# Deep Convolutional Networks are Useful in System Identification

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## 1 Introduction

Recent developments within deep learning are relevant for nonlinear system identification problems. In this work we establish connections between the deep learning and the system identification communities. It has recently been shown that convolutional architectures are at least as capable as recurrent architectures when it comes to sequence modelling tasks. They can match or even outperform the older recurrent architectures in language and music modelling, text-to-speech conversion, machine translation and other sequential tasks [1]. Inspired by these results we explore the explicit relationships between the recently proposed temporal convolutional network (TCN) and classic system identification model structures. We present a experimental study where we provide results on two real-world problems, the well-known Silverbox dataset and a the dataset originating from ground vibration experiments on an F-16 fighter aircraft.

## 2 Section Example

### 2.1 Silverbox

The Silverbox is an electronic circuit that mimics the input/output behavior of a mass-spring-damper with a cubic hardening spring [2]. Figure 1 gives the TCN performance on the test set (consisting of 40400 samples of a Gaussian noise with a linearly increasing amplitude).

### 2.2 F-16 ground vibration test

The F-16 vibration test was conducted on a real F-16 fighter. A shaker mounted on the wing was used to generate multisine inputs to this dynamics. We used the multisine realizations [3] for training, validating and testing the TCN. We compare this model with the classical NARX Multilayer Perceptron Network (MLP) with two layers and with Long Short-Term Memory (LSTM) network.

## 3 Conclusion

In this work we have applied recent deep learning methods to standard system identification benchmarks. Not surprisingly, deep learning methods scale well for large data sets which allows us to include more input features, for example in the F-16 data. On the other hand, methods which are used in traditional deep learning settings, do not always improve the performance. For example, dropout did not yield better results in any of the problems. All for all, we believe these models have potential to provide good results in system identification problems, even if this requires us to rethink how to train and regularize these models.

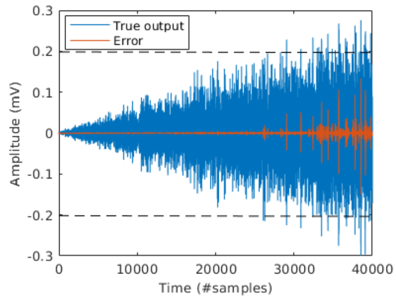


**Figure 1:** The true output and the prediction error of the TCN model in free-run simulation for the Silverbox data. The model needs to extrapolate approximately outside the region $\pm 0.2$ marked by the dashed lines. The free run simulation RMSE is equal to 1.68 on the first 25000 samples where no extrapolation is needed and is equal to 5.55 considering the entire training set.

**Table 1:** RMSE free-run simulation F16 on the test set for the three outputs of the system.

| Output | LSTM | MLP | TCN |
|---|---|---|---|
| 1 | 0.6793 | 0.4393 | 0.5425 |
| 2 | 0.8109 | 0.5338 | 0.7016 |
| 3 | 0.7413 | 0.4775 | 0.6505 |

## References

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