DOI 10.5162/SMSI2025/P23

Signal evaluation of force sensors based on silicon strain gauges using artificial neural networks

Th. Frank, St. Hermann
CiS Forschungsinstitut für Mikrosensorik, Konrad-Zuse-Straße 14, 99099 Erfurt, Deutschland
tfrank@cismst.de

Summary:
Artificial neural networks (ANN) are used to evaluate signals from complex piezoresistive force sensors. The neural network is integrated into a microcontroller.

Silicon strain gauges are widely used elements for setting up force measurement. Their high sensitivity and precision make them ideal for applications where precise measurements are required. These strain gauges are particularly suitable for multi-component force transducers. These strain gauges contain a full bridge and are preferably joined to the spring body by glass frit bonding. These are electrically contacted by wire bonding. A description of the process can be found in [1]

In conventional multi-component force transducers, springs are available for each force direction. The aim of the design is for the springs to be designed in such a way that there is only minimal crosstalk between the force directions. Our own analysis of various force transducers shows that the force directions are better separated in a larger installation space. Crosstalk increases with compact force transducers.

For some sensors, the classic signal processing methods are not successful or are very complex. However, these can be successfully trained by using neural networks. The target values are provided by the test equipment during calibration. The training data is provided by the sensors, the signals from the strain gauges and the associated temperature sensors. This procedure is illustrated using two selected examples. Initial tests were carried out with an artificial neural network using the Python library "tensorflow.keras". These tests showed that there are applications in which the use of a neural network is advantageous compared to classic signal processing. This is particularly the case with multiple input variables and a strong hysteresis as in the examples.

Fig. 1 shows the selected sensors. Fig. 2 and Fig. 4 show the real signals under load. The hysteresis is clearly visible. Fig. 3 and Fig. 6 show the comparison of the prediction and the current value. Fig. 5 shows the absolute error of the evaluation for the ring force sensor. The result for the ring force sensor is better because significantly more data was available

Compact ring force sensor with 3 Si strain gauges to compensate for oblique forces. The ring force sensor is used to determine the screw preload force. The tolerance for parallelism in clamped components is 2°. This leads to an uneven load and an incorrect measurement result. This is partially compensated for by the 3 strain gauges, the average value from all 3 strain gauges is used. Due to non-linear relationships and non-identical sensitivity, this solution is not very precise. The characteristic curve also has a friction-related hysteresis. The comparison of the actual values shows a small error. In particular, the hysteresis was well compensated, Fig. 6.

3D force sensor, this has 4 Si strain gauges for 3 force directions. Calibration is extremely complex and not very precise either, as the crosstalk is very pronounced. In the Z direction, all Si strain gauges are loaded in the same direction, for the X or Y direction, the two corresponding Si strain gauges opposite are loaded in opposite directions. A force in the X or Y direction causes a moment around the Y or X axis. This leads to this load. When loaded in the X direction, the sensors in the Y direction are ideally not loaded, and the same applies to force in the Y direction. However, this is not the case. Due to the manufacturing tolerances, the ideal values are not achieved. Fig. 3 shows the characteristic curves when loaded in the Z direction. The slope of the four curves is identical, a friction-related hysteresis can be seen and the offset is different. The comparison of the predicted and actual values is very good despite the simple configuration of the

DOI 10.5162/SMSI2025/P23

artificial neural network and the mechanical setup, Fig. 5.

Several different networks are investigated, especially for the data subject to hysteresis. To create a neural network that can handle a sensor with friction-related hysteresis, it must be taken into account that the sensor values depend not only on the current input values, but also on the previous direction and possibly on the previous values. This requires some form of memory or state awareness in the model.

One way to model these hysteresis effects is to use recurrent neural networks (RNNs) or long short-term memory networks (LSTMs). These networks are specifically designed to take sequence information and past states into account.

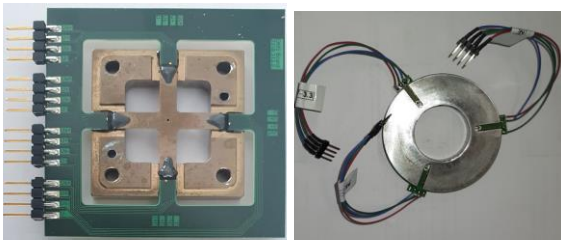

Fig. 1. Left: 3D force sensor, right: a compact ring force sensor

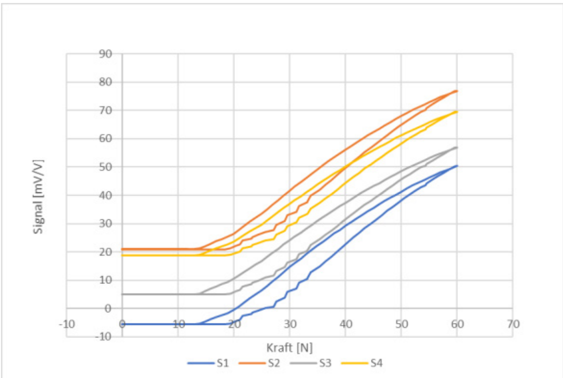

Fig. 2. Signals of the 4 strain gauges under load

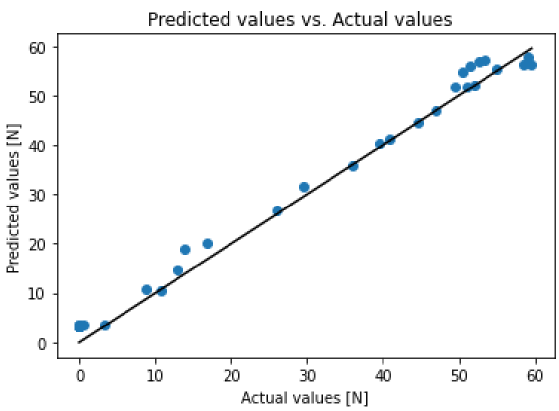

Fig. 3. The ANN of the 3D force sensor after training

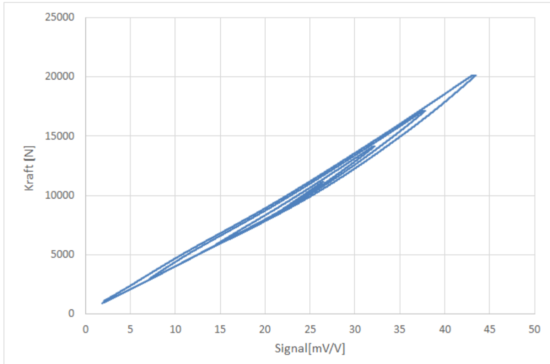

Fig. 4. Signal of the ring force sensor under load, sum of all 3 strain gauges

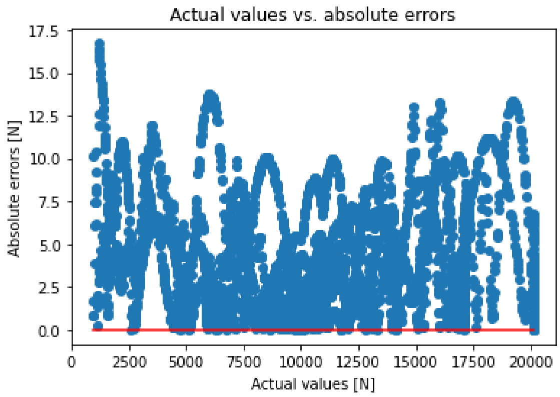

Fig. 5. The ring force sensor, absolute errors

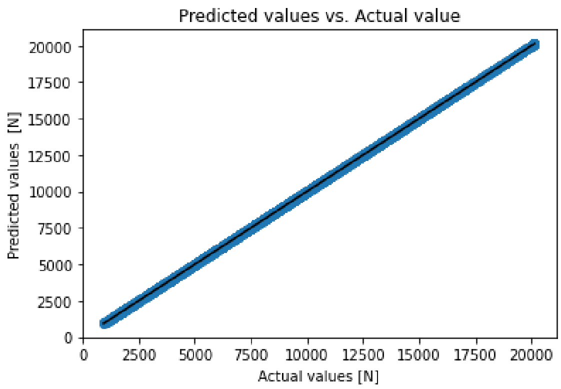

Fig. 6. The ANN of the ring force sensor after training

The last step is to implement the network on a chip for direct signal processing. Preferably, the final training takes place on the fully constructed sensor system. This has the advantage that all electronic components and their errors are incorporated into the parameters of the network.

References

[1] Thomas Frank, Stefan Hermann, André Grün, Danny Hanig, Manuel Kermann, Michael Hintz, Andrea Cyriax, Ralf Röder, Uwe Krieger, "Verwendung von Siliziumdehnungssensoren für makroskopische Prüfkörper", 10. MikroSystemTechnik Kongress 2023, Dresden, 23.-25.10.2023