Recurrent Auto-Encoder Model for Large-Scale Industrial Sensor Signal Analysis

Timothy Wong [1,2] Zhiyuan Luo [1]

[1]Royal Holloway, University of London, Egham TW20 0EX.

[2]Centrica plc, Millstream, Maindenhead Road, Windsor SL4 5GD.

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Background

- Gas compression sub-system at a gas terminal
  - Two centrifugal compressors driven on a single shaft
  - Powered by aeroderivative gas turbine
  - Regulates gas pressure at a certain level

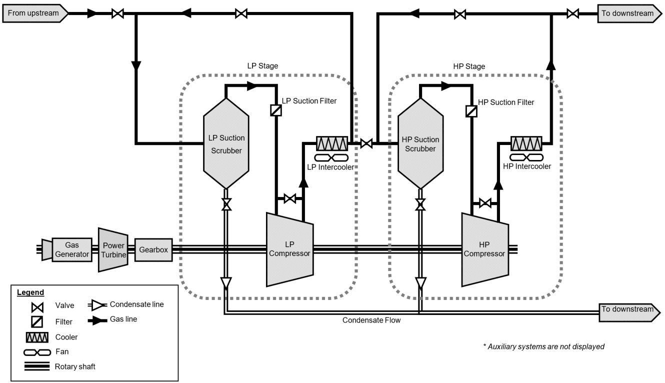


Figure: Simplified process diagram for the compression sub-system

Components

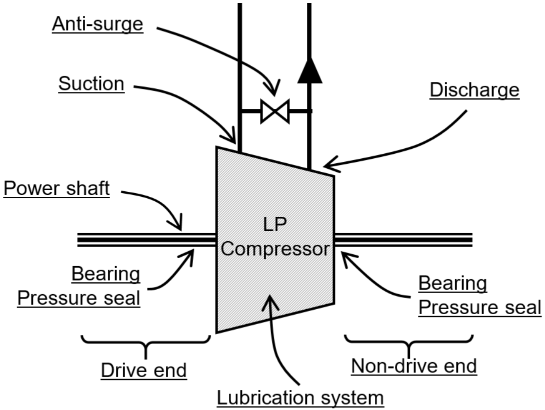
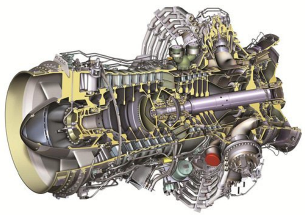


Figure: Centrifugal compressor (LP stage)

Components



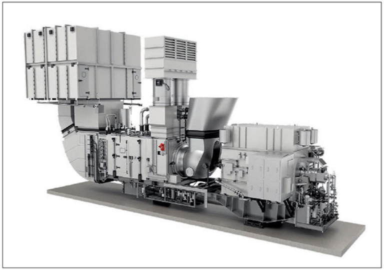


Figure: Jet engine package

Problem

- Large-scale industrial processes contains many sensors
- Sensor records continuous stream of real-valued measurements (e.g. temperature, pressure, rotary speed... etc.)

Research Question

Can we determine the underlying operating states of the process?

Data Preprocessing

- Unevenly-spaced time series (inconsistent interval)
- Can be convert into regularly-spaced time series through downsampling.
- P sensors can form a P-dimensional multivariate time series.

$$\{\mathbb{R}_t^P : t \in [1, T]\}$$

Recurrent Auto-Encoder Model

- RNN Encoder-decoder model
- Convert to recurrent auto-encoder by aligning input/output time steps
- Performs partial reconstruction on the decoder side
- Decoder dimension smaller than Encoder dimension
- Deep structure learns abstract temporal patterns

$$\begin{cases} f_{encoder} : \{\mathbb{R}_t^P : t \in [1, T]\} \to c \\ f_{decoder} : c \to \{\mathbb{R}_t^K : t \in [1, T]\} \end{cases} \qquad K \leqslant P$$

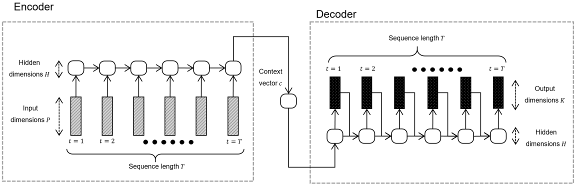


Figure: RNN encoder-decoder model

Long-short term memory

LSTM neuron [HS97]

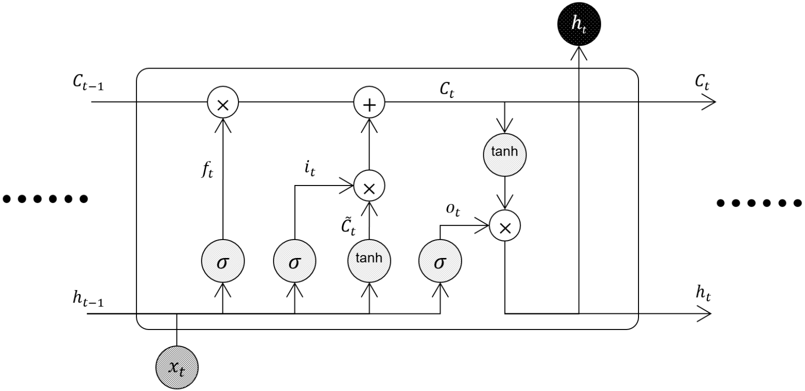


Figure: Internal structure of a long short-term memory block [Ola15].

Long-short term memory

Forget gate

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

Input gate

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

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_C)$$

Update hidden state

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t$$

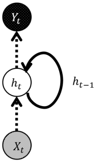
Output gate

$$O_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$h_t = O_t \times \tanh C_t$$

Regularisation

- Prevents network overfitting
- Dropout wrapper [SHK+14]
- Masks neuron inputs
- Non-recurrent connections only [ZSV14]



Sampling

- Recursively generating time series samples with fixed length
- Samples of length T can be generated from any time series dataset with length $T^{'} \geq T$
- $T^{'} - T$ samples can be generated

Algorithm 1: Drawing samples consecutively from the original dataset

Input: Dataset length T'
Input: Sample length T

```
i ← 0 ;
while i ⩽ i + T do
    Generate sample sequence (i, i + T] from the dataset;
    i ← i + 1;
end
```

Scaling

- Standardising dataset using z-score

$$z_p = \frac{x_p - \bar{x}_p}{\sigma_p}$$

Results

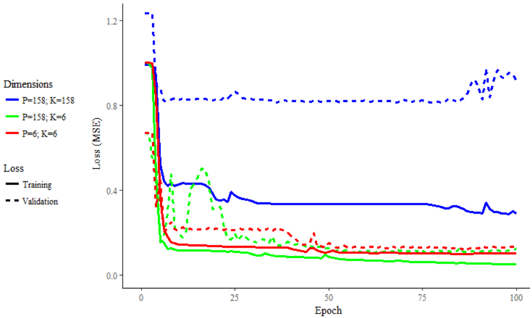


Figure: Effects of relaxing dimensionality of the output sequence on the training and validation MSE losses.

Sequence Reconstruction

- Specimens were selected randomly for qualitative examination
- Selected from held-out validation set

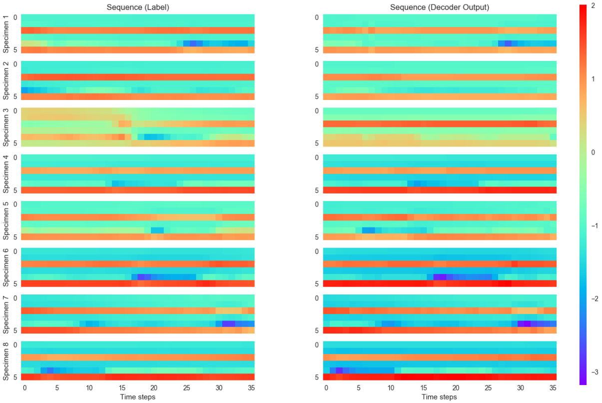
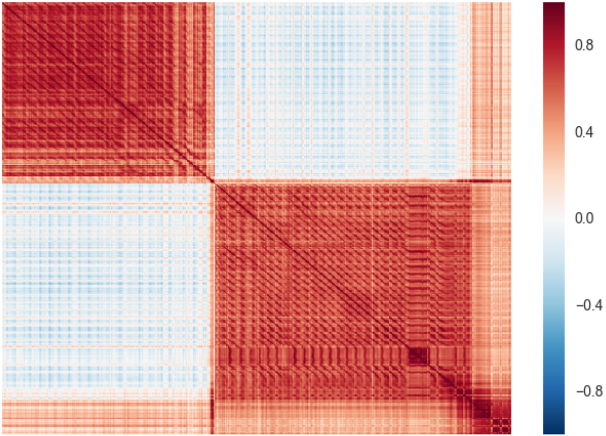


Figure: Randomly selected output sequences in the held-out validation set. Colour represents magnitude of sensor measurements in normalised scale.

Context Vector

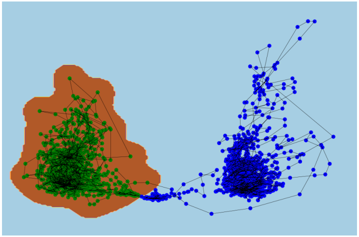
- Pairwise Pearson correlation
- Diagonal shows strong correlation among successive context vectors
- Showing gradual drift of operating state

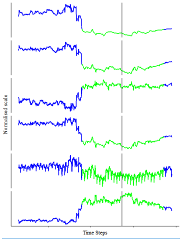


Context Vector

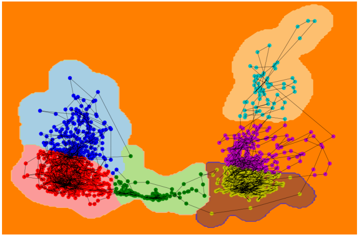
- Dimensionality reduction (PCA) to 2D
- Additional clustering algorithms can be applied (e.g. K-means)
- Decision boundary calculated using Support Vector Machine (RBF)

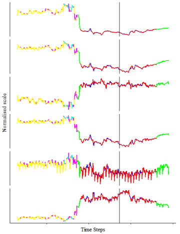
Context Vector: Example 1





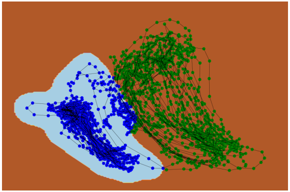
(a) 2 clusters

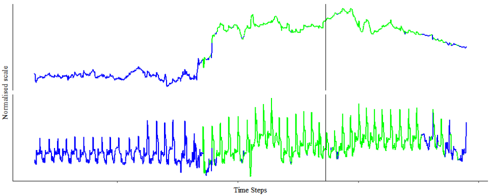




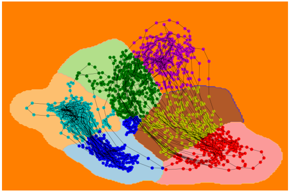
(b) 6 clusters

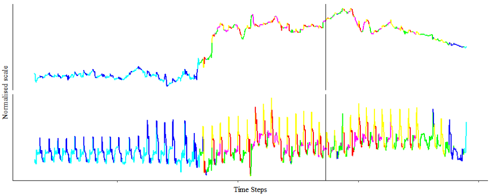
Context Vector: Example 2





(a) 2 clusters

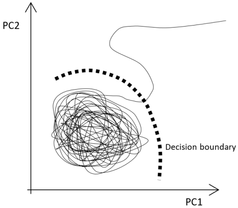




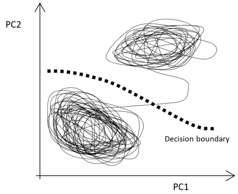
(b) 6 clusters

Identify Operating States

1. Drifts around same neighbourhood
2. Drifts across boundary



(a) Process with a single healthy state.



(b) Multi-state process with transition between states.

Figure: Travelling context vector.

Input Sequence Reversal

- Forward sequence: $\{\mathbb{R}_1^P, \mathbb{R}_1^P, \mathbb{R}_3^P, \ldots, \mathbb{R}_{T-1}^P, \mathbb{R}_T^P\}$
- Reverse sequence: $\{\mathbb{R}_T^P, \mathbb{R}_{T-1}^P, \mathbb{R}_{T-2}^P, \ldots, \mathbb{R}_2^P, \mathbb{R}_1^P\}$

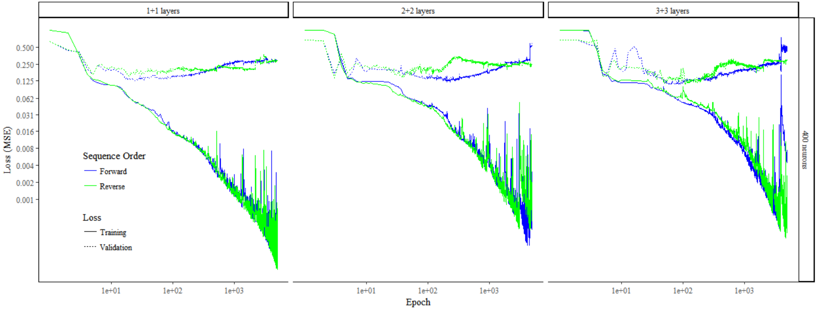


Figure: Effects of sequence reversal on training/validation MSE losses.

Adjusting Sequence Length

- Training/validation loss goes up when sequednce length T is increased.

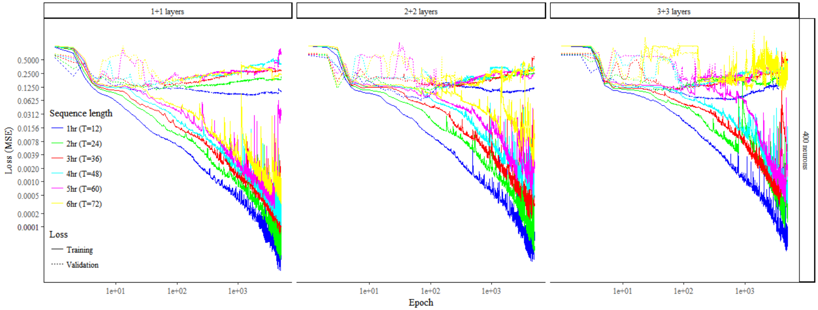


Figure: Effects of sequence length on training/validation MSE losses.

Summary

- Unsupervised clustering method for multidimensional time series
- Neural network-based time series feature selection
- Works with any real- valued temporal measurement (e.g. temperature, pressure... etc.)
- Operating states identification

Bibilography I

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