Preliminary Results for

Automatic Fault Detection for Solar Thermal Systems

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Why automatic fault detection?

It will keep your system running.

Monitoring of solar thermal systems ensures that each system lives up to its full potential. Thus, monitoring personnel frequently analyses the system data, to react to any unusual behaviour. However, with increasing numbers of sensors installed at the systems and more complex system layouts, it is not possible to perform this task manually.

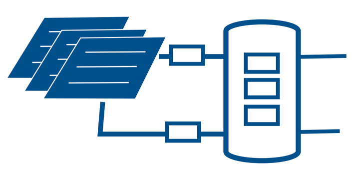
Fig.1: Solar thermal system located in Graz (SOLID)

Fault detection and diagnosis algorithms can support the monitoring personnel. They use various techniques to detect faults automatically, sometimes even before they can be spotted manually. This saves time, and allows to react to faults fast.

Why a new algorithm?

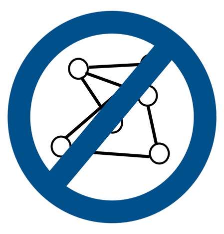
Our algorithm is flexible, easy, and accurate.

Not many Fault Detection algorithms for solar thermal systems exist yet. Our proposed algorithm has three superior attributes:



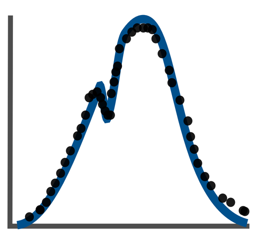
Flexible

Some algorithms require very specific measurement devices, measurement conditions or system layouts. Instead, our algorithm can be used at any system due to its flexible training mechanism.



Easy to Configure

Often, a considerable amount of time needs to be spend to configure algorithms, set parameters and adapt to special system layouts. In contrast, our method uses Machine-Learning to do so automatically.



Accurate

Sensor data of solar thermal systems is not always easy to interpret. Many correlations between measurements have to be kept in mind when analysing the data. In contrast, our algorithm is able to mimic the multi-dimensional, time-dependend and non-linear data very well.

What are the results?

High accuracy, early detection.

The results are quite promising. Preliminary tests on one of SOLIDs system shows that temperature, pressure and power measurements can be predicted with high accuracy. This allows our algorithm to spot anomalies both fast and reliably.

Based on these results we plan to intensify our investigation to provide detailed statistics on modelling and fault detection accuracy and test the algorithm on multiple systems.

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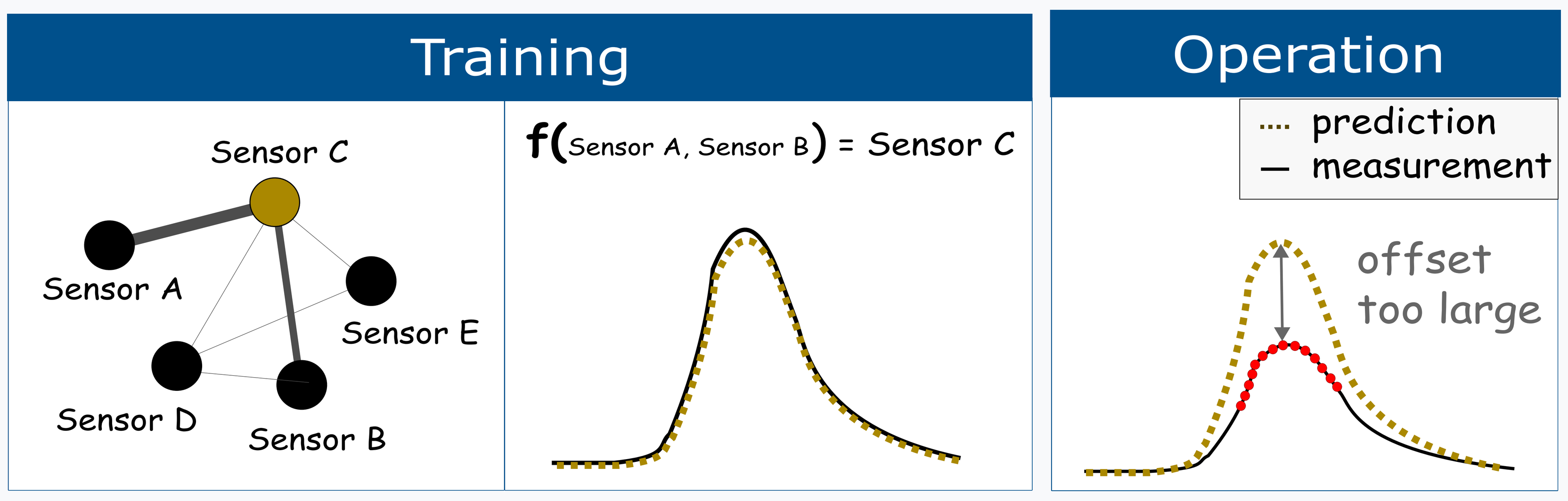
How does it work?

Our algorithm uses a three step approach:

1. Find Correlations.
In the first step, a small portion of the historic data (~1 week) is analysed to identify correlations between sensor measurements. For each target sensor in this dataset, a Random-Forest-Regressor (RFS) is used to model the behaviour of its measurement data. Conveniently, the RFS provides insights into which features (i.e., sensors) are the most important for predicting the measurements of the target sensor. By iteratively reducing the number of input features of the RFS and checking if the prediction is still accurate enough, a small set of highly correlated sensors can be identified for each of the target sensors.

2. Create Models.
The information obtained from the previous step allows to train more accurate machine learning algorithms. This can be done because using the correct input features typically increases both the training speed and the accuracy of machine-learning algorithms. In this step, a Gradient Boosting Regression algorithm is trained for each specified target sensor.

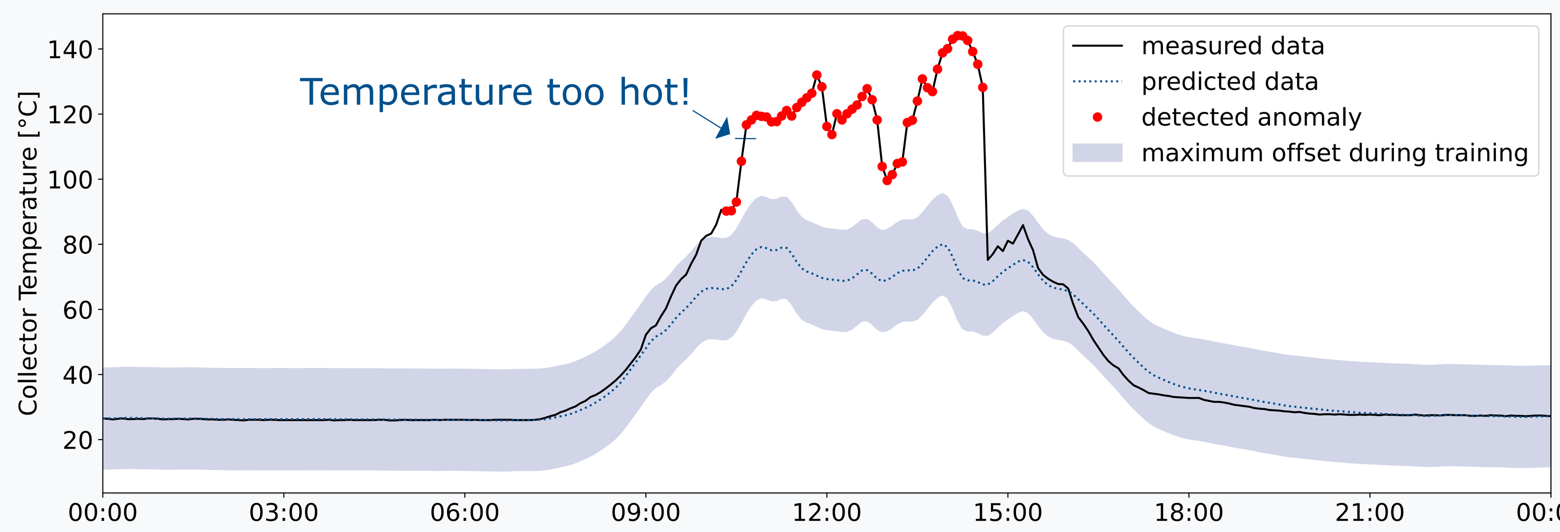
3. Detect Anomalies.
The trained algorithms can then be used to detect abnormal system behaviour. When provided with new data, each algorithm generates predictions for its respective target sensor. If the difference between prediction and measurement is unusually high (compared to the training) an alarm is raised



1. Find Correlations (Feature Selection) **2. Create Models** (Train Algorithms) **3. Detect Anomalies** (Fault Detection)

How does it help?

Prevent faults before they happen.



The figure displays measurement data showing the temperature of a collector (black line) and predictions provided by our algorithm (blue line showing predictions and blue area encoding the maximum offset observed during training). Half an hour before a stagnation occurs at approximately 10:30 o'clock, our algorithm already detects anomalous behaviour (red dots). This would have been enough time to react to the anomaly and prevent the stagnation.

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