# Fault detection and isolation in the DAMADICS system using recurrent neural networks



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## Introduction

In industry is required that the dispositives work free of faults. A fault is an undesired behabior of a system [1], being the fault detection the capability in recognizing an anomalous behavior, and the fault isolation is to know what fault is affecting the system [2]. There are some approaches used for fault detection and isolation (FDI) like principal component analysis [1], artificial neural networks [3], fuzzy systems [4]. In this work is shown the use of recurrent neural networks (RNN) which are simplets than deep learning and they can use past information to recognize the signals evolution early in time.



## Metodology

The RNN are applied in the benchmark known as Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems (DAMADICS) developed in 2006 by the European Commission. The DAMADICS model has three principal components: a control valve, a servomotor and a positioner. The model can simulate 19 different faults, and they can be simulated in an abrupt or incipient mode. In Fig 1 is shown an scheme of the DAMADICS, being the nomenclature shown in Table 1.

PSP Servomotor E/PZC Variables: T, P1, P2, F, CV Positioner



## Results

GRU was faster to train and gives the result of classification early than the LSTM for abrupt faults. The LSTM shows better results for incipient faults and was less sensitive to hyperparameters values. Table 2 shows the results obtained using both kind of RNN.





There are some RNN types, like the Long-Short Term Memory (LSTM) and the Gated Recurrent Unit (GRU). The first one has the input, output and forget gates (Fig. 2). The GRU uses only the Reset and the update gates (Fig. 3), and has less parameters than the LSTM [3].

#### Table 1. Nomenclature

Reset gate

## Fig. 3 GRU

## Conclusions

The best results were obtained using the GRU for FDI. However, if sample time is less than 250ms or the applications must be developed in a microcontroller, we propose to use a GRU because is simpler and easy to train and to program. Only the LSTM gives better results than GRU for F4.

### Table 2. FDI criteria

| Fault     | Precision |       | Memory |       | Accuracy |       |
|-----------|-----------|-------|--------|-------|----------|-------|
|           | LSTM:     | GRU:  | LSTM:  | GRU:  | LSTM:    | GRU:  |
| F1        | 0.995     | 0.998 | 0.993  | 0.997 | 0.991    | 0.996 |
| <b>F2</b> | 0.981     | 0.983 | 0.980  | 0.982 | 0.979    | 0.982 |

| Nomenclature | Description                     |  |  |
|--------------|---------------------------------|--|--|
| E/P          | Electro-pneumatic transducer    |  |  |
| FT           | Flow rate transmitter           |  |  |
| PSP          | Positioner supply pressure unit |  |  |
| ΡΤ           | Pressure transmitter            |  |  |
| TT           | Temperature transmitter         |  |  |
| ZC           | Internal position controller    |  |  |
| ZT           | Stem position transmitter       |  |  |

The LSTM can work with long data sets, being more flexible than the GRU. However, a GRU can be tuned faster due to the use of less parameters, and the final result is similar to the obtained by a LSTM. Three layers where used and it is proposed to use a LSTM or a GRU for each kind of fault in the control valve. The criteria to quantify the FDI task are the precision, memory, and accuracy given by (1), (2) and (3).

| <b>F3</b> | 0.962 | 0.970 | 0.961 | 0.968 | 0.959 | 0.967 |
|-----------|-------|-------|-------|-------|-------|-------|
| <b>F4</b> | 0.996 | 0.992 | 0.994 | 0.991 | 0.995 | 0.989 |
| <b>F5</b> | 0.951 | 0.956 | 0.949 | 0.955 | 0.948 | 0.954 |
| <b>F6</b> | 0.983 | 0.984 | 0.982 | 0.983 | 0.980 | 0.981 |
| <b>F7</b> | 0.974 | 0.976 | 0.973 | 0.975 | 0.972 | 0.974 |
|           |       |       |       |       |       |       |

### References

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