Low-cost Measurement of Industrial Shock Signals via Deep Learning Calibration

Houpu Yao[1*], Jingjing Wen[2*], Yi Ren[1], Bin Wu[2], **Ze Ji[3]**

1. Department of Mechanical and Aerospace Engineering, Arizona State University, USA;
2. School of Astronautics, Northwestern Polytechnical University, China;
3. School of Engineering, Cardiff University, UK.

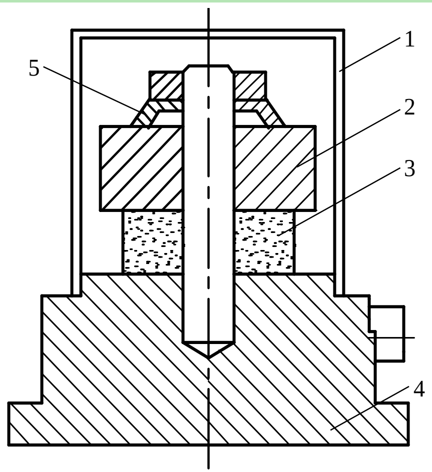
44th ICASSP, Brighton, UK
May 12-May 17, 2019

Contents

1. Introduction

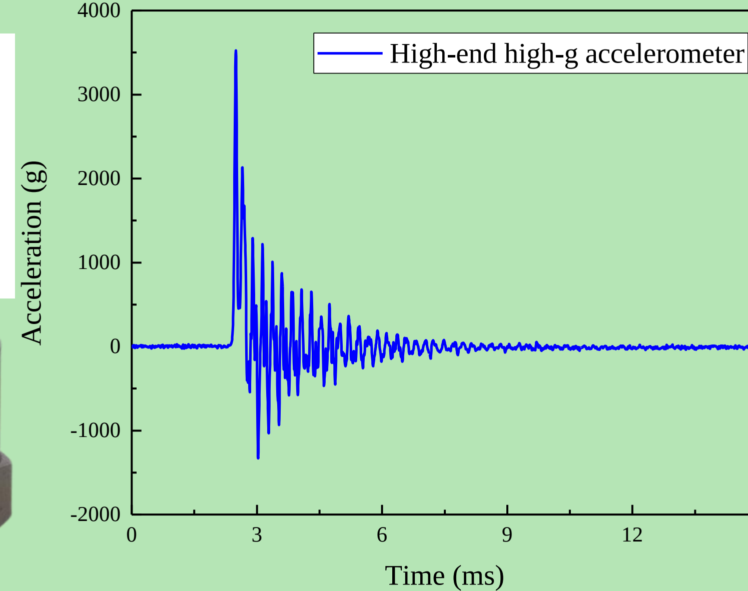
- Many conditions, such as drop of electronics, crashing of vehicles, earthquakes, mechanical engineering, etc., could be subjected to high-g shock excitations.
- To estimate the reliability of products under high-g shock conditions, high-g accelerometers are developed and widely used to measure shock responses.
- However, accurately measuring high-g shock signals is challenging because of the high magnitude, short duration time and complicated nonlinear frequency spectrum.

1. Introduction



Structure of the Piezoelectric Accelerometer

1. Shell
2. Mass Block
3. Piezoelectric Element
4. Base
5. Preloading Spring

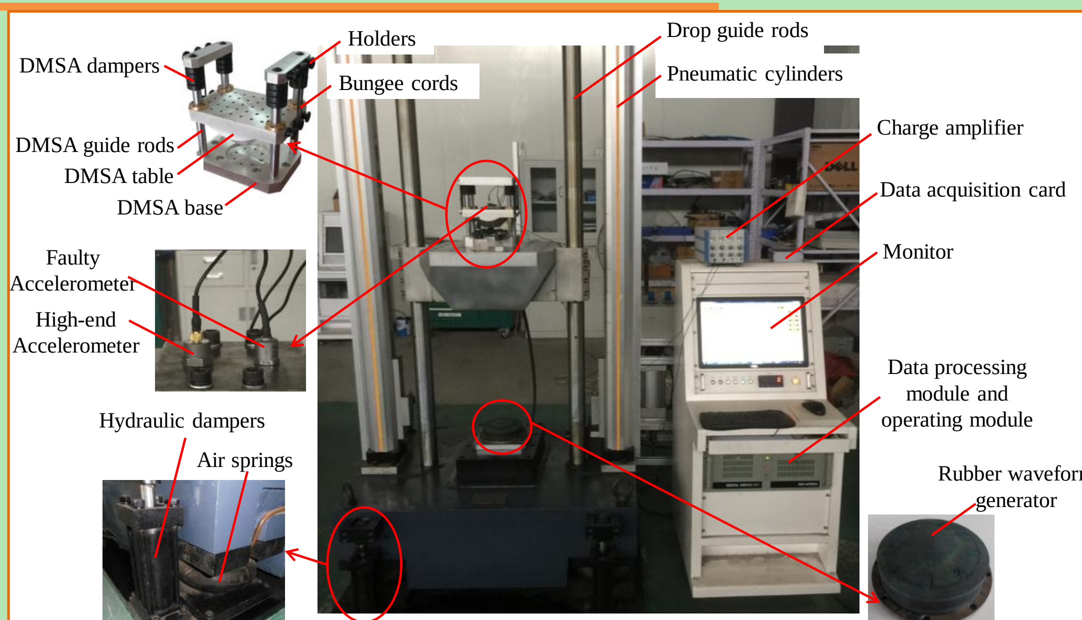


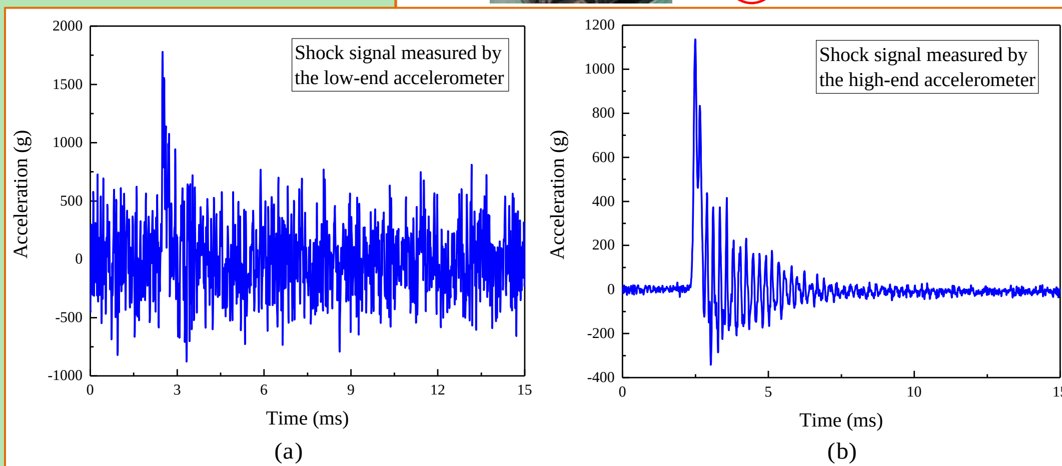
- The base fixing on the object move at the same acceleration with the object. The piezoelectric element is subjected to the inertial force of the mass block. Alternating charges are generated on both surfaces of the piezoelectric element. The acceleration can be measured.
- Existing work in shock measurement is mainly based on more reliable but expensive hardware, which leads to the high price of the high-end accelerometer.
- Due to the intellectual protections, it is almost infeasible to improve the measuring capacity of the low-end accelerometer by upgrading its hardware directly.

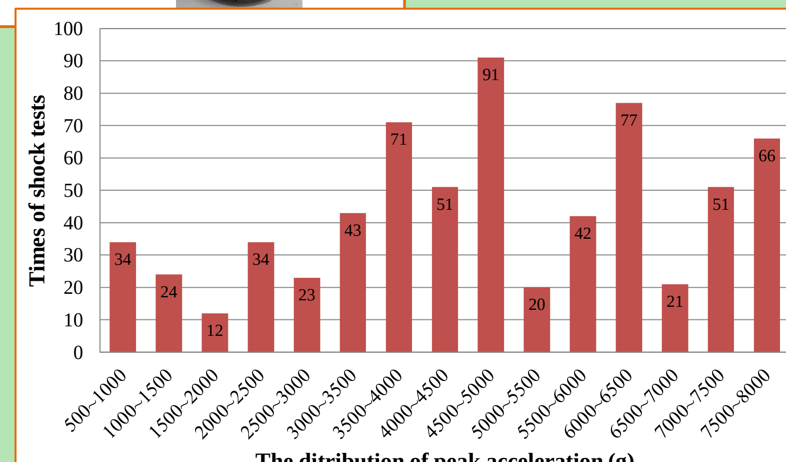
2. Research Programme

1. Instead of ameliorating hardware, a purely data-driven approach is proposed with the help of deep learning.
2. A pair of low-end accelerometer and high-end accelerometer as the ground truth is used to measure shock signals simultaneously.
3. A dataset containing vast shock signals from both low-end and high-end accelerometers is collected.
4. A deep neural network is trained to learn the mapping between the shock signals from the low-end accelerometer and the high-end one.

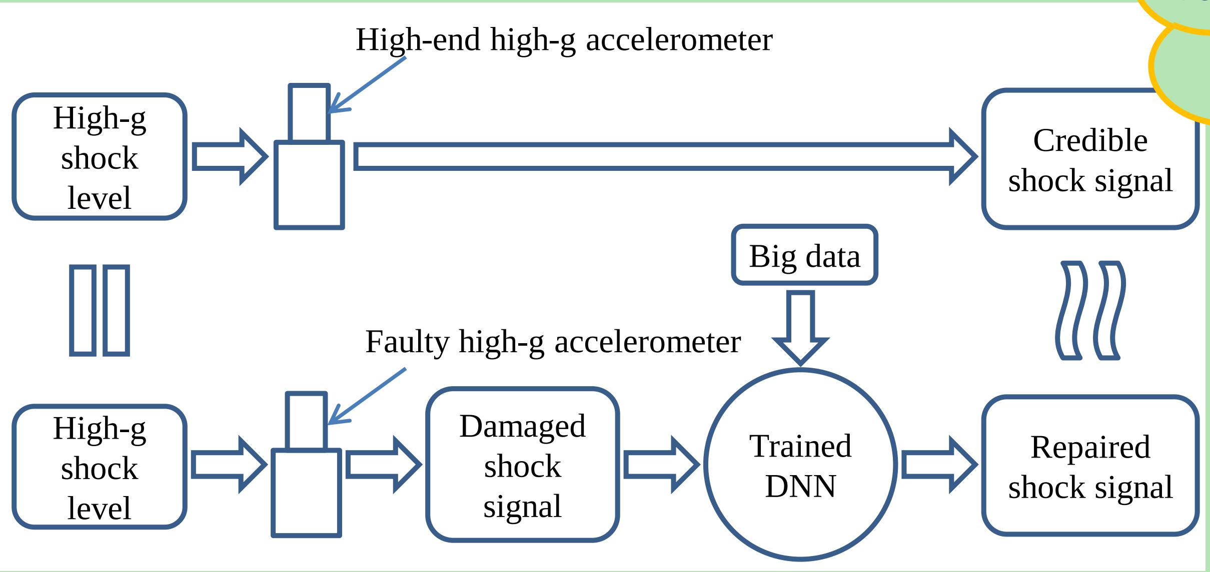
2.1 Data Collection



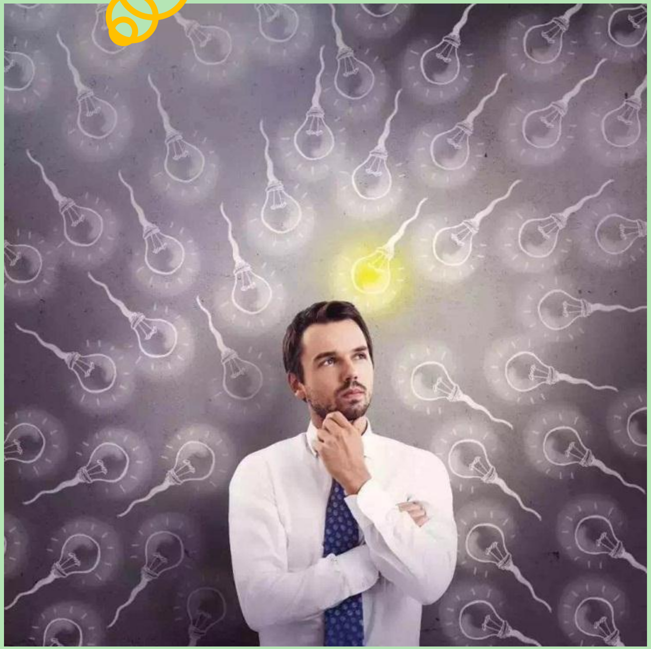




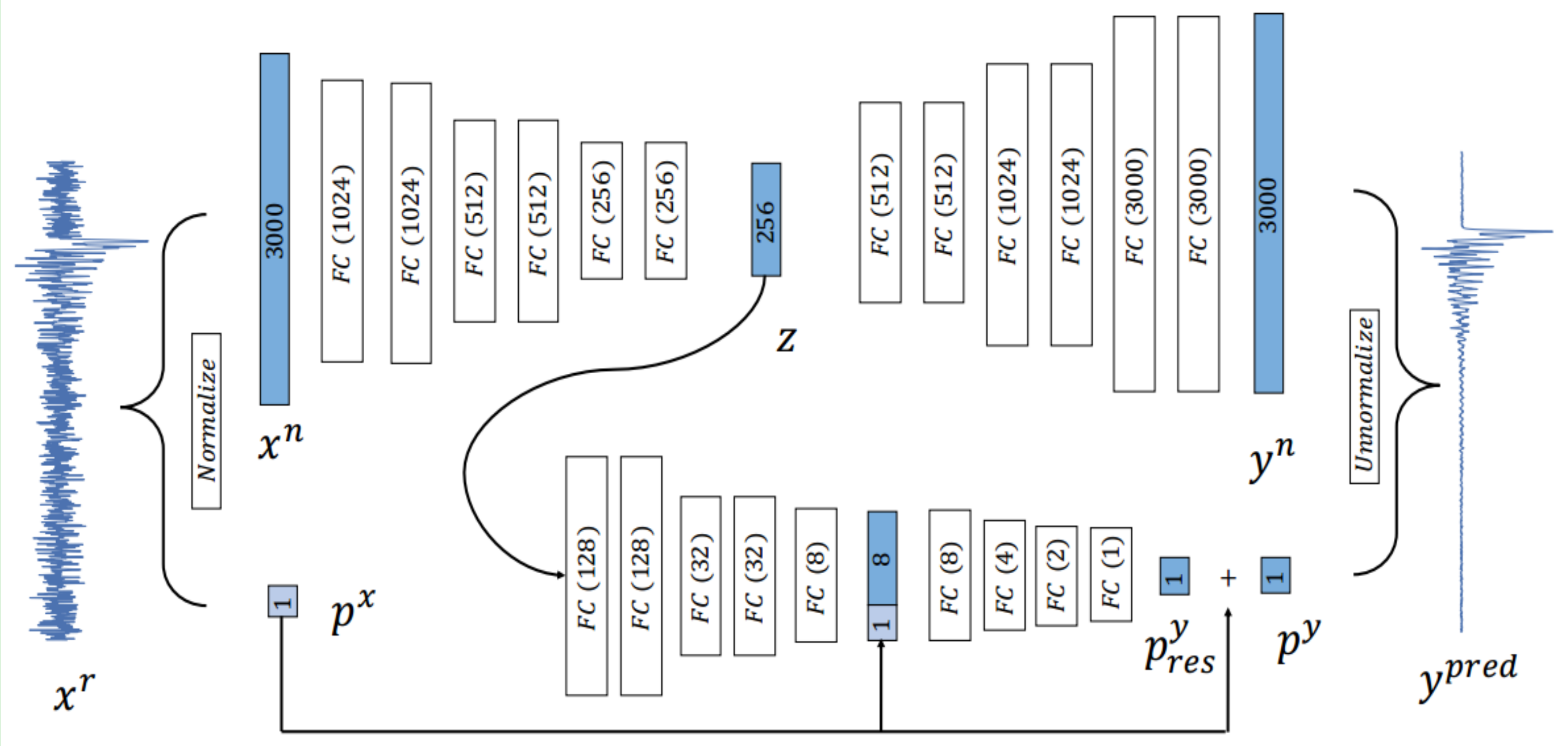
2.2 Proposed Network



So can sensor improve its performance through a lot of practice and training？



2.2 Proposed Network

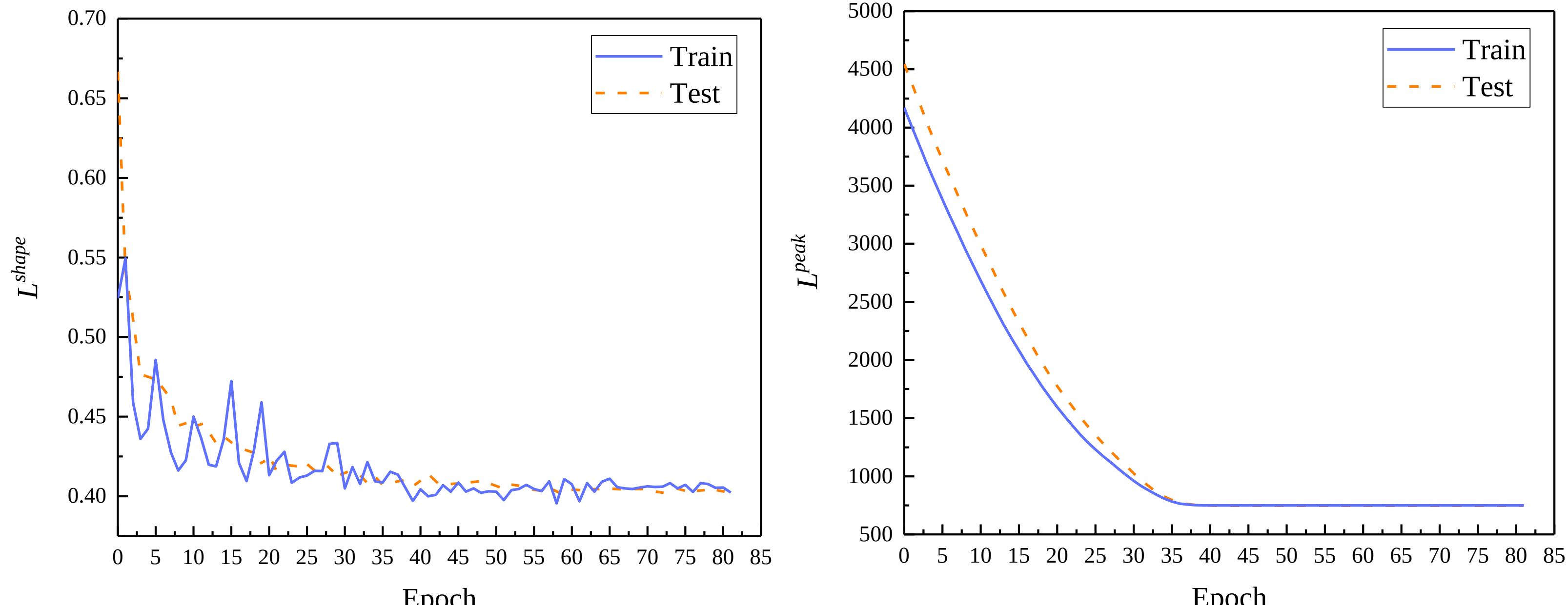


- Main branch: focus on calibrating the signal shape, because shock response spectrum is an important shock test index decided by the entire shock signal shape.
- peak prediction network (PPN) branch: focus on further calibrating the signal peak value, because the peak value of a shock signal is a very important index in JEDEC shock test of electronics.

2.3 Network Training

$$\begin{cases} \boldsymbol{z} = enc(\boldsymbol{x}^n;\theta_1) \\ \boldsymbol{y}^n = dec(\boldsymbol{z};\theta_2) \end{cases} \quad (1) \qquad \begin{cases} \boldsymbol{p}^y_{res} = ppn(\boldsymbol{p}^x,\boldsymbol{z};\phi) \\ \boldsymbol{p}^y = \boldsymbol{p}^x + \boldsymbol{p}^y_{res} \end{cases} \quad (2)$$

$$\begin{cases} L^s(\theta) = \left|\boldsymbol{y}^n - \boldsymbol{y}^{ref}\right|_2 + \left|\boldsymbol{y}^n - \boldsymbol{y}^{ref}\right|_\infty \\ L^p(\phi) = \left|\boldsymbol{p}^y - \boldsymbol{p}^{ref}\right| \end{cases} \quad (3)$$



(a) (b)

2.4 Results & Comparison

➤ Error metric:

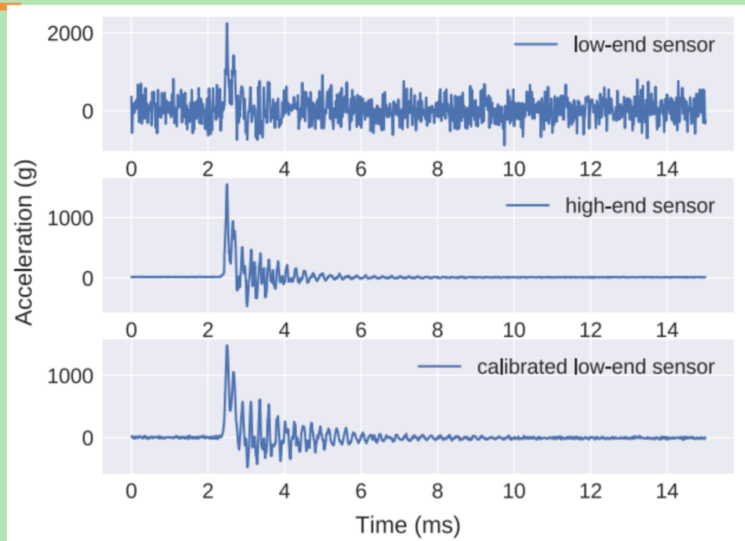
$$\begin{cases} \varepsilon_p = \dfrac{1}{N}\sum_{i}^{N}\dfrac{\left|\max\left(\boldsymbol{y}_i^{pred}\right)-\max\left(\boldsymbol{y}_i^{ref}\right)\right|}{\max\left(\boldsymbol{y}_i^{ref}\right)} \\ \varepsilon_s = \dfrac{1}{N}\sum_{i}^{N}\sum_{j}^{N}\dfrac{\left|y_{ij}^{pred}-y_{ij}^{ref}\right|}{\max\left(\boldsymbol{y}_i^{ref}\right)} \end{cases} \tag{4}$$

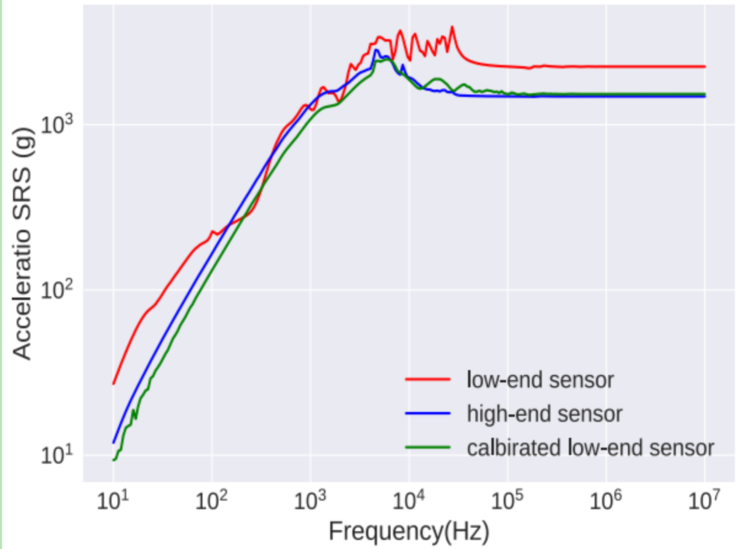
➤ Tab.1 Compare with other methods:

	Raw	LPF	LR	AE	Ours
ε_p	13.5%	48.8%	7.9%	6.9%	5.7%
ε_s	228.6	138.6	44.8	37.9	35.2

➤ Tab.2 Ablation study:

No concatenation	No L_∞ loss	No ResNet	Proposed
9.7%	6.7%	6.3%	5.7%



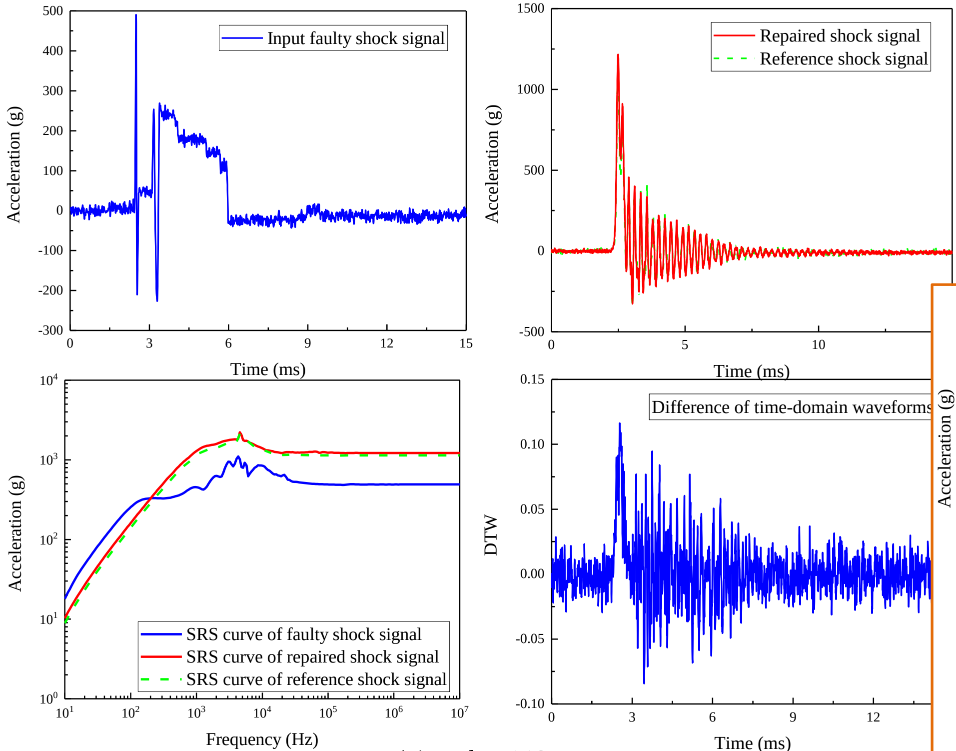


3. Highlights

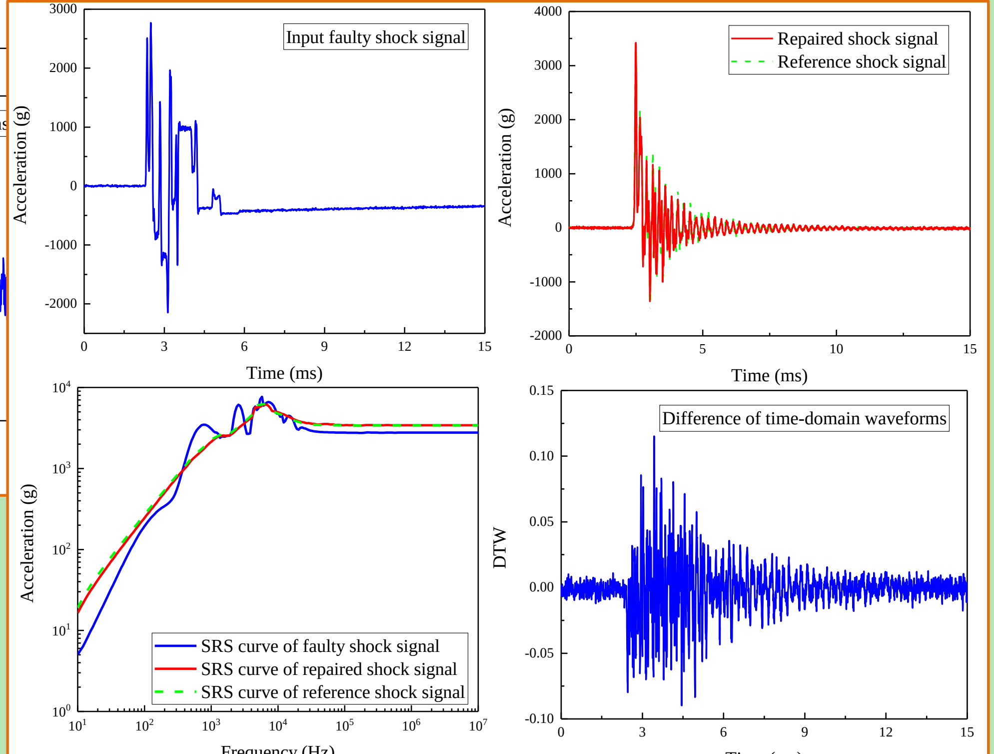
- We establish the first dataset for industrial shock signal, which will facilitate the future research in the field of shock signal measurement.
- We propose a novel network which is able to map shock signal to higher fidelity. Moreover, the designed network is able to correct both the whole time-domain shock signal and the peak value of the shock signal synchronously, making it both suitable for the shock response spectrum-based shock test standard and the JEDEC drop test standard for electronics.
- We show that data-driven approach is promising for measuring complicated shock signals at low cost, and the proposed method does not rely on the high repeatability of the low-end accelerometer.
- With the advancement of automation technology, various industrial sensor signals can be collected at a larger scale easily. This idea can be easily extended to other similar signal processing fields like the calibration of temperature transducers, dynamic load sensors and acoustic sensors.

4. Extending Study

- "Repairing" faulty accelerometer



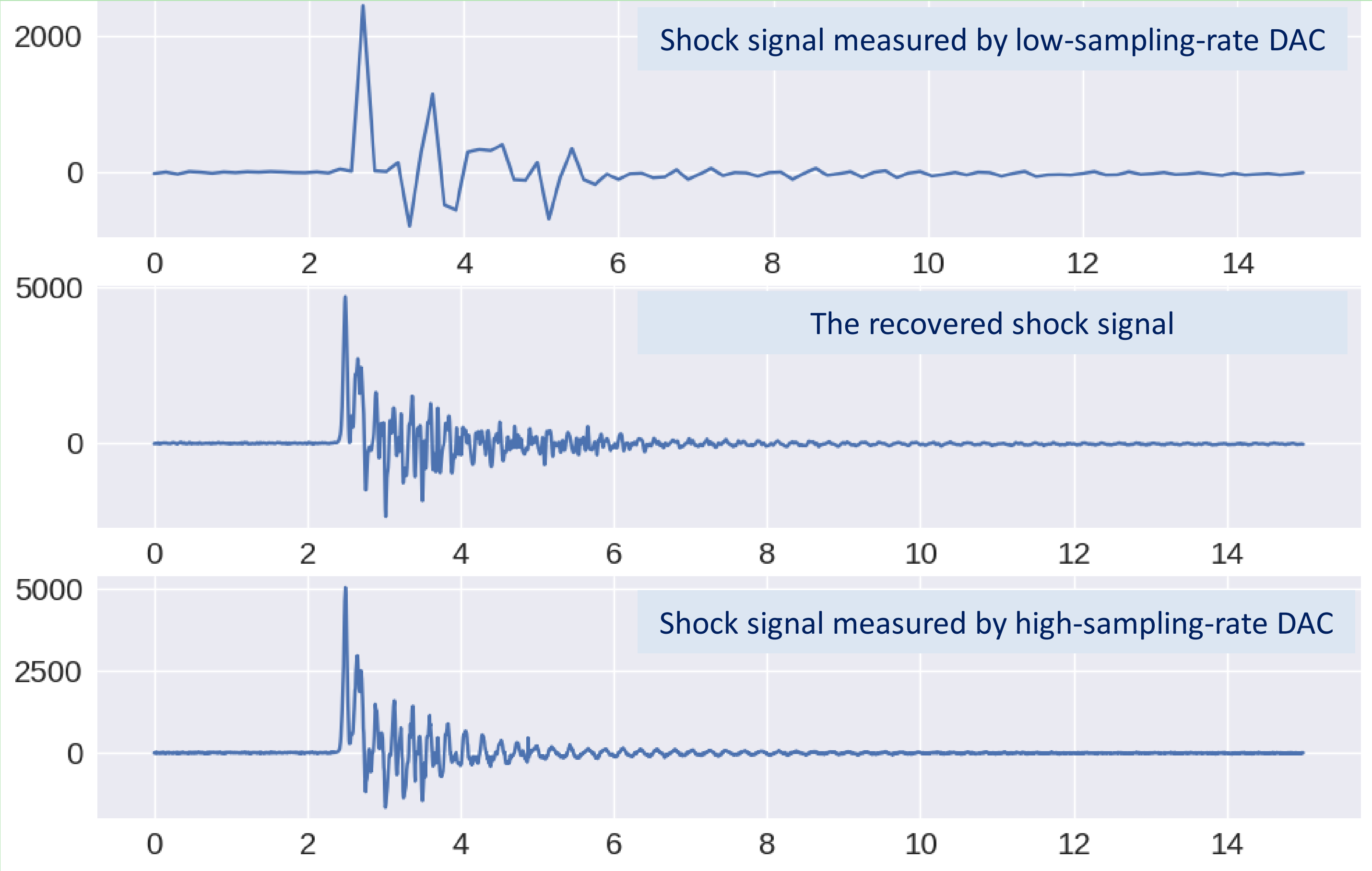
(a) Peak = 1135.5g



(b) Peak = 3401.5g

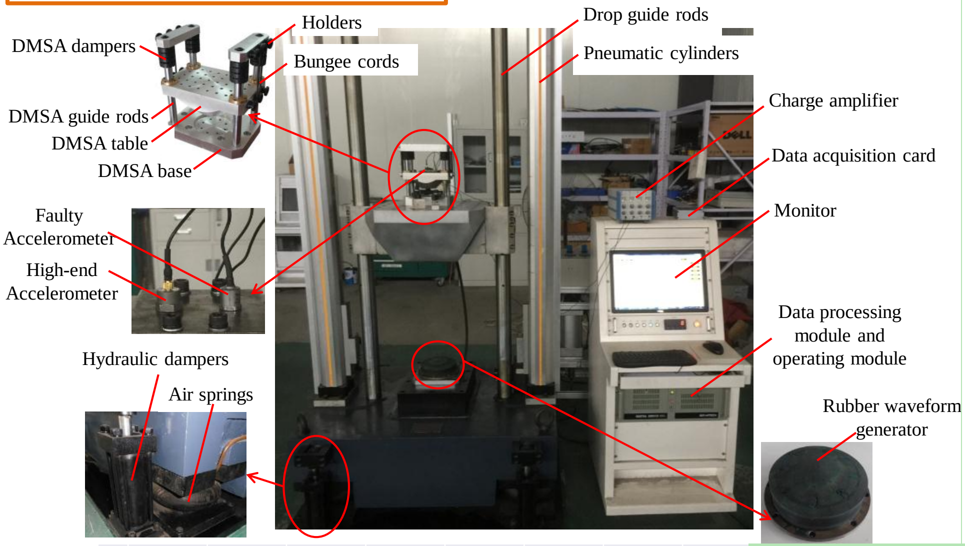
4. Extending Study

➢ Recovering shock signals measured from low-sampling-rate data acquisition card.

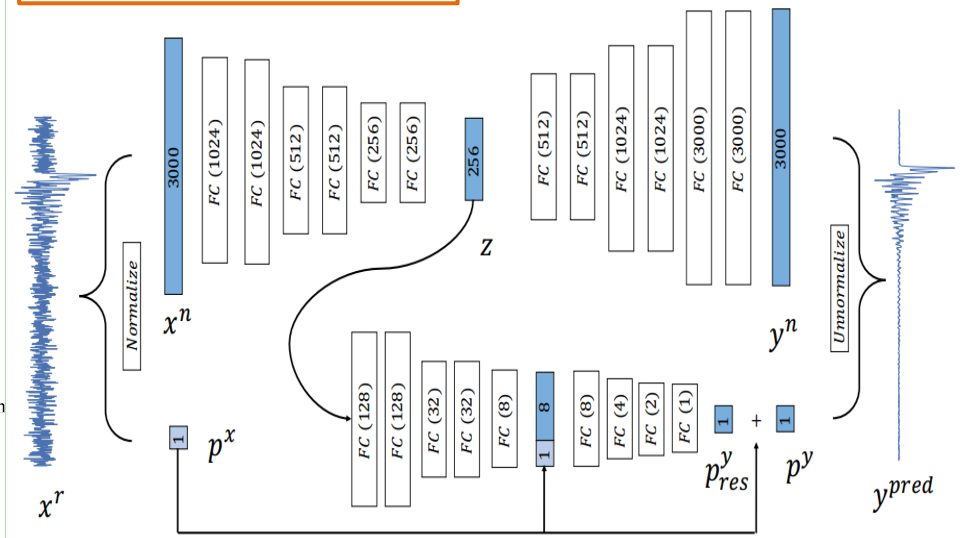


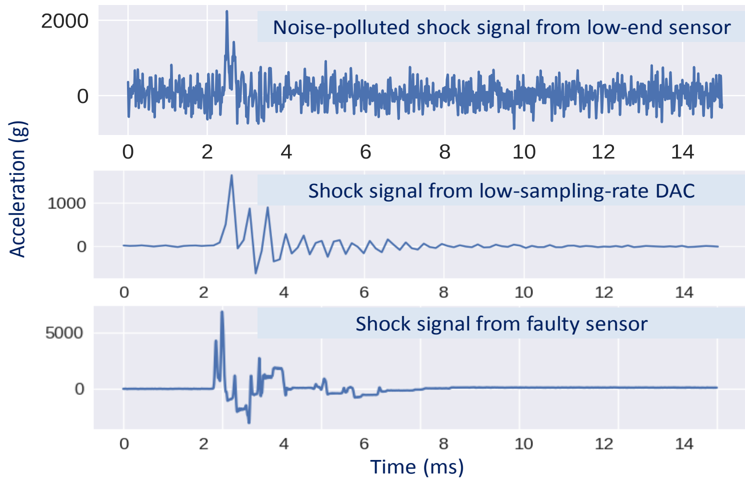
5. Summary

Data Acquisition

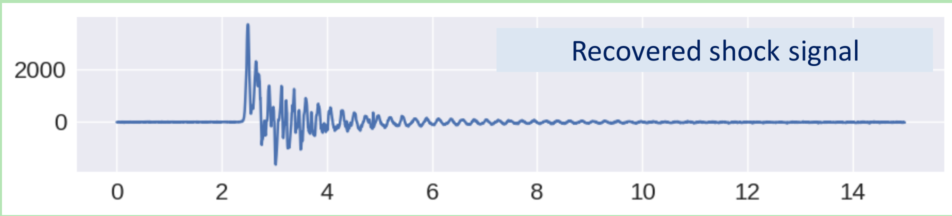


Neural Network





Deep learning



Thanks. Any questions?

- Data and model is available upon request. Any questions, please do not hesitate to contact us:

- Email (Houpu Yao): hope-yao@asu.edu
- Email (Jingjing Wen): wjj1990@mail.nwpu.edu.cn
- Email (Yi Ren): yren32@asu.edu
- Email (Bin Wu): wubin@nwpu.edu.cn
- Email (**Ze Ji**): jiz1@cardiff.ac.uk