Use of machine-learning for monitoring solar thermal plants

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Abstract. A machine-learning algorithm (MLA) was developed to assess the operational state of solar thermal plants, based on the data of only one temperature sensor, and the irradiance and ambient temperature data from the nearest weather station. A detailed requirements analysis of the situation results in the classification of a multivariate time series problem. Neural networks used in the field of data science are ideally suited for problems of this type. Data from the operational monitoring system, which runs a rule-based algorithm, were used to train the neural network using the software framework TensorFlow. It was shown that the chosen MLA can detect malfunctions such as heat loss due to gravity-driven circulation during night. However, further development towards a practical tool requires not only far more data for training and validation. It became clear that corresponding pressure data are needed to classify temperature transients and to attribute these classes to certain malfunctions.

1. Introduction

Numerous studies [1-5] show that a considerable number of thermal solar plants exhibit operational problems. By means of online monitoring, these operational malfunctions could be detected and eliminated at an early stage. However, all monitoring systems developed in the past involve far more than one sensor. Because of the high costs and the considerable effort for the installation, none of these techniques reached the market readiness. Based on extensive expertise the company, Energie Zukunft Schweiz AG (EZS), pursued a completely different and innovative approach. A system for online monitoring of solar thermal plants was developed based on a single temperature sensor attached to the supply line of the solar circuit near the collector exit. The Internet of Things (IoT) sensor is connected to a database via LoRaWAN (Long-Range Wide Area Network) [6]. A rule-based algorithm was developed and successfully used to interpret the data and assess the state of the solar plant. In the current project, the method was further developed as follows: For easy installation and maintenance, i.e. replacement of the sensor battery, it is intended that the sensor be installed in the utility room, which is usually located in the basement. However, data from a sensor that is far away from the collector field are more difficult to interpret. To compensate for this disadvantage, a suitable self-learning algorithm was developed and tested.
2. Description of the monitoring system

In contrast to traditional, extensive monitoring systems, the Low-Cost Solar monitoring (LoCoSol) system requires only a single, battery-powered IoT temperature sensor attached to the supply line of the solar circuit. Figure 1 shows the schematic diagram of the monitoring system. The IoT sensor transmits temperature signals via the LoRaWAN network to an Influx database where the data are analyzed daily. The database also contains information about the type and size of all monitored solar plants as well as their geographical positions. The operational state of a solar thermal plant is determined by the characteristic signatures of the temperature signal in combination with the irradiation and ambient temperature data of the nearest meteorological station. The dataset is analyzed by algorithms described in the following sections. The result of the analysis is added to the dataset in the form of a number indicating the operational state. If one of the following malfunctions are detected,

- No circulation in the solar circuit
- Heat loss from the storage tank by gravity-driven flow during night

the monitoring system sends an e-mail to the person responsible for maintenance. This allows repair within a short period of time, which can significantly reduce the loss of useful energy. The advantages of this low-cost monitoring system are balanced by the disadvantage that the operating status must be assessed based on a very incomplete dataset.

3. Proof of feasibility using a rule-based monitoring system

Based on expert knowledge of solar thermal systems and visual inspection of raw data from the daily files a rule-based algorithm was developed using the web-based software platform, Node-Red. This code provides the pre- and postprocessing of data and generates status indicators and failure messages. The web-application, Grafana, was used for the visualisation of data and analysis results. The monitoring system using this rule-based algorithm was used to acquire data from a steadily increasing number of plants over a period of 30 months. Currently 60 plants are being monitored. It was concluded that the assessment of a solar thermal plant based on data from a single temperature sensor is feasible.

However, the final decision on the status of the plant requires a local inspection. In many cases the informative value and the accuracy of the automatically generated conclusions was poor. Therefore, for the successful dissemination of the method, the analysis process must be automated, and the accuracy of the analysis must be increased. With the steady increase in the number of plants being monitored, other problems became apparent:

- Installing the sensor in roof-integrated collectors is time-consuming and requires safety measures.
- Access to collector fields arranged on flat roofs is often only possible via the top-floor apartment.
• The lifetime of batteries suffers from extreme temperatures during the year.

It was therefore decided,
• to install the sensor in the utility room, which is usually in the basement.
• to use a machine-learning algorithm (MLA) instead of a rule-based algorithm.

Figure 2 shows the data from a solar plant over 5 days analyzed using the rule-based algorithm. The temperature sensor is attached to the supply line in the utility room. The orange line indicates the solar irradiance and the blue line the ambient temperature, as provided by the meteorological station. The red line shows the temperature of the supply line in the utility room. The black dots are the numerical representations of the key performance indicators (KPIs) with which the algorithm indicates certain events.

In the morning hours of each day, the sharp increase in the supply temperature (red) indicates the arrival of hot liquid from the collector field shortly after the pump starts, which is indicated by KPI = 4. The irradiance profile in the first two days indicates a few passing clouds. Otherwise, the days are sunny with ambient temperatures of up to 36 °C. In the three first days, the supply temperature rises quickly, reaches values of almost 100 °C and then decreases to a temperature of around 50 °C. It can be concluded that the storage capacity is sufficient, but the area-specific flow rate is rather low. Compared to the radiation course, the temperature course is shifted towards the afternoon, indicating a south-west orientation. On each of the first three days, there is a sharp increase in the supply line temperature in the afternoon, after which the temperature decreases slowly during the night to values of between 25 and 30 °C. This is indicated by KPI = 8 and interpreted as gravitational circulation causing heat loss from the storage tank. On days 4 and 5 stagnation occurs, which is indicated by KPI = 1 and KPI = 2 in short succession.

4. Development of a machine-learning algorithm for the current monitoring system
Identifying the status of a solar plant from the time series data of a single IoT temperature sensor is a big challenge, especially if it is installed far away from the collector field. Eleven well known solar plants were selected, each providing more than 1.5 years of data. In nine plants, the sensor is installed at the collector exit. In two plants the sensor is installed in the basement. These data were pre-processed to facilitate the actual development of the MLA, for which the platform TensorFlow [7] was used. The development process [8] involves several steps, which are described as follows:

![Figure 2. The signature of the IoT temperature sensor (red) attached to the supply line in the utility room. Weather data (blue and orange). key performance indicators (black).](image-url)
Model Requirements: In a first step, neural networks were evaluated according to the type of problem, which is characterized by time-series based data with a periodicity of 24 hours. In the end, the CNN (convolutional neural network) \[8, 9\][6,11], and LSTM (long and short-term memory) \[8, 10\][6,12] were chosen for the training stage. The MLA is expected to produce statements on specific criterions. Among the four classes of applications, i.e. forecast, rare event, HAR (human activity recognition) \[7, 8, 11\]and ECG (electro-cardiogram) \[12\] considered, the HAR was found to be best suited. Since the data have a time-periodic structure, there is also a high level of correspondence with the ECG. Our amount of data is small, even for supervised learning. Therefore, unsupervised learning was not an option.

Data collection, cleaning, and labelling: To avoid interfering with the productive system running the rule-based algorithm, a second database containing the same datasets was established. In this database, the raw data were reprocessed using the latest and most advanced version of the rule-based algorithm, which analyzed the data for several KPI. These findings were scrutinized by visual inspection. If necessary, the rule-based algorithm was tuned until its accuracy matched the expectation. From this analysed dataset, around 6000 daily records with 144 entries each were generated. The set of daily records was split randomly into two subsets. The larger subset containing 80% of data was used for training the MLA. The other subset was used for validation. The datasets were labelled according to the analysis:

1. Sensor position at the collector exit (CE) or in the utility room (UR)
2. Start of circulation pump (yes or no)
3. Heat loss caused by gravity-driven flow, sensor position CE: yes or no
4. Heat loss caused by gravity-driven flow, sensor position UR: yes or no

Training: To decide which neural network is best suited, both the CNN and the LSTM were trained. By testing accuracy, loss and overfitting the LSTM is found to be significantly better than the CNN, so that in the following only the LSTM will be considered. Table 1 shows the final set of hyper-parameters used for the LSTM. The number of epochs was stepwise increased up to 160. Still, the loss-function did not show signs of overfitting for any of the labels. There seems to be room for improvement.

| Table 1. List of selected hyper-parameters for the LSTM |
|----------------|----------------|----------------|
| stage        | Hyper-parameter | Selected Values |
|              | model          | sequential     |
|              | neurons        | 100            |
| Architecture | Activation     | Relu, softmax  |
|              | Loss           | Categorical cross-entropy |
|              | Dense          | 100            |
| Training     | Optimizer      | adm            |
|              | Batch Size     | 64             |
|              | Number of Epochs | 160         |

Evaluation: After the training process the test dataset is applied to the fitted model. With these outputs the ROC-curves \[13\] for each label are generated, as shown in Figure 3. The ROC-curves allow a threshold for each label for the true/false classification to be determined. The curves for the labels 1, 2, and 3 are smooth while the curve for label 4 is not. This is due to the much smaller number of datasets available. Using these thresholds, the 2x2 confusion matrices of the four labels are generated as displayed in Figure 4. A 2x2 confusion matrix contains the correctly predicted cases in the diagonal, indicated by true positive (TP) and true negative (TN). The wrongly predicted cases are indicated as false positive (FP) and false negative (FN).
Figure 3. ROC-curves and thresholds (black dots) for each label.

The first matrix shows the accuracy of recognizing the sensor position. In 194 cases the MLA correctly identifies a sensor position in the utility room, while in 6 cases the answer is wrong. The accuracy for the sensor position at the collector exit is considerably higher.

The second matrix corresponds to pump starts. In 236 cases the MLA predicts a pump start correctly, while in 3 cases the prediction is wrong. Apparently, a pump start is not so easy to detect.

The third and fourth matrix show the accuracy for the prediction of energy loss due to gravity-driven flow. From a practical point of view, the accuracy for both sensor positions is not sufficient. The fourth matrix must be considered with caution because of the poor statistics in this case.

Figure 4. The confusion matrices of all four labels.

From the evaluation of the binary classification other metrics shown in Table 2 can be extracted, which describe the robustness of the evaluation. For example, a low recall indicates many false negatives. A low precision can also indicate many false positives.

Table 2. The metric of the different labels for the LSTM

| label                   | Position     | Pump Start | Energy loss, sensor CE | Energy loss, sensor UR |
|-------------------------|--------------|------------|------------------------|------------------------|
|                         | UR | CE | no | yes | no | Yes | No | Yes |
| Accuracy                | 0.96 | 0.97 | 094 | 0.78 | 0.82 | 0.63 | 0.87 | 0.88 |
| Precision               | 0.92 | 0.98 | 0.93 | 0.79 | 0.75 | 0.71 | 0.79 | 0.93 |
| Recall                  | 0.88 | 0.98 | 0.94 | 0.78 | 0.79 | 0.67 | 0.83 | 0.90 |
| F1-score                | 0.90 | 0.98 | 0.94 | 0.78 | 0.79 | 0.67 | 0.83 | 0.90 |
5. Conclusions
A low-cost monitoring system for solar thermal plants was developed and successfully tested. The system consists of one single IoT temperature sensor attached to the supply line of the solar circuit. The data are transferred via LoRaWAN to a database where they are automatically analyzed by a carefully tuned rule-based algorithm. A machine-learning algorithm (MLA) based on the LSTM type of neural network was trained and validated using datasets analyzed by the rule-based algorithm. The results are more than satisfactory. The disagreements are mainly due to the small number of datasets available for machine learning. Based on the experience with the rule-based, carefully optimized algorithm and the MLA, it can be concluded that the MLA has the far greater potential. The project will therefore be continued. The goal is to improve the accuracy and to extend the analysis to other malfunctions.

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