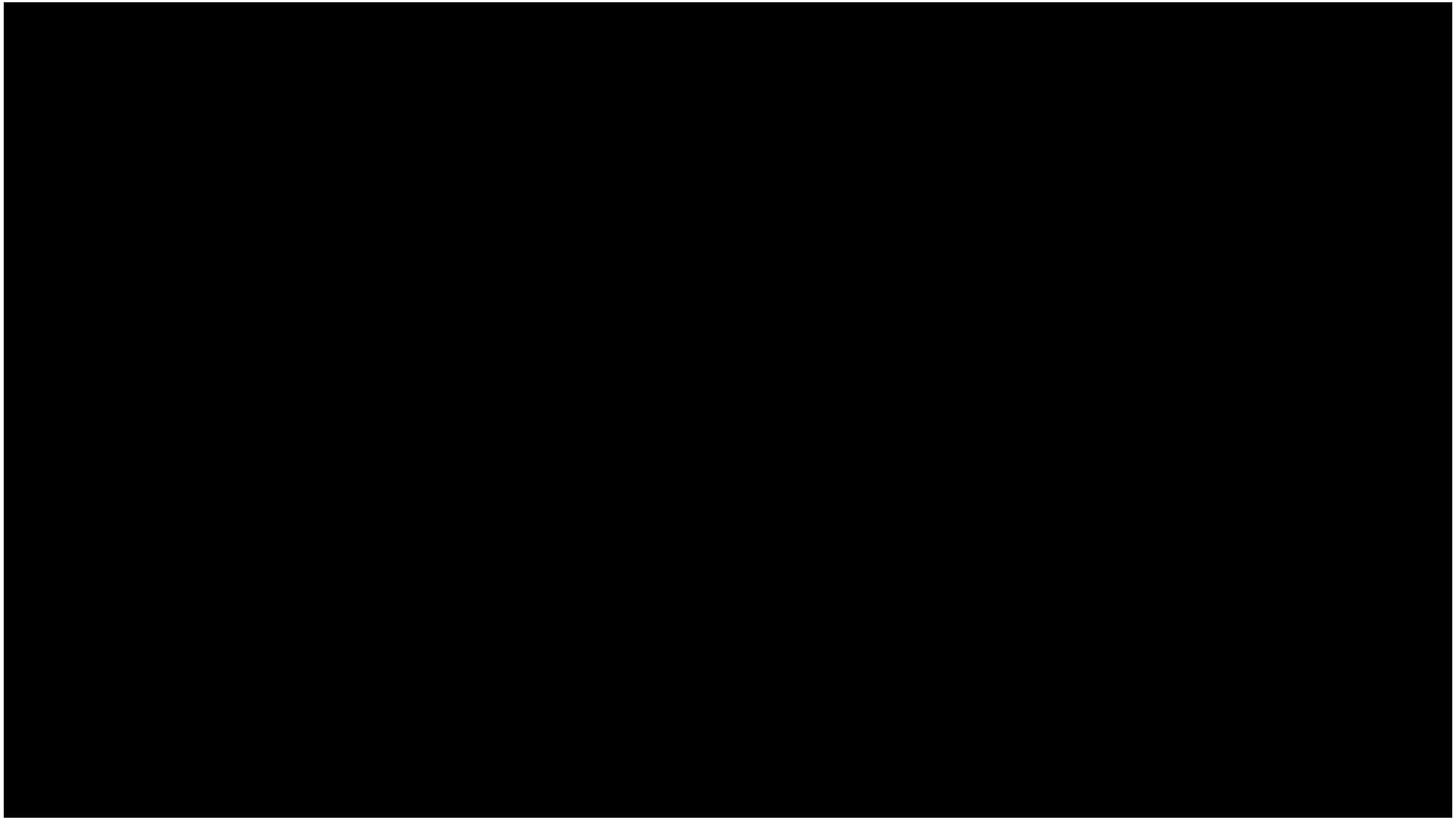
UAV-Deployable Sensor Package

Brooklyn SHM sensing node features:

- **Architecture:** 1x Arm Cortex-M7 at 600MHz with FPU, 1024 KB memory
- **Sensors:** MEMS accelerometer for vibration sensing
- **Deployment:** Magnetic base enables it to be attached to the structure using a drone



Sensor deployment and retrieval mission

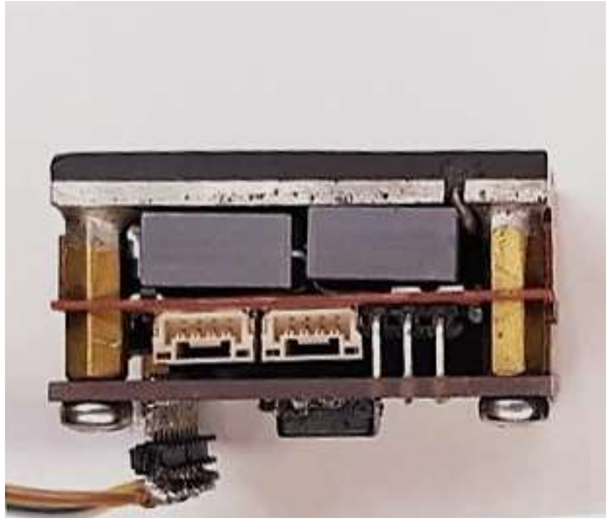


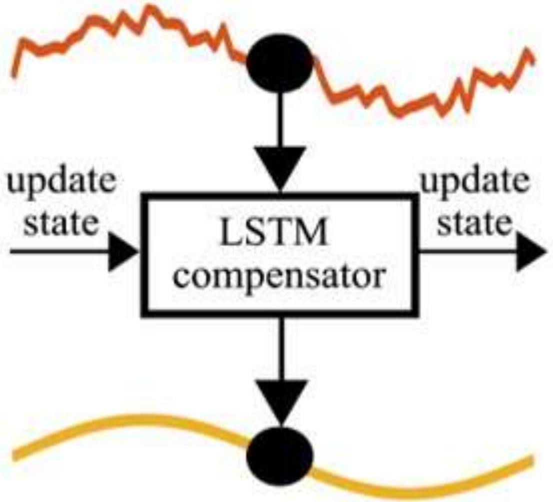
Vibration Signal Compensation

Challenges facing SHM sensing nodes:

- **Transmissibility loss:** low-frequency vibration information may struggle to reach the sensing node through the attachment point.
- **Cost:** SHM nodes need to be cost-effective, leading to sensor quality compromises

LSTM-based signal compensators have been shown to be effective at mitigating these problems.





Edge Machine Learning

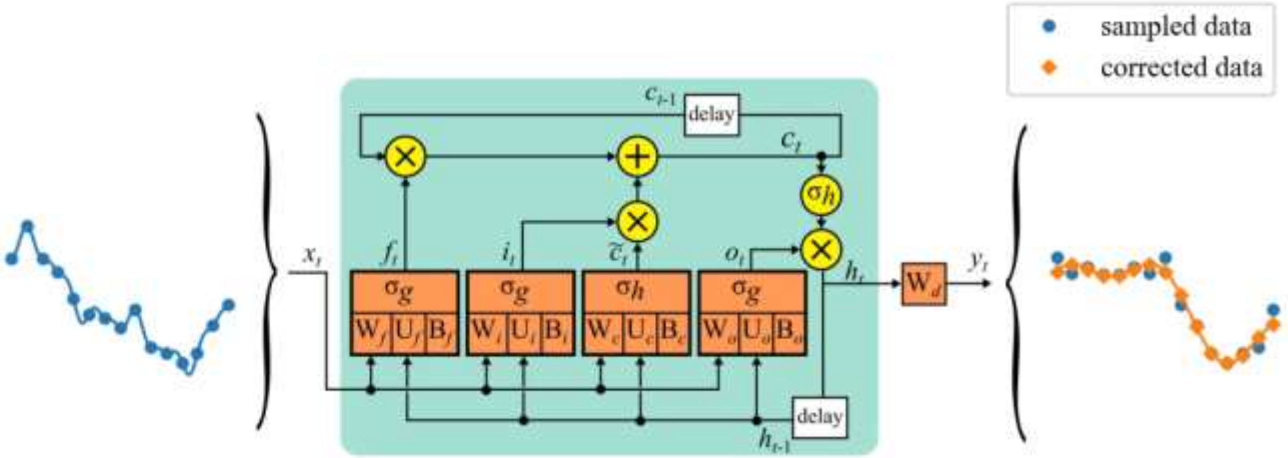
Why process data at edge?

- **Efficiency:** IoT devices like SHM sensing nodes are responsible for producing much of the world's data. Off-line processing puts a strain on cloud computing infrastructure.
- **Reduce transmission:** SHM sensing nodes have limited battery capacity. Processing data on edge saves power by minimizing radio use.
- **Location:** Some sensing nodes need to be placed in areas where constant communication is not possible.

Model Compression

Why compression is important:

- **Memory footprint:** Edge devices are often equipped with minimal memory, making the savings provided by compression essential.
- **Latency:** Compression may allow inference to be completed faster.
- **Complexity:** Compression enables models initially too complex for constrained edge devices to be deployed.



Long Short-Term Memory

- LSTM is a form of recurrent neural network that uses a gated structure to determine what information to retain and "forget".
- The complex structure of LSTM makes it an ideal candidate for model compression.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f),$$

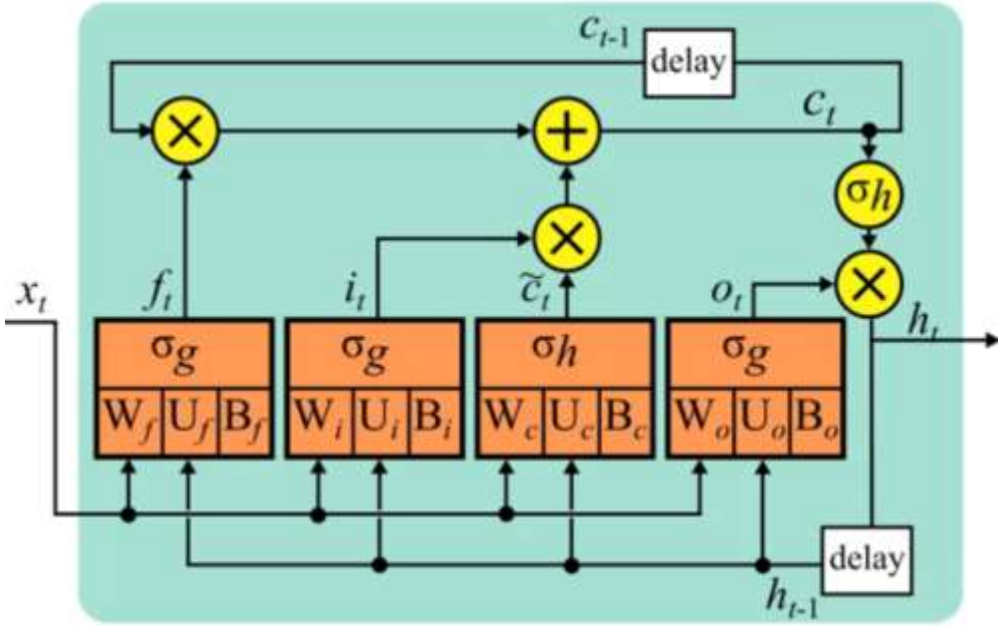
$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i),$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o),$$

$$\bar{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c),$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \bar{c}_t,$$

$$h_t = o_t \circ \tanh(c_t).$$



f: forget gate
i: input gate
o: output gate
c: carry state
h: hidden state / inference output

$\circ$: element-wise multiplication
σ: sigmoid activation function

Long Short-Term Memory

- Typical LSTM inference requires four separate weight matrices (assuming W and U are concatenated) – one for each gate. This leads to four separate matrix-vector multiplications being required for inference.
- These weight matrices can be combined to enable inference to be performed in a single matrix-vector multiplication.
- The consolidated weight matrix simplifies the model compression process, as only one matrix has to be compressed.

$$W = \begin{bmatrix} W_i & W_f & W_c & W_o \\ U_i & U_f & U_c & U_o \end{bmatrix},$$

$$b = \begin{bmatrix} b_i \\ b_f \\ b_c \\ b_o \end{bmatrix},$$

$$y = \begin{bmatrix} x \\ h \end{bmatrix},$$

$$\begin{bmatrix} z_i \\ z_f \\ z_c \\ z_o \end{bmatrix} = Wy + b,$$

$$\begin{bmatrix} i_t \\ f_t \\ \bar{c}_t \\ o_t \end{bmatrix} = \begin{bmatrix} \sigma(z_i) \\ \sigma(z_f) \\ \tanh(z_c) \\ \sigma(z_o) \end{bmatrix}.$$

The Driving Challenge

- The matrix-vector product Wy is the driving computation in the LSTM in terms of cost.
- We can make LSTMs fit on smaller processors and run faster if we can reduce the complexity of this matrix-vector multiply.

$$\boxed{Wy} + b$$

$$W = \begin{bmatrix} W_i & W_f & W_c & W_o \\ U_i & U_f & U_c & U_o \end{bmatrix} \qquad y = \begin{bmatrix} x \\ h \end{bmatrix}$$

Quantization

Quantization is the process of converting floating-point values to lower-precision fixed-point values.

Advantages:

- Significant reduction in memory footprint
- Preserves dense matrices
- May improve latency if platform lacks a performant FPU

Disadvantages:

- Inference still takes the same amount of adds and multiplies
- For non-parallel architectures with a performant FPU, latency is not improved

8.114	4.626
1.231	3.993

8	5
1	4

Pruning

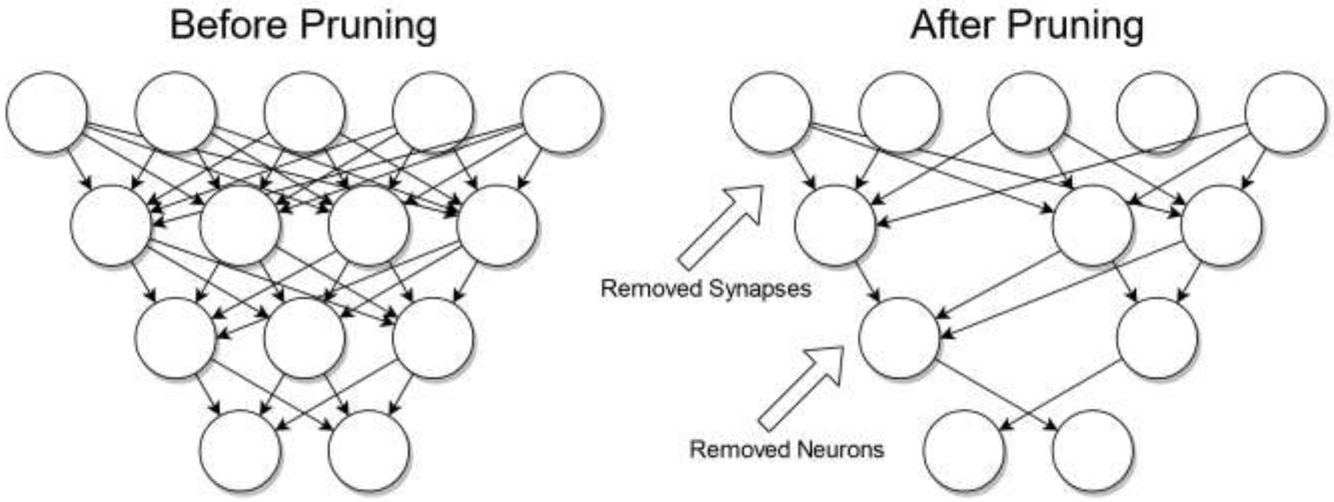
Pruning is the process of eliminating weights close to zero.

Advantages:

- Control over error threshold

Disadvantages:

- Sparse matrices are less efficient on general-purpose computers due to cache issues



Low-Rank Approximation

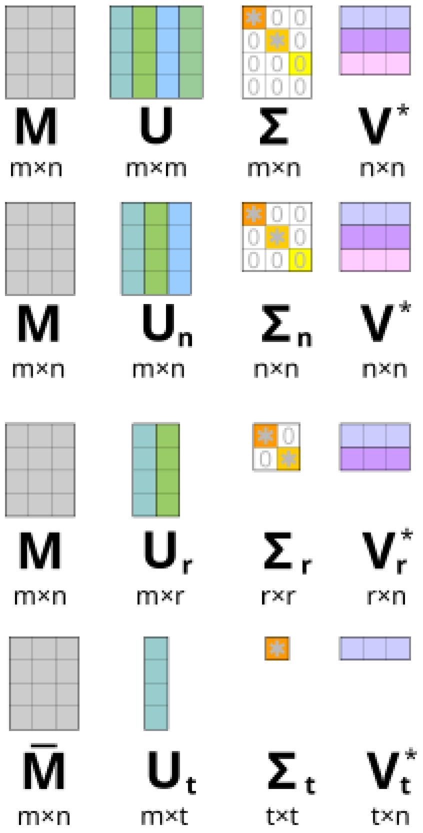
Low-rank approximation is the process of representing the information in a matrix with another matrix of a lower rank.

Advantages:

- Preserves dense matrices
- Control over error threshold
- Both saves space and improves latency

Disadvantages:

- Direct use of singular value decomposition (SVD) only provides benefits after over half the ranks are removed, which may not be possible



Methodology

Stating the Challenge

Problem: In traditional low-rank approximation, the truncated SVD is used directly for inference. This means we only save space after more than half the ranks of *W* in the LSTM are removed, which may be impractical.

Question: Can we create a more efficient way to store the information in *W,* enabling the deployment of LSTMs on smaller edge devices?

Degrees-of-Freedom Decomposition

Mathematical Reasoning:

- For a matrix with rank $r<\min(m,n)$, all rows exist in the span of only r ‘basis’ rows
- The remaining $m-r$ rows may be written as a transform of these ‘basis’ rows.

Using this information, we construct the following two-step process:

$$Ax_1 = Bx,$$
$$Ax_2 = Cx_1,$$
$$Ax = P\begin{bmatrix} Ax_1 \\ Ax_2 \end{bmatrix}$$

Here, B is an $r\times m$ matrix, C is $(n-r)\times r$, and P is a permutation matrix used to chose the r basis rows. Now, instead of storing U, Σ, and V^T , we only need to store B and C.

Degrees-of-Freedom Decomposition

Computing B and C

Split U into $\begin{bmatrix} U_1 \\ U_2 \end{bmatrix}$, where U_1 is $r \times r$,

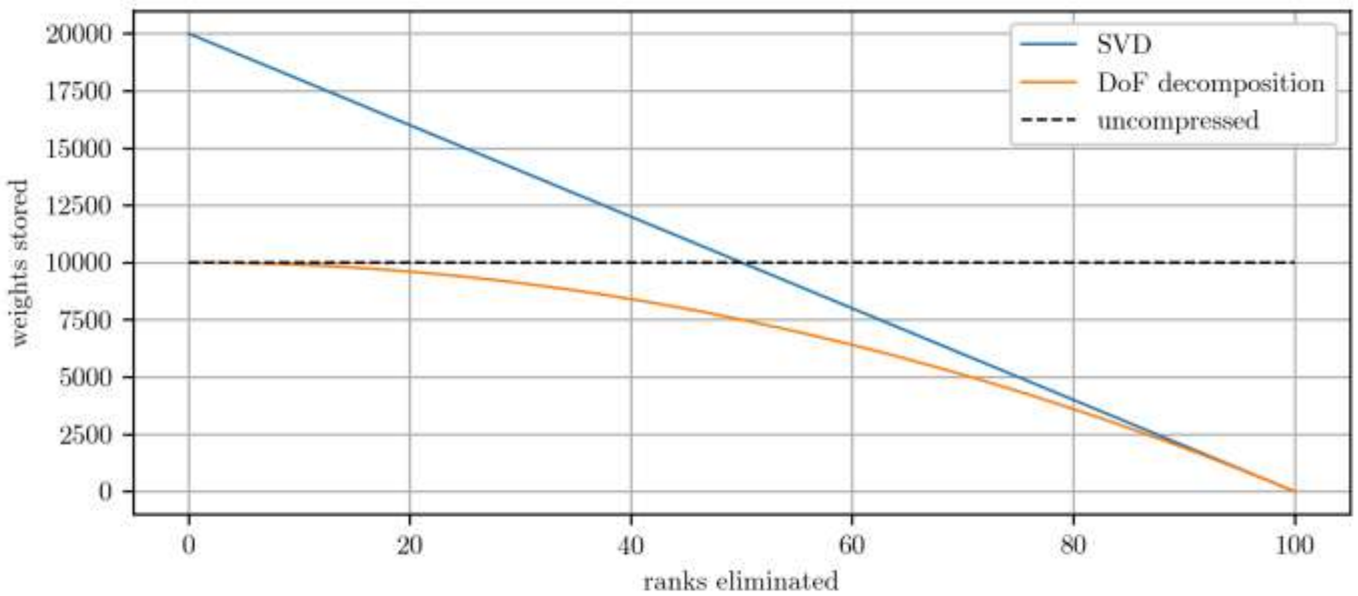
$B = U_1 \Sigma V^{\mathrm{T}}$,

$C = U_2 U_1^{-1}$.

Weights stored: $r \times m + (n - r) \times r$

Multiplies: $mn - (m - r)(n - r)$

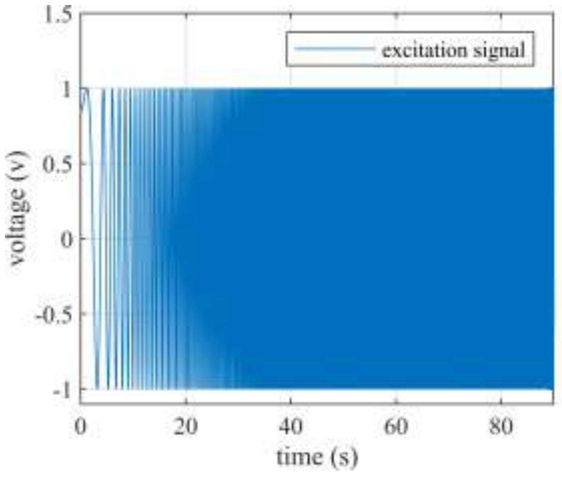
Adds: $(mn - n) - (m - r)(n - r)$

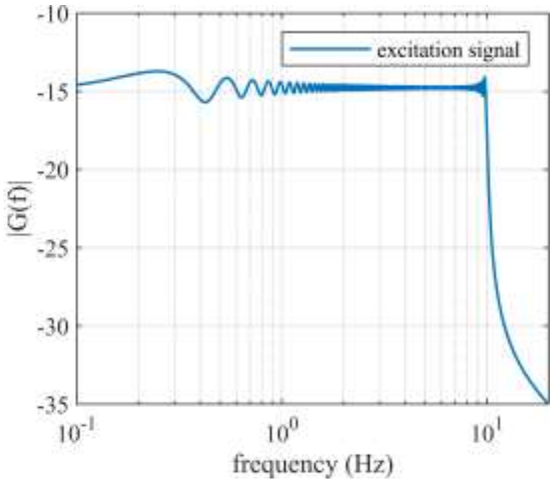


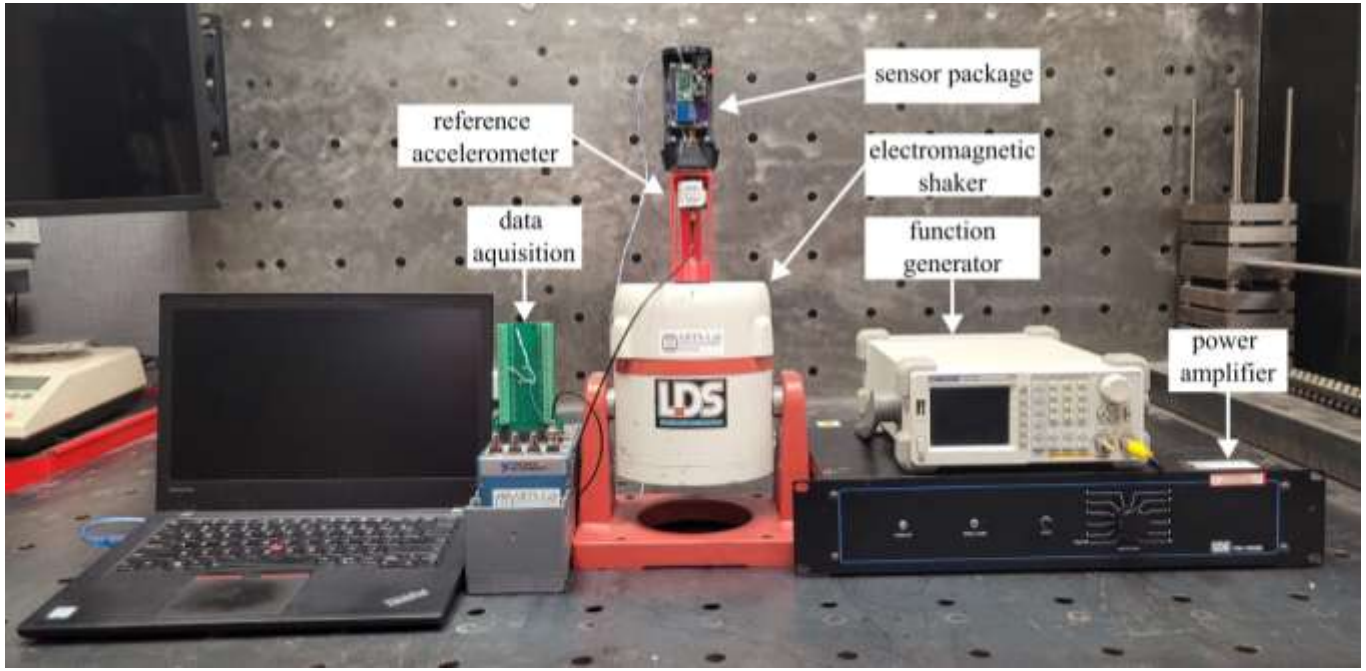
Using the DoF Decomposition, we see both memory and computational savings immediately, rather than after a set number of reductions.

Collecting Training Data

- A function generator is connected to an electromagnetic shaker.
- The sensor package is attached to a higher-quality reference accelerometer.
- The electromagnetic shaker was excited with frequency sweeps from 1-10 Hz.
- Phase between the two signals was aligned through interpolation.

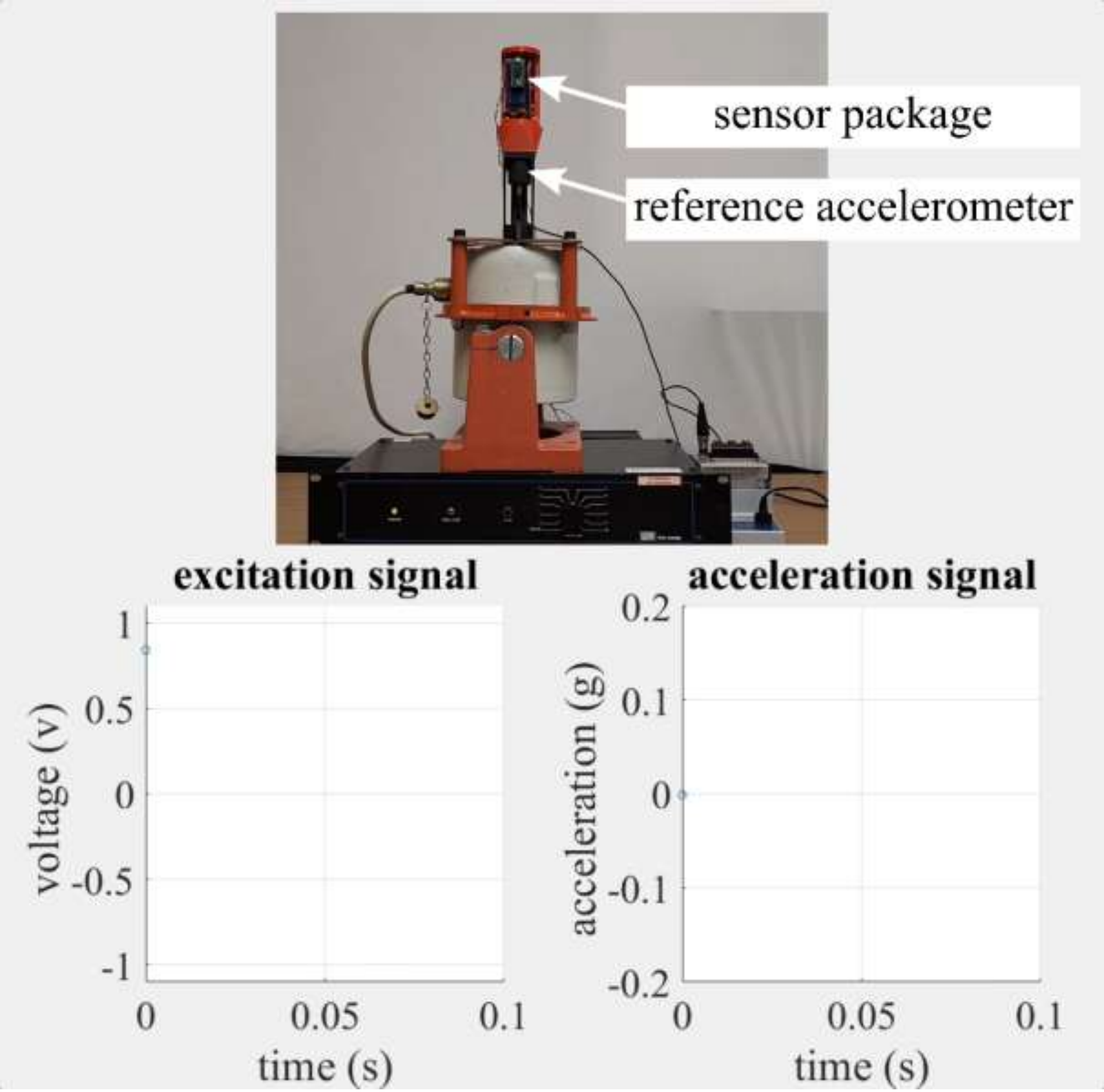






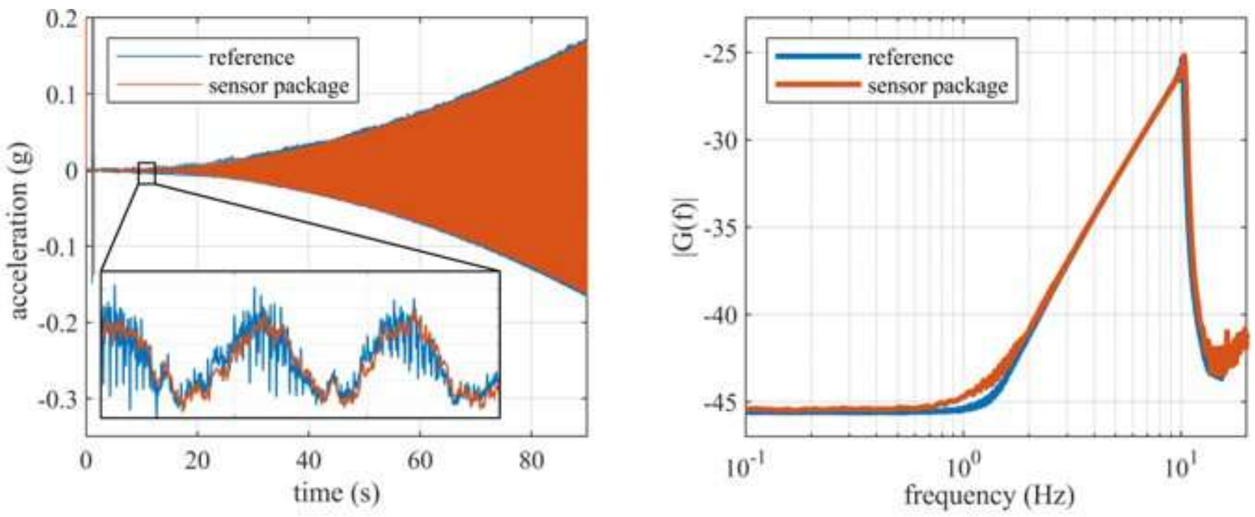
Bench top experiment

- Chirp excitation is fed into the electromagnetic shaker using an analog output module
- A data acquisition is used to record reference acceleration
- A digital trigger is set to synchronize both the reference accelerometer and sensor package
- Various dynamic ranges were used to expand the training range of the LSTM model



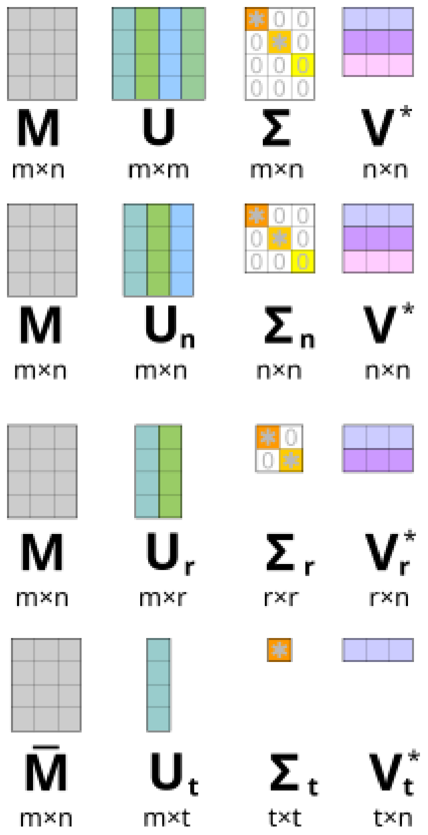
Training the Model

- **Model hyperparameters:** 50 unit, 1 input LSTM connected to a dense layer.
- Package data is fitted to the reference data in the time domain.
- Windowing is employed to reduce overfitting.
- Validated on a testing dataset.



Rank Reduction

- To prove the efficacy of the DoF decomposition, we employ the truncated SVD for rank selection.
- Weight matrix rank was reduced to 41 from 51.
- The B and C matrices for the DoF decomposition were then calculated.

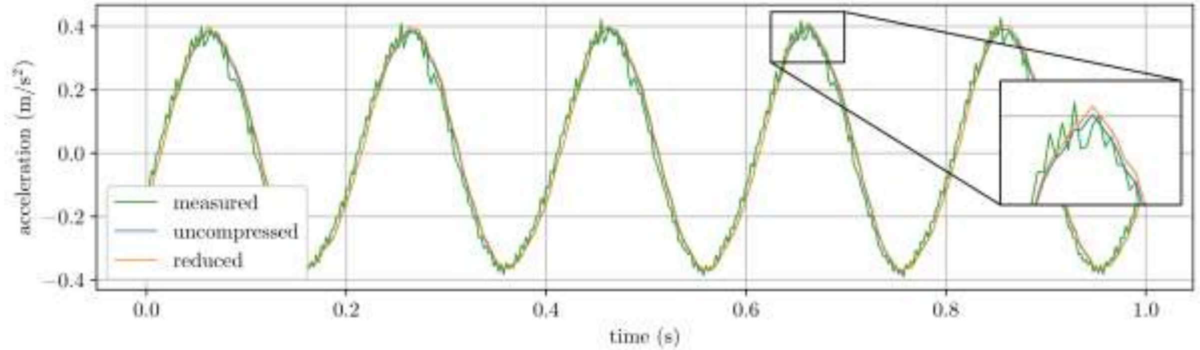


Results and Discussion

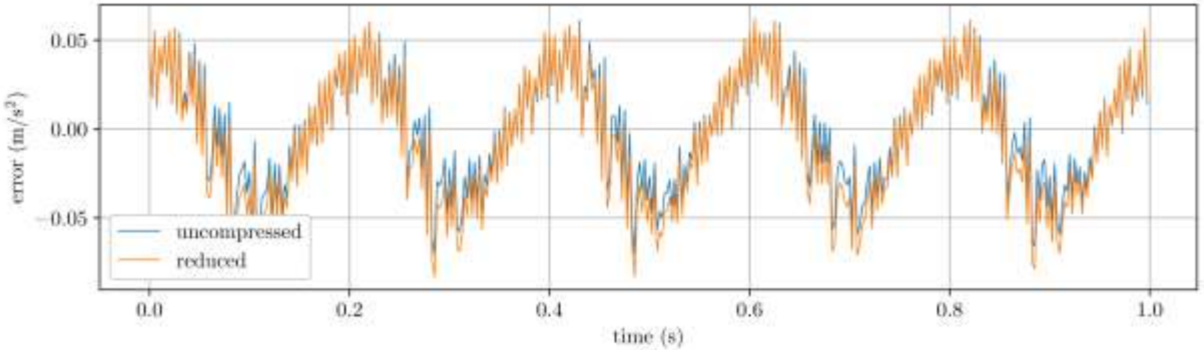
Model Performance

testing	SNR_{dB}	MSE	RMSE	MAE	TRAC	Parameters
uncompressed	14.8498	0.0005	0.0221	0.0168	0.9673	10451
compressed	14.0765	0.0006	0.0242	0.018	0.9616	8861
difference	0.7733	-0.0001	-0.0021	-0.0012	0.0057	1590
% difference	5.3466	17.7586	8.8969	7.1053	0.5925	16.4664

- SNR remained acceptable
- TRAC remained high, indicating strong similarity between the reference signal and the signal generated by the compressed model



(a)

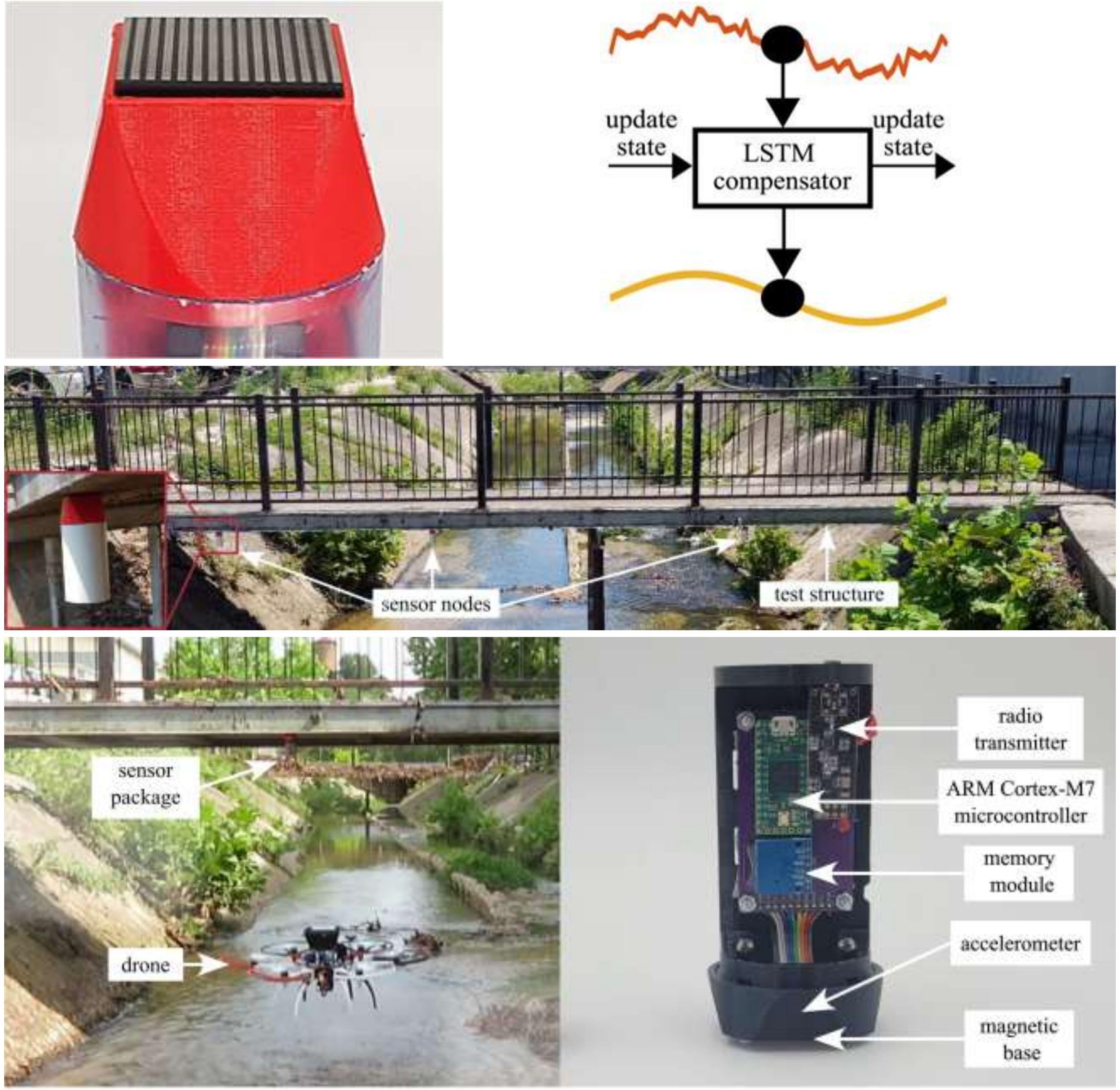


(b)

Note: Should more accuracy be desired, the DoF decomposition allows less ranks to be removed while still providing memory and computational savings over the uncompressed model.

Future Work

- **Edge Deployment:** We seek to apply this work to the first known deployment of a signal compensation model on an SHM sensing node.
- **Data Alignment:** Better techniques for aligning accelerometer signals for training will be explored.
- **Learning Rank Reductions:** Error-aware strategies for reducing ranks can provide better approximations for machine learning models than the truncated SVD.



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