Improving security and resilience of Cyber Physical Systems

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Cyber Physical Systems

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- physical processes;
- computational resources;
- communication infrastructures.

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These systems have to be reliable at all time and in all circumstances. Especially when anomalies occur, regardless of their nature, the system needs to react and overcome the issue.

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Discovered only in 2010 because it spread itself too far.

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Can it be used for real time systems?

And can it be an all purpose tool used on a wide variety of different systems?

Research method

Experimental based approach;

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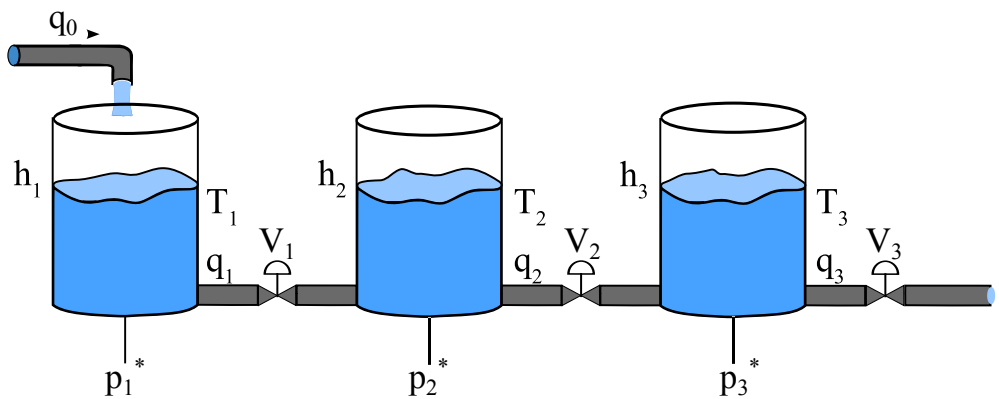
Currently experimenting on simulations of the three tanks model and its variations.



Model based approach

A CPS model can operate in different behaviours, called modes:

$$Modes : \begin{cases} y_{m_1} = g_1(x) \\ ... \\ y_{m_i} = g_i(x) \end{cases}$$

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Multi modes simultaneously active will increase exponentially the inverse inference computation.

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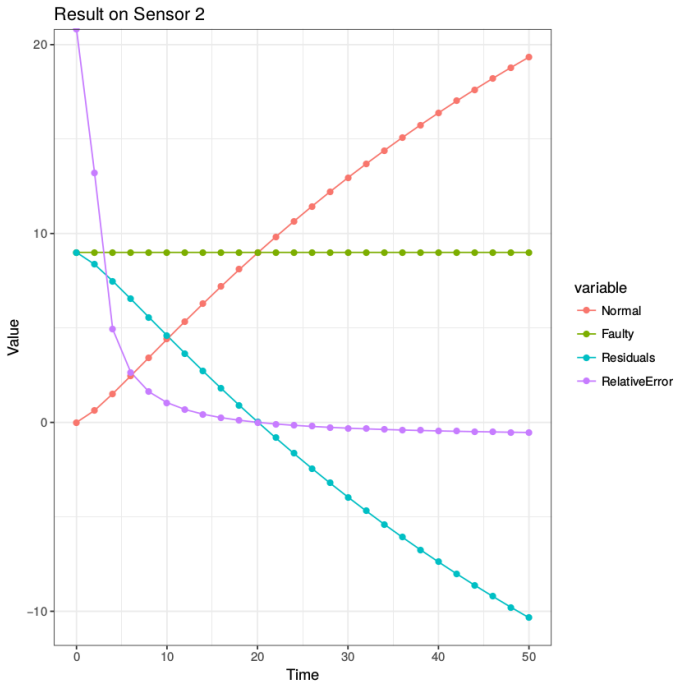
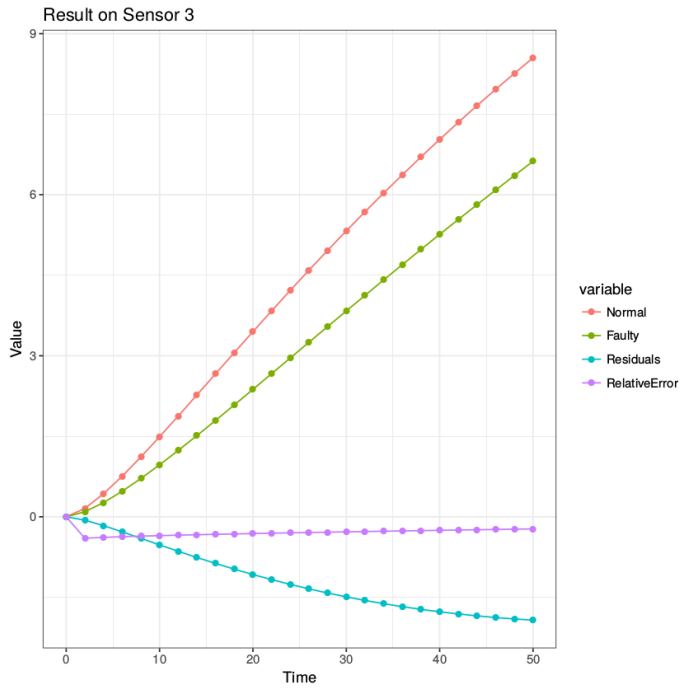
Results:

- Primitive and basic approach;
- Able to recognize some simple attacks;
- Plenty of false positives when the anomalies affects the internal components of the system.

Residual study results



A sensor of the system is attacked. Identifiable through: $\dot{y}_k = -\dot{r}_k$.



Synergies of the system make it harder to identify the anomaly.

Algebraic approach

Basic: Extend the sensors data study to higher order derivatives looking for particular patterns that could identify the anomalies;

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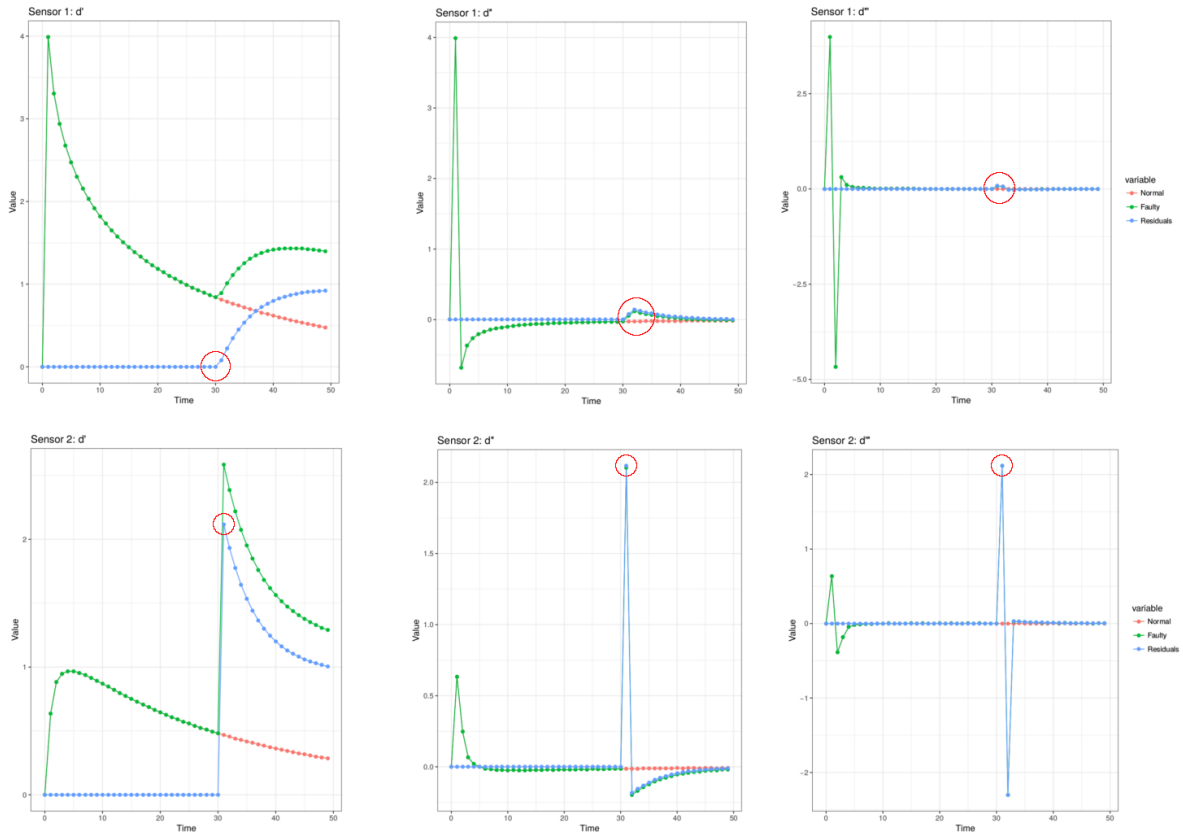
Improved: Use the patterns to find anomalies masked from other anomalies.

Example



Peculiar pattern of an actuator attack on the system and its side effects.

Data driven approach

Can we identify anomaly patterns automatically?

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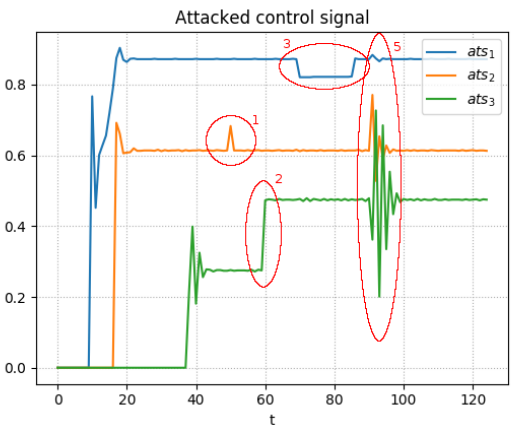
Classification of the anomalies' data behaviours through SVM, LSTM and HMM.

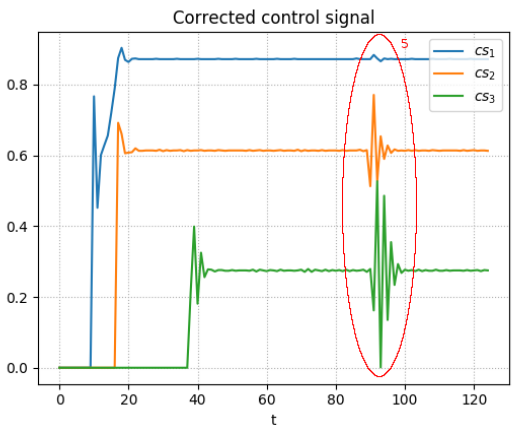
Results compared

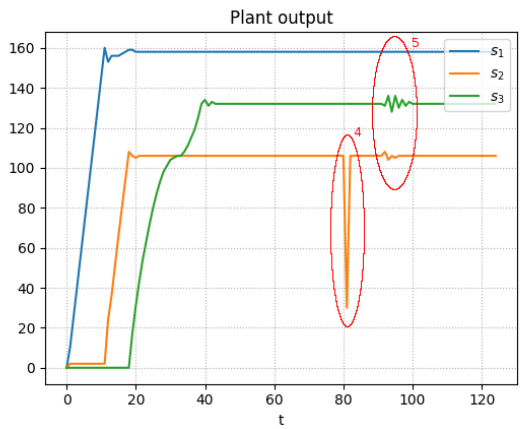
Method	Faults	Detected	False Positive	Missed	FR
Model based	78	53	32	25	0.345
AvF	78	57	15	21	0.607
IAA	78	54	8	24	0.597

Comparing the results of all the approaches studied to this point. The algebraic approach seems the best so far.

Attack or fault distinction: a novel method







Using the system to understand if the control signal has been tampered.

Future

Identify a small set of the best approaches for the diagnosis process, focusing mainly on data driven ones;

Increase the diagnosis efficacy combining different approaches;

Extend the tests to real systems;

Create a standalone diagnosis tool based on our method.


Thank
You