

SHC Systems into DHC Networks

B-D3. Automated monitoring, failure detection of key components, control strategies and self-learning controls of key components

IEA SHC FACT SHEET 55.B-D3.2

Subject:	Automated Monitoring of Solar Thermal Systems
Description:	Recommendations for an automatic monitoring process of solar thermal systems are given - starting from sensors to data acquisition, data storage, computation of benchmarks and fault detection.
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Introduction

To ensure the optimal performance of solar thermal systems good monitoring strategies are needed. With their help, faults can be detected in time which can save enormous amounts of money. As the size of new solar thermal systems and their complexity increases steadily in the past years and more and more sensor-data is available, the detection of errors can only be done efficiently by automated monitoring and analysis. Thus, recommendations for the automated monitoring process (see fig.1) are given in this work.

The monitoring process consists of sequential steps discussed in separate chapters in detail:

Chapter

Sensor Technology deals with the aspect of which sensors should be used for monitoring and how uncertainties can be minimized. Both is critical as the measurement data is the basis for further analysis. Additionally, it is described which measurements are recommended for evaluating solar heating systems. Chapter *Data Acquisition* gives helpful tips concerning how the data can be collected and handled at the system site. In order to use the data for automated fault detection algorithms, the data must next be pre-processed and standardized. Common techniques for pre-processing and recommendations for the storage of the processed data are given in chapters *Data Processing* and *Data Storage*. Finally, the last two chapters *Key Performance Indicators* and *Fault-Detection* deal with the aspects of automatically computing key performance indicators, error algorithms and notification management.

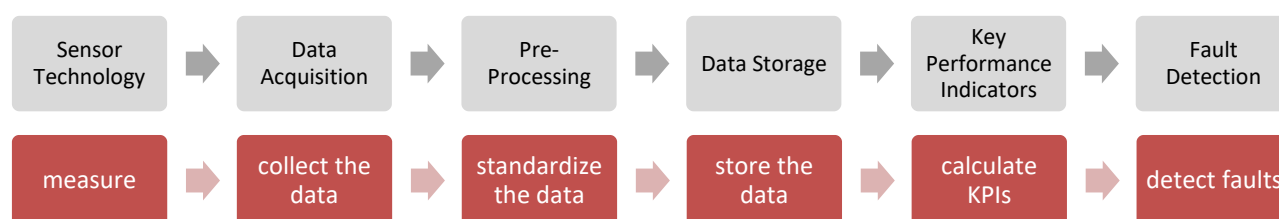


Figure 1: Overview of the monitoring process and corresponding chapters.

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Sensor Technology

Later chapters deal with how faults can be detected, and which indicators can be used to access the status of solar thermal systems. However, if the monitoring data consists of faulty or incorrect measurements, no meaningful results can be obtained neither automatically nor manually. Thus, in a first step, the availability of the data, the accuracy of the sensors, but also the credibility of the measurement devices must be good enough for properly analysing systems. Hence, this section deals with recommended sensors for different physical quantities and how the devices should be positioned. Additionally, the second part of this section describes which measurements are needed for evaluating solar heating systems.

Recommended Sensor Types

Temperature Sensors

Because of the thermal nature of solar heating systems, temperature sensors are essential to system control and monitoring. Often industrial platinum sensors are used by inserting them into pipes with thermowells. Because of their temperature-dependent electric resistance, the platinum can be used to deduce the temperature of the fluid in the pipes. The tolerances of the sensors can be determined based on the DIN EN 60751 certification (see Table 1 below).

Table 1: Tolerances for DIN EN 60751 certified temperature sensors.

DIN-certification	Tolerance (in Kelvin)
DIN AA ¹	$\Delta T = 0.10 + 0.0017 \cdot T $
DIN A	$\Delta T = 0.15 + 0.0020 \cdot T $
DIN B	$\Delta T = 0.30 + 0.0050 \cdot T $

However, there are multiple factors affecting the accuracy of the measurement if neglected (Fischer, 2008; Knabl, et al., 2012):

- To ensure proper heat transfer between sensor and measured fluid, the sensor must be placed inside the pipes using a thermowell, with good contact between fluid, thermowell and sensor. Thermic paste should be used to ensure good thermal contact (Knabl, et al., 2012). Any air between sensor and thermowell can lead to high systematic errors and thus must be avoided (See Figure 4).

¹ Note that previously to DIN EN 60751:2009-05 this certification class was also called 1/3 DIN B or just 1/3 DIN.

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- The pipes and the sensor should be properly heat-insulated (Knabl, et al., 2012). The temperature of both should be as similar as possible to the fluid inside the pipes.
- The thermowell must be placed such that the fluid engulfs the sensor properly. Optimally, the sensor is in the centre of the fluid and parallel to the volume flow direction (see Figure 2). This increases the heat transfer from fluid to sensor and prevents turbulences that might disturb other measurements – i.e. volume flow measurements that requires straight unperturbed inline streams.
- During operation of the system, the fluid in the outer parts of the pipes has slower flow speed and lower temperatures compared to the fluid in the centre. Hence, the insertion depth of the sensor must be sufficient to measure the temperature correctly. A rule of thumb for calculating the insertion depth l_d can be found in (Fischer, 2008):

$$l_d \simeq 15 \cdot d_s + 1.5 \cdot l_s$$

with d_s denoting the diameter of the sensor tip and l_s denoting the length of the sensor. Similarly, (Knabl, et al., 2012) demand:

$$l_d \geq 1.5 \cdot l_s$$

$$l_d > 8 \cdot d_r$$

with d_r denoting the diameter of the thermowell.

- Ideally, only the temperature-dependent resistance of the platinum sensor is measured in order to calculate the temperature of the fluid. However, if a two-wired configuration is used the two cables supplying the sensor with electricity as well as the terminal points add to the signal. This introduces an offset in the measurement and thus lead to a wrong temperature measurement. This can be prevented by using a four-wired or three-wired configuration (see further below):

In the case of a two-wired configuration, the offset can be measured after installation and then be subtracted (Fischer, 2008). Nevertheless, even after such a calibration, different ambient temperatures can still lead to changes in the resistance of the wires which introduces a systematic error for the measurement. As (Fischer, 2008) showed this effect introduces an error of about ± 0.18 K (in addition to other errors) considering a 500m long cable with a 1mm² diameter and a temperature difference of 20 Kelvin. Plus, the cables need to be properly isolated from humidity to prevent errors due to resistance decreases (Fischer, 2008). Also, the mechanical stress to the cable should be minimized in order to prevent changes in the resistance (Knabl, et al., 2012).

If instead a four-wired configuration is used, two wires are used to provide the sensor with a known current I_+ while the other two are solely used for the voltage-measurement (see Figure 3). Because of the high resistance

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of the voltage measurement, the current I_m in the measurement cables is very low in comparison to I_+ . As a result, the measured voltage U_m almost entirely corresponds to the resistance of the sensor:

$$U_m = I_m \cdot (R_1 + R_2) + (I_+ - I_m) \cdot R_{sensor} \approx I_+ \cdot R_{sensor}$$

Thus, there are almost no errors due to the resistance of the cables used for the measurement R_1 and R_2 . As a result R_{sensor} can be calculated accurately based on the knowledge of I_+ and the measurement U_m . To reduce the costs of 4-wired temperature measurements one can use smaller cable diameters, as their resistance is not influencing the signal anymore. Even in a four-wired configuration the sensor can be calibrated after installation as the resistance of the terminal points may introduce an offset to the signal. This is especially important if sensors are used for determining temperature differences. However, in this case paired sensors are available that are already calibrated carefully by the manufacturer.

In conclusion, when installed and calibrated correctly a DIN AA platinum sensor is recommended for temperature measurements (Knabl, et al., 2012; Fischer, 2008). With this, the required accuracy for monitoring purposes with about $\pm 1K$ (Fischer, 2008) is achieved.



Figure 4: Air between sensor and thermowell due to incompatible diameters (Fischer, 2008).

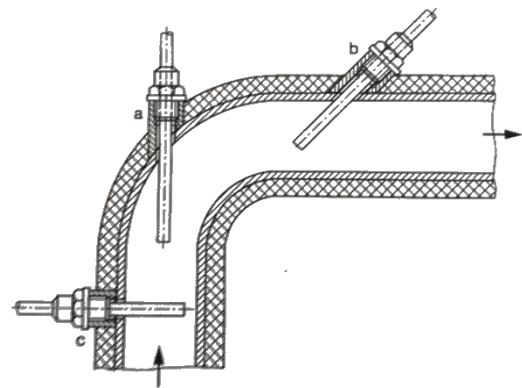


Figure 2: Different positions of thermowell in pipe. Option a is preferred over option b and Option c. (Fischer, 2008)

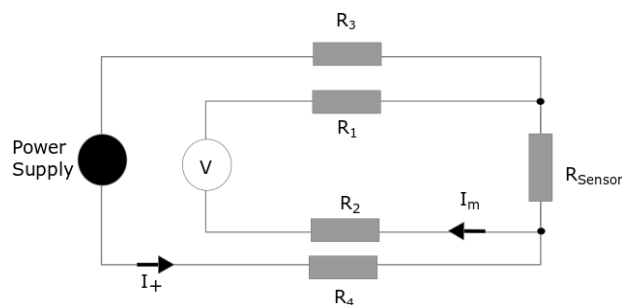


Figure 3: Sketch of four-wire measurement

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Pressure Sensors

Care must be taken that the sensors are installed in accordance to the manufacturer requirements and that the sensor supports water-glycol mixtures. Usually, pressure sensors for solar thermal systems need to operate in a range of 0 to 10 bar, which must be supported by the sensor. Also, the temperature stress on the pressure sensor should be minimized (Knabl, et al., 2012). This can be done for example by using syphon tubes with the pressure sensor on the end of the tube. With enough volume between the hot fluid and the sensor this reduces the heat transfer such that the sensor is exposed to low temperatures only. The accuracy of commonly used sensors is in the range of few tenths of a millibar, which is sufficient for fault-detection at typical solar systems (Fischer, 2008).

Heat-Meters and Volume Flow Sensors

Heat meters consist of a volume flow sensor in addition to two temperature sensors and an arithmetic unit responsible for calculating the energy yield. They must be installed based on the requirements of the manufacturer. This includes that the inlet and outlet pipes are straight and sufficiently long. Additionally, in the case of inductive flow meters the accuracy of the flow meter depends on the velocity of the fluid with high errors for very low velocities. To reach minimum thresholds for the fluid velocity, one can decrease the diameter of the pipes with concentric reducer and use a corresponding flow sensor. The resulting hydraulic resistance is neglectable while ensuring way better accuracy for the sensor.

The temperature sensors are chosen by the manufacturer and are often paired such that aging effects and offsets do not influence the measurement of the temperature difference. Care must be taken, that the heat meter supports the temperature range of the application. For example, different heat meters must be used for cooling and heating applications.

The components should meet at least the requirements of EN 1434-1 (Fischer, 2008) and the installation of the heat meter must follow the requirements of EN 1434-6 (Knabl, et al., 2012; Physikalisch Technische Bundesanstalt, 2014), including the following:

- If not specified by the manufacturer the inlet zone is recommended to be at least 10 times the diameter of the pipes and the outlet zone at least 8 times the diameter of the pipe.
- The pressure sensor must be free of tensile-, pressure- or torsional stress.
- If required by the measurement technology the fluid temperatures must be mixed sufficiently.
- The fluid and pipes need to be free from air and dirt. Pipes in front and below the sensor must be secured sufficiently.
- The wires of the temperature measurements must be continuous and are not allowed to be cut or extended.

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Table 2: Tolerances for heat meter measurements for EN 1434-1.

Volume flow sensor (volume flow measurement)	$\pm \left(2 + 0.02 \frac{q_p}{q} \right) \%$
Arithmetic unit (heat capacity calculation)	$\pm \left(0.5 + \frac{\Delta T_{min}}{\Delta T} \right) \%$
Temperature sensor (temperature measurement)	$\pm \left(0.5 + \frac{\Delta T_{min}}{\Delta T} \right) \%$

With q_p denoting the nominal flow rate [m³/h], q denoting the measured flow rate [m³/h], ΔT_{min} denoting the minimum required temperature difference between flow and return [K] and ΔT denoting the measured temperature difference between flow and return [K].

Radiation Sensors

Based on (Knabl, et al., 2012) the radiation sensor should be certified by ISO 9060 with class ‘first class’ and be able to measure irradiation values in the range of 0 to 1500 W/m². Care must be taken that the sensor is clean in order to measure correct irradiation values (see **Fehler! Verweisquelle konnte nicht gefunden werden.**).

Conclusion

In conclusion the sensor types depicted in Table 3 are recommended for measuring physical quantities at the solar thermal systems. Additionally, one can analyse the effect of different sensor types on measured and calculated quantities following strategies similar to (Zirkel-Hofer, et al., 2016) by applying uncertainty propagation methods. With these considerations, sensors can be chosen in order to get the desired accuracy and precision of different quantities.

Table 3: Recommended certificates and tolerances for monitoring for different sensor types.

Sensor Type	Recommended Certificate	Required Tolerance
Temperature	DIN AA	± 1.0 K
Pressure		± 0.1 bar
Volume Flow	EN 1434-1	$\pm 5\%$
Energy	EN 1434-1	$\pm 5\%$
Radiation	ISO 9060	$\pm 5\%$

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Recommended Measurements

This section describes which physical quantities should be measured, giving an explanation why the measurement quantity is important in the monitoring process.

Based on (Fischer, 2008; Knabl, et al., 2012; Dröscher, et al., 2009) there are various possible layouts for solar heating systems making it difficult to describe recommendations for each layout at the same time. There are multiple ways to account for this, for example by using representative layouts or by building up modules. This topic will be discussed in section Data Storage, describing the effect of datapoint mapping on the monitoring process. However, for this section a modular concept is used separating the system in various parts that can be recombined to form a large variety of systems. The considered sections include the solar collector circuit, the heat storage, external heating, solar cooling and domestic heat and district heating in accordance to (Ohnewein, et al., 2016). This allows to give recommendations for useful measurements in a simple and compact way that reduces redundancies.

The following list of recommended measurements follows the results of (Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020) closely. In addition to the recommended measurements, short descriptions of their advantages have been added by the author. A more compact representation of the list including the sources can be found in Appendix A.

Solar collector Circuit

The solar collector circuit is the core component of each solar heating system, including the primary and secondary solar collector circuit with the collector units, solar pumps and piping. One of the most important information for evaluating the solar collector circuit is how much energy was produced by the system. This information is sometimes even needed for billing but can also be used to analyse the collectors and the overall system efficiency. Hence, either a heat meter should be installed at the solar collector circuit or at least a volume flow sensor and temperature sensors should be installed such that the energy yield can be calculated.

Usually, radiation sensors are installed to measure global radiation. This information can be used for system control but is also vital to calculate the specific solar yield, the collector efficiency, or compare measured and expected solar yield. Care must be taken that the sensor is sufficiently aligned with the collector plane, or that at least the tilt and orientation is known (see Figure 6). If this is not the case, however, the radiation on the collector surface can be approximated by methods described in (Duffie & Beckman, 2013). Plus, the sensor must be clean in order to measure the right amount of irradiation. Results from the research and development project MeQuSo show that the error caused by dirt can be as high as 10% (see **Fehler! Verweisquelle konnte nicht gefunden werden.**). Optimally, multiple sensors are used, and beam and diffuse radiation are measured as well. This allows to calculate the irradiation on different angles more accurately and can be used to check whether the irradiation is measured correctly. This is especially important if large scale solar heating systems are monitored to detect measurement errors early.

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For comparing measured and expected solar yield (see the section on *Key Performance Indicators*), the ambient temperature is needed to calculate the heat losses. To compute accurate values, an ambient temperature sensor should be placed close to the collectors. Note that the sensor must be placed in the shadow as the air temperature is needed for the calculation.

Generally, the ambient temperature can be used for calculating the expected heat losses of multiple components of the system, allowing to compare the expected with the measured heat losses. However, as some components may be placed in different environments, multiple temperature sensors are needed for each respective environment.

Additionally, pressure sensors in the solar collector circuit are vital for detecting leakages or high pressure that may lead to serious damage. If multiple sensors are installed, the change of pressure may also indicate where the problem occurred. If sensors are placed in front and after the pump, the performance of the pump can be checked via the pressure difference.

Temperature sensors should be placed in each collector row after the last collector. This allows to monitor the hydraulic balancing of the collectors or if air or dirt impede the volume flow.

Furthermore, a temperature sensor at the collector joint can be used to compare to the measurement of the heat meter or different collector rows. If a heat exchanger is used, temperature sensors in the primary and secondary circuit can be used to calculate the efficiency of the heat exchanger. Furthermore, the signals of pumps like the on/off-signal, errors and the speed of rotation should be recorded as well, allowing to optimize parameters for overall performance.



Figure 5: Picture of a radiation sensor before(left) and after cleaning (right). As part of the MeQuSo-project a deviation of roughly 10% of the currently measured value was identified due to the dirt on the sensor.

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Figure 6: Radiation sensor not aligned with solar collectors as indicated by the yellow and red line.

Heat Storage

A heat storage or buffer tank can be used to store the solar yield for a certain amount of time such that energy can be delivered also when there is no radiation available. For controlling charging and discharging of the heat storage, multiple temperature sensors can be inserted into the tank. For monitoring purposes, at least three sensors should be placed inside the tank, measuring the temperature at the top, the bottom and the middle of the heat storage. However, in large-scale applications at least 5 to 10 temperature sensors are typically used. With this information, the quality of the stratification can be estimated. In addition, when combined with the ambient temperature and some meta-information about the tank, heat losses as well as the energy stored in the tank can be computed (see the section on *Key Performance Indicators*).

The flow and return temperatures of the input and output of the heat storage should be measured to analyse heat losses from piping, and better evaluate in- and outtake. When the charging and discharging behaviour of the storage needs to be analysed too, signals from mixing valves must be recorded as well. Otherwise the temperatures of different storage layers cannot be computed correctly and no statements about the quality of the storage stratification can be made.

Additionally, like at the solar collector circuit, either a heat meter or a volume flow sensor accompanied by temperature sensors should be used to measure the heat outtake from the storage tank. Similarly, signals from pumps should be recorded as well.

External Heating

In case an external heating source is used, a heat meter or volume flow sensor together with temperature sensors should be installed to measure how much energy was produced by the external source. Pump signals and set temperatures can be used to further analyse and optimize the system control. As with the solar collector circuit, the pressure should be measured in order to detect leakages and other faults. Alternatively, the fuel or electricity consumption of the external heating may be used to calculate the heat introduced by the system, for example by measuring the electric consumption of electric boilers or the gas consumption of gas boilers. This requires an efficiency model of the external heat source.

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Absorption Cooling

The absorption cooling section typically consists of an absorption chiller, a cooling tower and a consumer circuit where the chilled water is requested. In order to evaluate the performance of the chiller, the temperatures of feed and return as well as the respective volume flow need to be measured for each of the three circuits. For the chilled water side, a heat meter is typically installed to measure the cooling energy provided to the consumer. With the temperature and flow measurements of each circuit estimated values for the energy yield can be calculated by using a simulation model of the chiller. Plus, key performance indicators like the thermal coefficient of performance (COP) as well as the energy efficiency ratio (EER) can be computed (see the section on *Key Performance Indicators*). In order to calculate the electrical COP and EER, an electricity meter must be installed as well. For the cooling tower, fan speed and especially the water intake are important properties to analyse the efficiency of the re-cooling circuit or detect accumulation of mud in the tower. Again, signals for pumps, fans and valves should be recorded in order to analyse the system properly, and pressure should be measured to detect leakages.

Consumer (Domestic Hot Water, District Heating)

Similar to the other circuits, the temperature of the flow and return of the circuit should be measured, together with the pressure and control signals. As the consumer typically is the system boundary of the solar heating system, it is recommended to install heat meters which can be used for energy flow analysis.

Data Acquisition

Before data can be used for monitoring purposes, it has to be acquired from the sensors and transformed to digital data. Usually a data logger is installed at the system site to collect the data and provide a short-term data storage. Plus, this allows on-site devices to display the data, which is crucial for services or if network errors occur. Hence, this section deals with the requirements of data acquisition and how data should be stored and exported.

Data Logging

As (Knabl, et al., 2012) describes, the system responsible for logging the data must be as fail-safe as possible in order to guarantee the measurement of the data at any time. In order to minimize communication problems, it is recommended to apply the logger directly at the PLC. Even if network errors occurred, the data should be available at least for 3 months. In conclusion, a data logger is recommended to be used which writes data in at least daily files on a non-volatile memory, which is as independent of other network components as possible. With this setup, even if there are network issues, the data can be visualised on-site and can be accessed during services.

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Logging Interval

The frequency of storing the data greatly influences the subsequent processing of the data. If the logging rate is too low, the data may not be usable as high uncertainties in the results are introduced and the dynamics of the system cannot be studied anymore. For example, if the daily solar yield is to be compared to the solar irradiation during the day, the integral of the irradiation must be calculated. With a one-hour sampling rate, high errors in the radiation energy would occur as the radiation varies a lot during a one-hour time interval. On the other hand, if a high sampling rate is used for logging the data, more measurements need to be stored. This drastically increases the computational resources needed for storing and processing the data. Based on (Knabl, et al., 2012) the data should be logged at least once per 5 minutes. Based on (Fischer, 2008) an interval of 1 minute is recommended. For control parameters, logging “on-change” is recommended.

Naming Standards

Based on the results of (Fischer, 2008; Ohnewein, et al., 2016) a naming schema can be used to standardise the names of sensors at different plants. This greatly improves the re-usability of algorithms and improves the readability. While there is no agreed standard on naming yet, usually the scheme includes English shortcuts for the type of measurement (te – temperature, pr – pressure, ...), for the circuit (solar, heat storage, ...) and for the part that is measured (col – collector, pmp – pump). The focus is to create small, easily readable and clearly defined names for each type of measurement at each system that can be used by the database and algorithms.

Data export

Finally, it often makes sense to only temporarily save the data at the system site for access during services, but to export the data to a centralized server where data from multiple systems are stored and processed. This is important as on the PLC on-site only calculations with small numbers of data points and small timeframes are feasible. On a PC or server much more sophisticated operations on larger portions of the data are possible. A benefit of a central system approach is that changes in algorithms can be applied once instead of at each solar system individually. In addition, the space requirements on the computer at the system site can be relaxed. To decrease the risks for the system in case of a network error, nevertheless either a certain amount of fault detection must be done on a PLC or at system-site level, or a redundant setup must be used.

To enable an automatic monitoring process which saves time and reduces costs, the data export must happen automatically (Knabl, et al., 2012). The needed frequency of the data transmission depends on how fast faults should be detected. For very high frequencies the overhead for sending the data is higher compared to sending the data in batches. It is recommended to export the data at least daily. The transfer

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itself can be done as seen fit as long as the channels for transmitting the data are encrypted. For example, SSH or FTPS protocols can be used to ensure the security of the data.

Data Processing

Optimally, the data acquired during logging is standardised and works perfectly for all further calculations. In practice, however, often pre-processing steps are needed to use the data. This is especially the case when multiple systems are considered or if the data comes from different sources and must be re-combined. Another example is historical data where other standards might have applied.

In many of these cases the quality control and pre-processing of the data is done manually. However, there is a lot of time involved in doing so, while also requiring the personnel to have a high knowledge of the system. Hence, the automatization of pre-processing the data has big potential for saving time and reducing costs.

Extracting regular expressions

In some cases, there are expressions or unit annotations in the raw data that must be extracted in order to convert the data to numeric values. For example, annotations like “kWh” or “°C” may be present in the data. These expressions may be filtered out by using regular expressions (Fischer, 2008; Ohnewein, et al., 2016).

Conversion of units

When multiple systems are analysed that are installed in various parts of the world, data is often logged in different units, like for example SI units or the metric system. It is recommended to (automatically) convert all units to standardised ones, such that the data can be used for cross-system computations (Ohnewein, et al., 2016).

Time Format

The international standard for the representation of dates and time is defined in ISO 8601. Hence, UTC format should be used for storing the data. If instead other datetime formats are used for logging, it is recommended to convert to UTC during pre-processing. However, using UTC offsets like for example UTC+1 increases the interpretability and comparability of the data, as certain measurements like the radiation follow local time.

Sometimes time shifts are present in the data if the data logging uses time formats with daylight saving time. In this case there exists a one-hour gap in the data at one day when summertime starts, and a one-hour overlap of the data when summertime ends. Unfortunately, at the overlap the data is often overwritten by the logger without any means to extract the data (Fischer, 2008). Nevertheless, the

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conversion in UTC should be performed introducing a one-hour gap in order to correctly compute solar angles for example.

Plausibility Checks

At this early stage in the monitoring process, most error algorithms cannot be applied to the data before completing the pre-processing step. In contrast, simple plausibility checks that only consider single data points can easily be applied in the processing (Ohnewein, et al., 2016).

Min-Max Thresholds

One simple algorithm is to introduce minimum and maximum values for each data point and check if no measurement exceeds these values (Ohnewein, et al., 2016). For example, the radiation is unlikely to exceed 1500 W/m^2 , ambient temperature is unlikely to fall below -30°C (for most cases). Such detections can indicate uncalibrated or faulty sensors. As another example thresholds can also be used to detect leakages when applied to pressure measurements (Knabl, et al., 2012). Note that different minima and maxima are needed to check that the sensor measures physically plausible values and to check that the measured quantities are plausible for the specific part of the system. For example, negative pressure measurements indicate faulty sensors. However, a measurement of 0.5 bar at the solar collector circuit is physically plausible but too low for a running functional system. In both cases setting appropriate threshold can be used to trigger warnings in an early step of data processing.

Constant values

Another problem is that faulty recording of sensor data at the PLC sometimes might introduce constant values in the data, while the measured values are discarded for a period of time. It is easy to identify such occurrences as most measurements at solar thermal systems vary slightly even over short periods of time. When values are exactly constant for 5 minutes, it can be assumed that the data was recorded incorrectly.

It is important to apply the plausibility checks before the resampling step (see below), as errors in the data would e.g. corrupt the interpolation.

Down-Sampling

As part of the pre-processing one might resample the data to a common time grid. This is a requirement for being able to perform basic calculations like addition or subtraction of multiple data points. Plus, a uniform time grid may simplify some calculations (like the integration of values) or even be a requirement for certain algorithms (i.e. a recurrent neural network assuming equidistant timestamps). As a rule of thumb, a time grid of 1 minute for high accuracy or 5 minutes for faster accessibility is good enough for most calculations. For down-sampling the data, multiple algorithms might be considered:

Nearest

The first alternative is to use the nearest measured value for each timestamp in the grid. This is a fast and

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simple algorithm, because only one value must be considered per timestamp. As a disadvantage, a lot of data is lost when the original data has a very high resampling rate, losing the corresponding information. In contrast, when the frequency is low but if there is a lot of missing data, the algorithm might lead to many constant values or sudden jumps in the resampled data.

Averaging

An alternative is to calculate the average over some period of time. This way, the measurements around each of the desired timestamps is condensed in a single value.

However, this approach might introduce artificial information into the resulting resampled data. For example, a pump rotation signal suddenly decreasing from 100% to 0% might be averaged to 20% - even though if pump rotation speeds below 40% are not supported by the system control. Similar problems might arise if the conditions of the measurement change during the time-interval. For example, assume that the temperature of the fluid in the pipes of the solar primary circuit is measured and pumps started to run during the considered time interval. In this case, temperatures before starting the pump may be low (fluid in pipe is still cold) but abruptly increase when the hot fluid from the collector passes the sensor. Again, averaging these values might indicate medium temperatures when indeed only hot and cold temperatures were present at the system. Another issue with averaging is that a single outlier in the data can affect the aggregated result (i.e. many measurements of 10°C and one with 175°C resulting in 25°C). In all the three examples above using median values instead of averages would yield better results. Additionally, implausible values should be identified before down-sampling to reduce the effect of outliers. In any down-sampling method some information is lost due to the aggregation. By using averages, minima and maxima are smoothed down. This might be a desired effect or introduce issues based on what the values are used for later in the monitoring process. For example, if the data is used for spotting outliers or used to recalculate other measurands, averaging the data is not always beneficial if the time-interval is too high. If, on the other hand, values are used for summations (i.e. calculating daily energy yield based on power) averaging is a better choice than using 'nearest' values as only aggregated information is needed instead of individual measurements.

In summary, averaging is a good method to identify representative values in a certain timeframe, however, can only be used well if the measurand conditions do not change too much during the time. In this case, artificial information might be introduced and outlier might be smoothed too much.

Spline-Interpolation

Alternatively, one can use spline interpolation to interpolate the data first and using the results to create an equidistant time grid. In the case of linear spline interpolation, one can think of lines drawn between every adjacent datapoint of the measurement data. All the values which lie on the desired equidistant time grid are used for the resulting down-sampled data. The process can also be done with higher order of spline interpolation, however resulting in increased running time of the method of the method.

In comparison to the nearest method, more than one datapoint is used for each down-sampled result. In

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contrast the linear-spline interpolation assumes that the value in-between two timestamps must be in-between the range of the two measurements, being the closer to a value the closer the timestamps are to each other. This is true for most measurements because of the inertia of thermal processes but not for signals and similar conditions as described in the averaging-method section. In the case of the desired grid being aligned with the logging-interval the linear-spline interpolation and the 'nearest'-method yield the same results. In contrast to the averaging-method, the 'nearest' and the spline interpolation method assume that only adjacent values should be used in order to not smooth outliers too much.

The linear-spline interpolation method is used for example by (Ohnewein, et al., 2016) for resampling the logging-data, using additional modifications to ensure consistency when applied to discrete variables.

Other methods

Finally, there are many more methods that deal with how time-series can be down-sampled while still ensuring that trends and characteristics are well captured. A list of methods used for reducing the number of datapoints for visualisation have been studied by (Stainarsson, 2013). For example, the Largest-Triangle-Three-Buckets algorithms shows good results. It separates the data equidistantly in buckets and for each chooses the datapoint which is the *most significant* as representative. The significance-score is calculated based on the effective area of the datapoint – that is the area which is spanned by a triangle from the considered datapoint to the most significant points of the adjoining buckets. In this sense, only datapoints are used which are discriminant compared to the adjacent datapoints in order to capture the most important information. A more detailed description can be found in (Stainarsson, 2013).

While the methods discussed in the paper yield good results especially for visual interpretation, results from (Ohnewein, et al., 2016) stressed that there are some disadvantages of using more elaborated methods. First, typically more sophisticated methods lead to more computation time and second, they are harder to understand which results in less user acceptance. Other than that, algorithms selecting datapoints for each measurand separately cannot be parallelized for multiple datapoints. Thus, the algorithms might use values from different timestamps for two measurands, leading to inconsistencies. For example, the down-sampled data may indicate running pumps and no volume flow at the same time, due to using measurements at different timestamps for each measurand for the down sampled data.

In summary, more sophisticated methods play a high role for visualising data. However, for down-sampling during pre-processing simpler methods typically suffice. This is because of the rather small difference between the logging- and down-sampling rate together with the typically low inertia of the measured values of solar thermal systems. In addition, computation time can be kept to a minimum with simpler methods and inconsistencies can be minimized.

Missing Data

Even though resampling algorithms are essential for further analysing, they might introduce artificial information in the monitoring data. While for some data points the introduced error can be estimated to be very small, for other data point interpolating missing values should be omitted. For example, missing

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data of ambient temperature for ten minutes can be replaced with interpolated data quite easily due to its low thermal inertia. On the other hand, missing irradiation measurements should not be filled artificially with the same simple approach, as high fluctuations might have occurred during the time frame. If naming standards as described in section *Data Acquisition* are used, this behaviour can be easily implemented in a modular way. For example, by using a different “maximum gap” parameter for each individual measurement type and assigning measurement types to measurements (Ohnewein, et al., 2016).

Of course, missing data itself may also hint to various problems, such as network issues, power failure, broken cables, connection problems between the PLC and sensors, or problems at the sensors. Thus, even if the missing values can be guessed with high probability and replaced in the monitoring data, the presence of missing values should be recorded and stored as well for further analysis. Missing data should be prevented, and faulty data acquisition remedied as soon as possible!

Data Storage

Once the data has been acquired and pre-processed, the data must be stored in a way that fault-detection algorithms and benchmark calculations can access the data they need. As some algorithms may require a lot of different measurements or long time periods of data, it is important to store the data in a way to ensure that the selection and filtering of data is fast and reliable. Especially if some analyzation is done manually by a domain expert (for example for diagnosis after a fault-detection algorithm spotted a malfunction), a fast retrieval of the data can save a lot of time and money.

In summary, a data management system is essential for automated monitoring as it provides an interface for algorithms to the data. With a good setup, time can be saved due to reducing the implementation time of new algorithms and reduce the time for fetching data. Thus, this section deals with discussing the properties of the data, following recommendations about which data storage technology to use.

Properties of the data

To analyze which data storage technology works best, first it is important to understand some properties of the data which needs to be stored.

Volume of the data

As described in (Fischer, 2008) the amount of monitoring-data very quickly reaches values above multiple gigabyte. Estimated very conservatively, a solar heating system has a technical lifetime of 20 years². Combined with the recommendations of chapter

² In fact, the lifetime modern solar thermal systems is expected to be at least 30 years. However, the consideration in the text only serve as a minimum threshold to clarify the magnitude of the acquired data, so a more conservative estimation is used.

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Sensor Technology, each system should have at least 15 different sensors, with values stored each minute, resulting in 1.2 GB of data as the absolute minimum:

$$V_{\text{lifetime}} \approx 20 \left[\frac{\text{years}}{\text{Lifetime}} \right] \cdot 365 \left[\frac{\text{days}}{\text{year}} \right] \cdot 1440 \left[\frac{\text{minutes}}{\text{day}} \right] \cdot 1 \left[\frac{\text{measurements}}{\text{minute}} \right] \cdot 15 [\text{measurements}] \cdot 8 \left[\frac{\text{Bytes}}{\text{measurement}} \right]$$

$$\approx 1.2 \left[\frac{\text{GB}}{\text{Lifetime}} \right]$$

However, in practice the number of sensors used in big-scale systems is in the range of 100 to 1000 measurements, depending mainly on the amount of collector temperature sensors and thus on the amount of collector area. When more than one system is stored in the same database, we arrive at approximately:

$$V_{\text{system}} = \frac{V_{\text{lifetime}}}{20[\text{years}]} \approx 4 \left[\frac{\text{GB}}{\text{year}} \right], \quad V_{100 \text{ Systems}} = 100 [\text{Systems}] \cdot V_{\text{lifetime}} = 8 \left[\frac{\text{TB}}{\text{Lifetime}} \right]$$

In conclusion, this shows that the volume of data is in the range of multiple GB to few TB. However, this can easily scale to a much higher amount. Based on current trends in the energy sector, higher frequencies for data logging are used and the number of systems is increasing. Plus, more and more system control parameters are added to the monitoring data and the number of sensors per system is increasing. Due to the exponential data growth that can be seen in a lot of sectors, the values above merely serve as conservative estimate for a lower bound.

Data Categories

The focus of the data storage is to store the monitoring data of the solar heating systems. However, depending on the application, also additional data might be stored, for example details that are needed for some fault-detection algorithms and KPI calculations. For example, meta-info such as the number of collectors at the system, their orientation, the geographical location of the system and similar values might be interesting for many algorithms and thus should be stored in the database as well. Additionally, it makes sense to add information regarding the system control, like reference or set temperatures, which might be needed to interpret the sensor data. Finally, also the result of fault-detection algorithms and key performance indicators need to be stored, as they need to be accessible for further analysis.

In effect, the following categories of types of data could be categorized – following in large parts the results of (Fischer, 2008):

Category	Description
Sensor Data	Typically consisting of timestamp, value, and ID specifying what was measured. Recommended to be stored in equidistant timesteps to allow calculations concerning different measurements.
System Control data	Data describing the system control parameters of the system, typically in similar form to sensor data with values for timestamp, values and parameter

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	ID. Depending on how often the control parameters change, it makes sense to either store the data “on-change” so a new entry is written only if the parameter was changed, or in equidistant timesteps similar to the sensor data. In the first case, less data needs to be stored while in the second case calculations in combination with sensor data can be done easier.
System Info	This category consists of additional information on the systems, such as the number of collector units, the orientation and tilt of collectors, the type of fluid used in the primary circuit, or the expected amount of solar yield based on the design of the system. The corresponding values can be of different type or may be implemented as references to documentation. Naturally, the system info stays the same over long periods of time. However, some values might also change, as for example more collectors are added to the system.
KPI results	Key performance indicator data is very similar to sensor data. However, they are often calculated for time periods instead of consisting of timestamp/value pairs. Instead they typically consist of values for the period-start, period-type, value and KPI ID. For the periods it makes sense to use time periods that correspond to the behavior of the system, which in turn depends on the irradiation and the demand. As these typically follow seasonal, daily or more frequent patterns, periods like minutes, hours, days, weeks, months and years are the most interesting for the calculation of KPIs.
Fault-Detection results	Depending on the type of fault-detection algorithm, the results are either timestamp/value pairs where values derived by a model are stored for each equidistant timestamp (e.g. Parity-Space methods) or consist of error-notifications like the detection time, the time the fault has occurred, a message explaining the fault, and a severity rating and information about which algorithm detected it.
Fault-Detection Parameter	In addition to saving the results of the fault-detection algorithms, sometimes it is important to also save the parameters of algorithm for each system. For example, if machine learning is used for training a classifier to detect faults, the data from the trained algorithm can be stored such that it does not need to be trained at every run. Because of the different types of fault-detection parameters, the type of data that needs to be stored cannot be generalized. In addition, it might be interesting to analyze how the parameters change, which increases the complexity for storing the values.
User Management	Finally, as the data might be used for visualizing the data or might feature applications that allow notifications, a user-management might be stored in the data storage as well.
Additional data	Additional data might be stored which help during the process of analyzing the data. For example, information regarding the system representation (see below) or the conversion of units to standard units.

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Data-Storage Technologies

In the previous section the characteristics of the data that need to be stored have been elaborated. With this information it is possible to analyse which storage technology works best for storing it. In fact, the storage technology should have the following properties:

Usability: Easy to use for automatically storing the data and fetching data manually as well as via algorithms. The implementation of new algorithms working with the data storage is fast.

Query speed: Data can be selected and filtered in a reasonable amount of time.

Writing speed: Writing data of multiple systems into the storage does not prevent users from running queries for a long period of time. The data is stored fast enough such that fault-detection algorithms can respond reasonably fast to malfunctions of the system (i.e. an algorithm always can use the data from at least the previous day).

Security: Allows to prevent unauthorized users from changing values in the data storage.

Safety: Allows easy backup of the data. Ensures that values are stored correctly.

Flexibility: Allows to store the data of all data categories described above.
Allows to add additional sensors or delete sensors during operation of the system.
Allows to cope with name changes or similar operations.

Scalability: Allows to scale for multiple systems and high numbers of sensors at the solar system, more accurately for storing data volumes in the range of GB to multiple TB.

Independence: Independent of the solar system network. No software/hardware needed at the customer site.

File-based storage (CSV format)

Traditionally, monitoring data was often stored in files with yearly, monthly or daily data in a comma-separated-file (CSV) format. As these files can be viewed and edited by Excel and similar tools domain experts, scientists as well as customers can easily interact with the data. Additionally, appending new data to files is very fast, which makes data logging in this format beneficial.

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However, there are some drawbacks to this kind of data storage:

First, as hinted above, data must be stored in (daily-, monthly-, yearly-) chunks rather than in one large file. If not separated, the file would quickly grow too large to be read (by Excel for example). As some algorithms need the whole data, an algorithm must be implemented to recombine data from different files. If on the other hand, only a small section of the data is needed – for example the values of one sensor for a larger time-period – all files containing some part of the data must be read in. In effect, much more data than the desired output needs to be fetched initially, and filtering can be applied only after reading the whole file. Again, this selection-and-filtering would have to be implemented by some file-management algorithm, to allow fault-detection methods to access the data.

Secondly, organizing and updating the data can be troublesome for CSV files. For example, datapoint names might get changed or added during the lifetime of a solar system. This would result in changes in the CSV file structure which either need to be applied to all files or the algorithms accessing the data would need to deal with structure changes. Additionally, there might be references from one table to another, for example for system representation and datapoints. As this is not implemented in CSV, changing values in one table need to be updated in other tables manually. Aside from references, it can be complicated to store the different categories of the data in a file-based format.

Finally, there is no inbuilt user-management which allows and disallows users to read and write the data. However, this could be implemented by altering the security properties of the directory.

In summary, CSV files are good for intermediate storage of sensor data but lack the functionality to select, filter and organize the data efficiently and securely. Nevertheless, the format is easily interpretable and can be understood by almost everyone as Excel is a very commonly used software.

Relational Database Management Systems (RDBMS)

In more modern approaches relational database management systems (RDBMS) are used (Fischer, 2008; Ohnewein, et al., 2016) for storing the data. These databases with their origin in 1975 save the data in tables, each consisting of multiple columns and rows of data. A user can interact with the tables via using SQL (structured query language) for querying and writing new data into the database. To allow faster selection and filtering, special data structures like indices can be used. In addition to the SQL interface for writing and selecting the data, the RDBMS includes other features such as auto-updating references to other tables when some value is changed, secure transactions such that changes are consistent and inbuilt user management. Due to storing the data in a row-column manner while references to other tables can be made, RDBMS can be used for any of the above-mentioned data categories if designed correctly. However, changing the structure of the database during operation is not well supported and should be avoided. Hence, care must be taken during the initial design of the RDBMS layout.

While they avoid most of the drawbacks of CSV, relational databases require more knowledge to work with and if designed badly, can still have high computation times for storing and selecting data. Plus, many people want to use Excel for their analyses. This can however be tackled as most RDBMS software tools support exporting the data to CSV format easily. In summary, SQL is a good way to store the monitoring

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data as this type of data storage technology is well-established and has lots of documentation while providing the most necessary properties described in the introduction of this section.

NoSQL-databases

There are some cases where relational databases reach their limit. For example, when a lot of data needs to be stored, the volume of the data may not be stored on one server anymore. However, classical RDBMS are based on the premise that all the data is accessible on one device. Instead of increasing the server capacity, which can be very costly, one approach is to use many devices which share the data. Another problem for relational databases is when too much data needs to be stored at the same time. In this case again a distributed system can be used to process and store the data in parallel. Another idea is to use data-structures other than relational tables to store the data more efficiently. Additionally, as described above, RDBMS need a predefined structure to store the data. However, there may be cases where the structure of the data changes rapidly over time or is unknown at all, calling for databases which can deal with this kind of data.

The problems described above are the so called the four big V of Big Data: Volume, Velocity, Veracity and Variety. For these problems new database concepts called NoSQL (Not only SQL) databases were developed that cope with some of the problems above. In fact, it is possible to differentiate between some main types of NoSQL databases:

- **Distributed SQL databases:**

One way to cope with huge amounts of data is to store the data on different servers. In this way, costs can be reduced as multiple smaller servers are often cheaper than one very large one. However, this means that data is not stored together but is separated upon multiple devices. While for the user this should not make a difference, the database system thus needs to cope with knowing where to store and find the data and how to combine it. To ensure that the database is still functioning if some of the servers are offline, data is often stored redundantly on multiple servers.

The famous CAP theorem states that for any distributed database system, the properties Consistency, Availability and Partition tolerance can never be fulfilled simultaneously. Here, consistency means that the data in the database is the same for all devices which store the same data. Availability means that a user can always access the data in a reasonable amount of time without being locked, and partition tolerance means that the software still works even though some of the servers are offline due to network errors for example. Implementations of all distributed data storages thus guarantee these three properties only to a certain extent, focusing on different trade-offs of between consistency, availability and partition tolerance.

Thus, there is a lot of overhead and additional work required to distribute the data and manage it. However,

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even though this may increase the computation time for writing data (as data is stored redundantly) and makes operations on the data more complex, it makes the database highly scalable for huge amounts of data and it can reduce the reading time as data from different servers can be read in parallel.

One way to separate the data meaningfully would be to store all information regarding one system on the same partition. This way a user focusing on one system has all the data needed on one server performing the computations, while other systems can be accessed via other partitions in parallel. Hence, this distribution approach makes sense if datapoints are more often compared internally than across systems. Another approach would be to enforce fast access to recent data by storing historic data separately. This follows the assumption that recent data is of much more interest to users than measurements multiple years ago.

In summary, distributed databases are recommended if the data exceeds volumes such that increasing the storage capacity of one centralized server is not cost-effective anymore. In addition to allowing more data to be stored it can also be used to handle operations on each server in parallel. Thus, it can also be used to speed up the extraction speed of data. Another benefit is that data can be stored at system site while still making access from algorithms easy. This is the case as distributed database management systems typically provide an interface which is the same independently from where the data is stored. The drawbacks are higher complexity in handling the software in comparison to classical relational databases and slightly more time needed for writing data.

- **Column-oriented Database**

In SQL databases data is stored in tables in a row-wise manner, such that if a row is selected all the data in the columns are read into the memory. If the table has a lot of columns, but only a small amount of them are needed during a query, still all the columns must be read with this behaviour. Column-oriented databases instead store the data in column-wise fashion where for each column, key-value pairs are stored. Hence, the columns of the table are not connected and if a query is run only the relevant columns need to be read in. While this increases the speed for fetching column-data from tables with large number of columns, this also increases the storage requirements. This type of NoSQL database might be relevant for sensor- or system-control data to store timestamp value pairs in one column for each measurement making it easy to extract the information without loading many columns.

- **Key-Value Stores:**

Key-Value databases save data in key-value pairs, while the value can be of arbitrary shape and is more flexible than in the SQL case. For example, one can store XML files containing the values of all sensors at a certain

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timestamp as values and retrieve the values by querying for the corresponding timestamp. This key-value design can be especially helpful when facing very unstructured data – for example if the amount of datapoints varies from one timestamp to another – as the information in the value can be of arbitrary size. This contrasts with the relational database system, where new columns would have to be created to store new data, or a lot of NULL values would be inserted.

Because of this behaviour and the simplicity, key-values stores are very good at handling data with high velocity and veracity. However, the compromise in storing unstructured data sometimes makes analysing the data more troublesome, as the algorithms accessing the data must deal with inconsistencies in the content of the values. While this type of data-storage technology is good at collecting vast amounts of unstructured data rapidly, the data gathered after the pre-processing step in monitoring (as described above) is already structured. Additionally, the velocity of the monitoring data with minutely measurements is rather low. Therefore, both main advantages of key-value stores do not have a significant effect on storing the monitoring data.

- **Document Stores:**

Relational database systems try to minimize the redundancy of the data by allowing references from tables to one another. If this data is selected both tables need to be read and filtered, and the results recombined (joined) again to give the requested data. Depending on the frequency of such queries and the structure of the tables this may be very time-consuming. In contrast, document-stores allow to store information together which may be needed together. For example, in for a web-application comments to a page would be stored together with the page as this information is highly related to each other's. Other than the Key-value store the structure of the database must be defined, however this allows the user to use the information inside the documents for queries.

While this set up seems not very helpful for sensor data, it might be good for storing system-information. As the structure inside the documents can be used for filtering but are less strict then the fields of relational databases, one could for example store data related to a component in a document. Thus, when meta-information about the system-part is needed all valuable information would be fetched together.

- **Graph Databases:**

Finally, relational databases are less powerful when storing data about relations between objects. For example, in the case of Facebook, graph databases are used to store the relationships between the users. However, they offer less benefit when storing sensor data for example.

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In conclusion there are good reasons to consider NoSQL databases for some of the data categories needed for monitoring. However, if the data does not exceed high volumes or extremely fast responses are needed, relational databases are enough to provide the needs for automated monitoring.

System-representation

As described by (Dröscher, et al., 2009) solar systems often vary in terms of their hydraulic setup. This makes it difficult to automatically interpret the data and assign processing- and fault-detection-algorithms accordingly. To make the information of the hydraulic setup accessible to monitoring-software various approaches exist:

System-based design:

If only one system is monitored, then algorithms and software-components could be designed especially for the corresponding system. This approach is sometimes used by researchers that focus on single systems with special applications. As an advantage, algorithms can be designed to give detailed insights into this special system. In the case of multiple systems, however, this method prevents the re-usability of the algorithms and leads to a high time-consumption upon including new systems in the monitoring process.

Representative layouts:

If multiple systems are addressed, often they are analysed in terms of representative layouts like “solar system with district heating”, that are used as representative for a wide range of similar system concepts (for example in (Knabl, et al., 2012; Fischer, 2008)). If a system fulfils the requirements of the representative-layout, the corresponding algorithms can be used for evaluating the system. As advantage, this approach allows to generalize system-layouts such that multiple systems may be monitored with the same algorithms. Plus, upon introducing a new system to the monitoring software, minimal resources are required to do so. On the negative side, the layouts may be too inflexible to be applied on more complicated system hydraulic setups but can only be applied to a small portion of systems. Plus, implementing new algorithms needs more domain-knowledge as they should be able to generalize to more applications.

Component-based modularisation:

As a different approach, one can build up the system hydraulic by specifying each component of the system and combining them to the form different system layouts. This approach is used in the simulation software TRANSYS for example to build up various systems. The benefit is that similar to the system-based-design the hydraulics of the system can be modelled quite exact, making the evaluation more accurate. In contrast to the System-Based Design, the modularisation of the components allows to formulate re-usable algorithms. As a disadvantage, the user must specify a lot of information during the implementation of new system and manually combine components, which is a tedious task.

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Modular framework design:

As an alternative to the component-based modularisation and the representative layouts (Dröscher, et al., 2009) suggested using modular framework design. The solar systems are separated into sections like the solar circuit or the heat storage to form multiple modules, that can be recombined to form various system layouts. The idea is to use the fact that at each module the components are the same independently of the system application. To compensate small differences in the hydraulic setup, variations of each module are proposed. The method discriminates between modules describing the basic function of the components, module-variants describing various forms for hydraulic setups and detail-variants which deal with different variants at specific positions inside the module (Dröscher, et al., 2009; Feichtner, 2010). The goal of this approach is to minimize the time-consumption when implementing new solar systems to the monitoring software while still allowing more complicated setups.

Block-based modularisation:

Another more object-oriented approach to map the data to the system-layout is to use a block-based modularisation that was introduced by (Ohnewein, et al., 2016). It was developed to enable a highly flexible, efficient, effective and intuitive representation of the system. It works by defining system blocks, each consisting of one or many datapoints and system-parameters similar to the modular-framework approach. However, the difference to the modular-framework representation is that the blocks can be both formulated on high- or very abstract levels of detail. Plus, the blocks can be combined in different ways and may be hierarchically dependent on each other.

For example, one block could be the “heat-meter” block consisting of two temperature, a volume flow and a power measurement. This block can be assigned to all heat-meters of a plant, as the same calculations should be performed on all of them (i.e. checking that the heat meter works correctly). However, the block-based approach would also allow to formulate a “solar-circuit” block, which may consist of different sub-blocks for example an instance of a “heat-meter”, “pump” and “collector” block.

In conclusion, this allows to formulate algorithms both on small subsections that are always similar like the heat meter, but also on larger-sections of the systems to give insights about the overall-performance of the solar plant. Thus, it is a combination of the modular-framework design and the component-based modularisation

One of the drawbacks of this approach is that - while being flexible - the system layout must be specified by assigning blocks to datapoints and blocks to blocks for each system. However, this can be automated if a good naming scheme is used (see Data Acquisition). In this case, helper algorithms may easily be able to assign datapoints to blocks simply according to their name.

Key Performance Indicators

In order to detect trends in the long-term performance of solar heating systems, component- and system-related benchmarks can be computed. With this, the measurement data which is hard to interpret without

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visualisation can be distilled into key-performance-indicators representing the status of the system or components. Thus, they allow to get an overview of the system quickly, enable comparisons to other systems and make it possible to share the potential of the technology with others. However, they may also be a prerequisite for certain alarm algorithms. For example, analysing the key performance indicator of a component may show that the efficiency of the component steadily decreases, and repair is needed.

Recommended Benchmarks

Thermal Energy Yield:

The thermal energy yield is one of the most important benchmarks for monitoring personal and stakeholder as producing as much usable energy as possible is the main task of the solar system. By comparing the energy yield with historic values or design, obvious dysfunctions of the system can be detected. Usually, the energy yield can be calculated based on the heat meter reading:

$$Q_{period} = em_{period_end} - em_{period_start}$$

Where em is the accumulated energy meter reading and E_{period} [kWh] is the yield corresponding to the section of the system that is measured via the heat meter. If not directly measured by a heat meter, the energy yield can be calculated via inlet and outlet temperatures and volume flow of the section:

$$Q_{period} = \int_{period} \dot{Q}(t) dt = \int_{period} \Delta T(t) \cdot c_p(T_{mean}(t)) \cdot vf(t) dt$$

Where $\dot{Q}(t)$ [kW] is the instant power, $\Delta T(t)$ [°C] is the temperature difference between inlet and outlet temperature, $vf(t)$ [m³/h] is the current volume flow and $c_p(T_{mean}(t))$ [kWh/m³.K] is the heat capacity of the fluid in the pipes at the average temperature $T_{mean}(t) = \frac{T_{inlet} + T_{outlet}}{2}$ [°C] of inlet and outlet flow.

Radiation Sum:

In addition to the thermal energy yield the amount of radiation energy on the collector is a very important benchmark as it is the main source of energy of the system. Without this information a low thermal energy yield may correspond to a critical fault or simply low irradiation during that time. Plus, the knowledge about solar radiation enables to analyse energy balances (see below) and the efficiency of solar collectors (see below). However, in contrast to the thermal energy, which is accumulated by the heat meter, for the radiation only instantaneous values are measured. Thus, the radiation values must be integrated to get the radiation energy I [Wh/m²]:

$$I = \int_{period} G(t) dt$$

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Energy balance:

Based on (Knabl, et al., 2012) the calculation of energy balances is recommended in order to analyse heat generation and consumption. Both the input and the output of sections of the system of different time periods from days to years can then be compared to historic or design values.

The energy can be calculated with heat meter measurement or temperature and volume flow measurements as described above. Based on the principle of conservation of energy the energy flow of system-sections can be analysed:

$$Q_{in} + Q_{out} + Q_{loss} = \Delta Q_{stored}$$

Where Q_{in} [kWh] is the sum of energy going in the system during some time period from various sources, Q_{out} [kWh] (typically negative) is the energy yield leaving the section to various sinks, Q_{loss} [kWh] (typically negative) is energy lost to surrounding due to heat losses and ΔQ_{stored} [kWh] is the additional energy stored at the sections components. The latter is important for sections such as the heat storage and the heat stored in the pipes.

By comparing with historic values, changes can be visualised to detect dysfunctions. Furthermore, it may enable the operator of the system to tune the energy flow in a way to create the highest benefit for the customer. Apart from analysing the direction from inputs to outputs the energy balances can also be used to detect increased heat losses that indicate faults.

Specific Solar Thermal Energy Yield:

It is hard to compare the solar yield Q_{sol} [kWh] of different systems as the yield depends linearly on the size of the collector area A [m²] installed at the plant. Thus, by dividing the energy yield by the gross collector area this enables to compare different systems independently of their collector size, resulting in the specific solar thermal yield E [kWh/m²].

$$E = \frac{Q_{sol}}{A_{col}}$$

However, factors such as different weather conditions and orientation is not covered when comparing the specific solar yield of different systems.

Effective Collector Efficiency:

As described above the specific solar yield is an important key performance indicator as it decouples the energy yield from the number of collectors used at the system. However, the specific solar yield is also dependent on the weather conditions of the system making it hard to compare the efficiency of the collectors. Thus, by dividing by the radiation sum during the time-period, a more potent benchmark can be created.

The effect can be more easily be understood when looking at the solar key mark equation, considering the parameters η_0 , a_1 and a_2 only:

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$$\eta_{col} = \eta_0 - a_1 \frac{T_m}{G} - a_2 \frac{T_m^2}{G}, \quad T_m = \frac{(T_{inlet} + T_{outlet})}{2} - T_{amb}$$

With coefficients η_0 [%], a_1 [W/m².K] and a_2 [W/m².K²] describe the efficiency and first and second order heat losses of a collector for radiation values $G > 1000$ [W/m²], with T_m [K] being the temperature difference between the average collector temperature [°C] and the ambient temperature T_{amb} [°C]. Thus, the specific energy yield E can be approximated by:

$$E = \frac{Q_{Sol}}{A_{col}} \simeq \int_{period} G(t) \cdot (\eta_0 - a_1 T_m(t) - a_2 T_m(t)^2) dt$$

By dividing with the irradiation energy during that period we arrive at:

$$\begin{aligned} \bar{\eta} &:= \frac{Q_{Sol}}{A_{col} \cdot I} = \\ \eta &\simeq I^{-1} \cdot \int_{period} G(t) \cdot (\eta_0 - a_1 T_m(t) - a_2 T_m(t)^2) dt = \\ \bar{\eta} &\simeq \int_{period} \frac{G(t)}{\int_{period} G(t) dt} \cdot (\eta_0 - a_1 T_m(t) - a_2 T_m(t)^2) dt \end{aligned}$$

If we follow the (wrong) assumption that that the radiation is independent of t we can extract G and get to:

$$\bar{\eta} \approx \int_{period} (\eta_0 - a_1 T_m(t) - a_2 T_m(t)^2) dt \cdot \frac{1}{t_{end} - t_{start}}$$

Note that the equation above is the definition of an average: $\bar{x} = \int_a^b x dt \cdot \frac{1}{b-a}$. Because of this, $\bar{\eta}$ can be interpreted as the average efficiency of the solar collectors over the time period. Even though the assumptions made in the process are not true, the resulting KPI $\bar{\eta}$ [%] as defined above can nevertheless be seen as an “effective” collector efficiency and be helpful to analyse the efficiency decrease of the collectors for example or to compare collectors to another. Alternatively, this can also be seen as energy efficiency ratio (see below) between the available radiation on the collectors $A_{col} \cdot I$ and the solar yield Q_{Sol} .

Thermal Energy-Efficiency-Ratio:

By dividing the energy yield of each circuit by the amount of energy that was introduced in the system during the time-period, one can also compute the Energy-Efficiency-Ratio:

$$EER_{th} = \frac{Q_{out}}{Q_{in}}$$

For example, at the solar circuit this can be used to analyse how much of the available irradiation was converted to heat and transferred to the consumer (Knabl, et al., 2012). If the collectors are for example covered by dust, the energy efficiency ratio of the solar circuit would be decreased. As the energy-

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efficiency ratio is less dependent on external factors compared to the energy yield, it makes the comparisons to historical or design values much easier. While this can be done for each circuit, the Energy-Efficiency-Ratio is especially used for describing the solar and the chiller circuit.

Electric Energy-Efficiency-Ratio (Chiller, External Heating):

In addition to the thermal energy efficiency ratio, it might also be interesting to see how much electric energy is needed to produce the required thermal energy:

$$EER_{el} = \frac{Q_{out}}{Q_{el}}$$

Thus, high values mean that there is not much electric energy needed to produce energy. While this key performance indicator can be applied to each section of the system, the electric consumption of pumps, system control and similar components is usually considerably lower than the produced energy of the solar system. Some exceptions where the electric consumption cannot be neglected however are external (electric) heating, absorption cooling machines and cooling towers. For all these applications, high EER_{el} values are critical to prove the competitiveness of the technology in contrast to traditional heating and cooling methods.

Operating Hours:

Even though the operating hours of certain components may seem unimportant, this information is very important to detect faults at control levels. Assume for example a fault at the control which disables the chiller even though enough energy is available and there is a demand for cooling water. No balancing method or energy efficiency ratio algorithm can be used, as there is simple no energy provided to the chiller. When looking at the operating hours however and compare with historic values, the fault would be detectable. Of course, a more sophisticated algorithm may check this behaviour as well by comparing available energy, production and demand. Nevertheless, information about operating hours may also be interesting to study the amount of time a certain component is unused, serviced or out of order, or to predict the wear of the component.

Number of Starts:

The number of starts is especially interesting for identifying clocking behaviour of the system. For example, some components like absorption chiller work best when operated continuously for some time due to warm-up and cool-down effects. Hence the number of starts may be used to optimize the system production.

Amount of missing data:

The occurrence of missing data is also a very important information for analysis of solar systems. First of all, it might be indicators to bad communication-networks, black-outs at the plant-site, sensor faults or various other problems during data acquisition. Furthermore, this information may be crucial for understanding the

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results of machine learning approaches, as biased measurement data may lead to wrong estimations. Most importantly, if data is missing no other faults can be detected during that time, thus introducing a high risk for the system. Because of that, it must be the top priority to reduce the amount of missing data as much as possible.

Statistics (Average/Count/Median/Min/Max/Quartiles...):

Finally, various statistics of the measurement data may give insights and a good overview of the operation of the system. For example, leakages can be detected easily when looking at the minimum pressure and compare with thresholds. The same applies for the detection of collector-stagnation or overheating of heat-storages and chillers.

Fault-Detection

The detection of faults is the core part of the monitoring process and allows the monitoring-staff to detect problems or malfunctions at the solar system. This information is crucial to react to system failures in time or to prepare and plan for repairs and services. Hence, high-performing fault-detection algorithms and good error-management is needed in order to ensure the system performance and reduce operating costs.

Properties of faults

The International Federation of Automatic Control defines a terminology for fault-detection related terms:

Table 4: Terminology related to fault-detection based on (Isermann & Ballé, 1997).

Term	Definition
<i>fault</i>	An unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable / usual / standard condition.
<i>failure</i>	A permanent interruption of a system's ability to perform a required function under specified operating conditions.
<i>Disturbance</i>	An unknown (and uncontrolled) input acting on a system.
<i>malfunction</i>	An intermittent irregularity in the fulfilment of a system's desired function
<i>error</i>	A deviation between a measured or computed value (of an output variable) and the true, specified or theoretically correct value.
<i>Symptom</i>	A change of an observable quantity from normal behavior.
<i>Residual</i>	A fault indicator, based on a deviation between measurements and model-equation based computations.

The definitions above provide helpful insights to understand some important properties of faults and fault-detection algorithms:

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Fault-indicators:

It is important to keep in mind that *faults* cannot be detected by itself but only via the *errors*, *residuals* and *symptoms* the fault introduces. Unfortunately, as a result, similar symptoms may occur for different types of faults, making the task of identifying the fault harder. Hence, fault-detection algorithms may only notify the user of the fault and leave the interpretation to further analysis or to a fault-diagnosis algorithm.

Hierarchy:

In addition, faults at data-acquisition and transmission also effect the monitoring data. As a result, faults at later steps of the data-flow-chain like the transmission might make it impossible to correctly interpret faults at earlier steps such as component or system faults. In fact, one can formulate a hierarchical dependence of faults corresponding to different parts of the data-flow chain (Fischer, 2008). For example (see Figure 7), if the transmission of the data fails, there is no way to deduce the status of the components of the system. Similarly, data from broken sensors cannot be used to interpret the correctness of the system control and the components. Finally, some faults at system control may make it impossible to detect component faults, as for example the collector field might not be evaluated if the pump is not activated correctly.



Figure 7: Dependency of faults at different steps of the data-flow chain.

It is therefore recommended to run fault-detection algorithms dealing with “higher-level” of faults first. In contrast, “lower” level algorithms can be run only if the corresponding “higher” ones are successful to ensure the proper execution of the algorithms. Again, the dependency visualises the importance of proper data-acquisition and processing.

Categorization of faults:

As the definitions in Table 4 suggest, *faults* only describes an abnormal behaviour of the system but give no insight about the effect on the system. For example, a fault may either lead to a minor and insignificant *disturbance* or even to a serious and costly *system-failure*. Because of their different properties, faults are often categorized by their risk for the system. One possible way to evaluate the effect on the system is by using the Failure Mode and Effect Analysis (FMEA) often used in risk-management (DIN EN 60812). With this method, faults are rated with integer numbers based on their occurrence rate, severity and detection rate. As extension to the Failure Mode Effect and Criticality Analysis further introduces the Failure Risk Priority Number which can be derived by multiplying the severity with the occurrence rate to give a measure about which fault poses the biggest risk (Feichtner, 2010; Faure, et al., 2016). The identification and categorizations of faults is extremely helpful in order to evaluate and optimize monitoring tools by

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checking their coverage and encourage new fault-detection methods where needed.

For example, the results from the literature study of (Faure, et al., 2016) can be found in Figure 8.

System-Part	Component	Failure Mode	Occurance Rate	Effect	Failure Risk Priority Number
controller	Solar collector temperatur sensor	wrong measure	5	4	20
	heat exchanger input/output temperature sensor	wrong measure	4	4	16
	Solar collector temperatur sensor	no more measure	3	5	15
	heat exchanger input/output temperature sensor	no more measure	2	5	10
	pyranometer	no more measure	2	5	10
	controller	breakdown	2	5	10
	controller	non-optimal control	3	3	9
Primary transport	Solar Pump	never starts	5	5	25
	hydraulic connectors	leak	4	3	12
	heat transfer fluid	bubbles in the heat transfer fluid	3	4	12
	pipes	leak	3	3	9
	pipes	bad hydraulic balancing	2	4	8
	expansion vessel	too low pressure	2	4	8
	solar pump	too low flow	2	4	8
Secondary transport	pumps	never starts	3	5	15
Storage	storage tank	heats less than expected	4	3	12
Solar Collection	solar collector	produces less energy than expected	5	2	10

Figure 8: FMECA result of (Faure, et al., 2016) displaying most critical failure modes.

Fault-Detection-Algorithms

According to (Faure, et al., 2020) fault-detection algorithms can be split into three main groups depending on the model and knowledge they rely on (see Figure 9). For example, the quantitative-model-based methods uses physical models of the system to compare expected and measured data. In contrast, the qualitative-model-based methods use functions defined by solar experts relying on their experience to detect faults in a decision-based manner. Finally, process-history-based methods use machine learning approaches to compare the system behaviour with historic data. Based on (Faure, et al., 2020) quantitative and qualitative methods are most commonly used while history-based approaches are emerging in the last decade.

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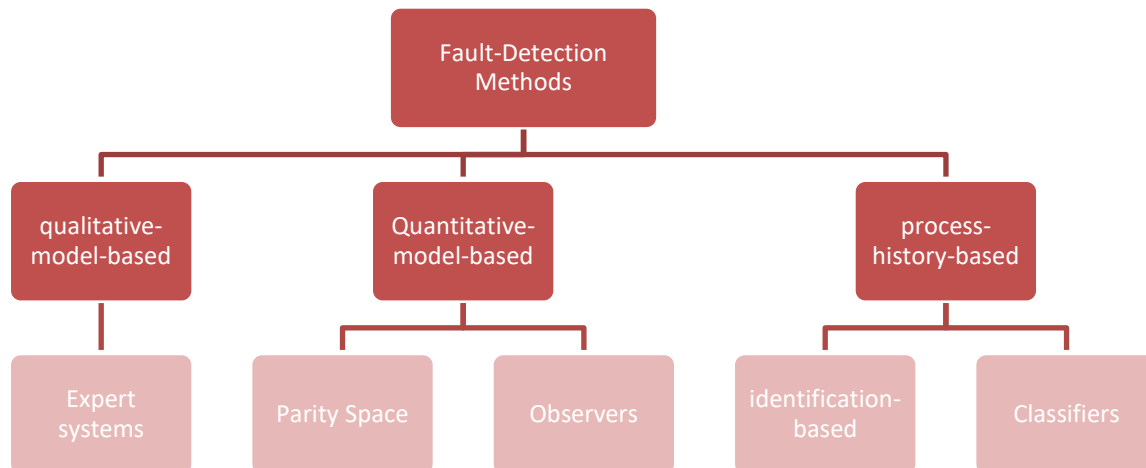


Figure 9: Hierarchical classification of fault-detection methods

Expert Systems:

Expert systems use decision-based rules formulated by solar experts to detect faults. They are typically algorithms that don't require sophisticated calculations but simply throw an error if a measurement or benchmark is above or below a certain threshold. For example, leaks at the solar circuit can easily be detected by setting a minimum threshold for the solar pressure. The advantage of this type of fault-detection method is that it is easy to implement and interpret, and that fault-isolation is often included. That means that the algorithm can tell accurately in which part of the system the fault occurred. As a drawback, expert-systems-methods often focus on specified faults, leading to lower fault-coverage-rates than other methods. Examples for expert-system-methods can be found in (Feichtner, 2010; Fischer, 2008).

Parity Space:

Parity space methods use physical models to calculate the difference from measured quantities to the values derived from the models. If the difference is too high a notification is thrown. For example, differential equations that describe the behaviour of components can be used to simulate the performance of the component. By comparing measured and predicted values faults can be detected. One common example is to use the solar key mark specification of collectors and calculate the expected solar yield based on the measured radiation, return temperature and ambient temperature. Again, high residuals may suggest a fault at the solar circuit. As a drawback, the formulation of parity space models often needs considerable amount of domain knowledge. An overview of methods for analysing the collector efficiency can be found in (Ohnewein, et al., 2020) containing an overview of collector array tests and introducing a new approach called D-CAT.

Observer:

As quantitative model-based approach it uses a physical model of the system in order to detect faults. With Observer methods a mathematical formulation of the system is constructed that can be used to mimic the

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behaviour of the system, also enabling to calculate parameters which are not measured by the system. The observer build with this model then operates on monitoring data in real-time, such that the measurement data is used to predict the values of the next timestep. When the estimated and measured values differ to much this indicates a fault.

The benefit of this method is that it models the system very closely and in real-time. Thus, it is easier to isolate the fault in contrast to parity-space methods which are vaguer about which component might be malfunctioning. Secondly, the response to a fault is very fast and can be handled immediately. Observer methods can especially be used for optimizing system-control as done in (Lichtenegger, et al., 2016) and as they rely on physical models, can be used in the design phase of the system or as “digital-twin” for testing new control- or optimization-strategies. On the hindsight, the methods are hard to understand due to their sophisticated mathematical formulas. Moreover, translating the models to other systems is not always easy as they should follow the layout of the system very closely. Another problem is that most physical models of solar systems rely on assumptions that make the computation easier or possible at all. Thus, some system behaviour might not be modellable by this approach.

Identification-based:

The identification-based methods are similar to the quantitative-model-based methods in regard that measured values are compared to values calculated with a model of a component or system part. The big difference is in the way the model is created. In the parity-space methods the (sometimes very complicated) underlying physics of the components is used to derive models, while in the identification-based method the model is created using machine learning approaches in combination with the historic measurement data.

For example, artificial neuronal networks (ANN) can be trained to model any kind of correlation between some input and output variable. When used correctly, the ANN can be trained with historic data until the output of the network matches with the data. When used with new data and comparing measurement to the derived output of the ANN, changes at the system can be detected (Feierl, et al., 2019).

As a more specific example, historic data of the irradiation, the ambient temperature, the solar return flow and solar yield might be used to predict the future solar yield of the system.

As machine learning approaches only use the data from the system, the created models often more accurately predict the behaviour of the system in comparison to parity-space models. This is because the physical models often use simplifications or approximations in order to keep the model simple. If instead very accurate models would be used in parity-space methods the resulting calculations are very complicated, hard to implement and lead to a long runtime. Instead machine learning approaches enable the user to model complicated functions very accurately in reasonable amount of time. However, there are two major drawbacks of the identification-based methods:

First, as machine learning approaches, the methods need real measurement data in order to work sufficiently. This is especially a problem as these methods are hard to apply in the design phase of the system as no data of the system is available yet. Even if some similar input data is available, it cannot be

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guaranteed that the trained model performs well as it only learned to approximate a completely different system. Another problem with the training data is that only operating states can be modelled well which also are present in the training data. This also means that it is not possible to compare measurement to an optimal behaviour but only to system-states previously observed. Hence, if faults do already exist during the acquisition of training data, machine learning approaches will not be able to detect these dysfunctions. Second, identification-based methods are often black-boxes, which means that it is very hard to interpret how the trained method works. Thus, it is often only possible to detect a fault, however, the diagnosis of the fault (i.e. what is wrong and how to fix it) is left to domain-experts and further analysis.

Classifiers:

Instead of identification-based methods which model a system part and compare expected and measured values, classifier try to detect faults directly. In the classical approach, both historic measurement data and information about the faults occurred during that time-period are provided to the classifier. The algorithm then tries to find out correlations between data and faults. If sufficiently trained, the classifier can be applied to new data in order to detect these trained faults. While the classifiers above belong to supervised methods, where fault labels are known, also non-supervised classifiers can be considered. One example are outlier-detection algorithms that scan the data for unusual measurements or clustering algorithms that separate the data into groups according to faults.

The benefit of this approach is that not only detection but also diagnosis of faults is possible. However, most of the drawbacks of the identification-based method apply to classifier as well: Again, if black-box methods are used, there is no way to understand how the classifier works. The biggest drawback, however, is that supervised classifier needs labelled faults as input. However, data with labelled faults are not very common. Plus, if the faults occur very rarely, supervised classifier cannot easily be trained to detect them. In contrast, results of unsupervised algorithms are harder to interpret.

Conclusion:

In conclusion a combination of the fault-detection systems is recommended if possible. Expert systems should be used as they can detect and locate faults at a low level of complexity. To ensure a better coverage of faults quantitative-model-based methods may be applied where possible to check component and system performance. The advantage of these more traditional fault-detection methods is that they do not rely on system-data and thus can also be used during design and construction. In contrast, process-history-based methods may perform better and give more novel results and hence should be used as well. A review of current fault-detection methods can be found in (Faure, et al., 2020).

Notification-Management

Finally, if a fault gets detected the correct people need to be informed about it as fast as possible. Hence it is critical to install some type of error and notification management that send out mails and SMS. Depending on the criticalness of the fault, notifications should be sent to the relevant personal. When the

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responsible person does not respond in time an escalation scheme can be used to notify representatives. A notification management is also important to not overload personal with a wide range of small notifications. Instead it combines the information in a way such that the problem can be identified and dealt with best.

In practice, often a criticalness factor for faults is introduced similar to the FMECA analysis discussed previously. Mails are then sent according to the type and criticalness to service personal, monitoring staff, persons responsible for system-operation or stakeholder (Feichtner, 2010) (Fischer, 2008). For less critical notifications or faults that were detected where no immediate action is needed, accumulating faults and sending for example monthly notifications is often sufficient. It is also very important to provide a framework such that the fault can be analysed and understood efficiently and fast, providing meta-information about the fault and recommend actions.

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Appendix A

Table 5: Recommended Measurements at the solar circuit.

Solar	
Recommended Measurement	Sources
radiation sensor (global in collector plane)	(Knabl, et al., 2012; Faure, et al., 2020)
ambient temperature	(Fischer, 2008; Faure, et al., 2020)
pressure sensor (primary)	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
flow temperature (primary)	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
return temperature (primary)	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
flow temperature (secondary)	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
return temperature (secondary)	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
collector temperature	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
volume flow sensor (secondary)	(Knabl, et al., 2012; Faure, et al., 2020)

Table 6: Recommended Measurements at heat storages.

Heat Storage	
Recommended Measurement	Sources
heat storage temperature (bottom) ³	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
heat storage temperature (top)	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
heat storage temperature (middle)	(Fischer, 2008)

Table 7: Recommended Measurements at external heating.

External Heating	
Recommended Measurement	Sources
volume flow sensor	(Knabl, et al., 2012; Fischer, 2008)
flow temperature	(Knabl, et al., 2012; Fischer, 2008)
return temperature	(Knabl, et al., 2012; Fischer, 2008)

Table 8: Recommended Measurements at solar cooling circuits

Cooling	
Recommended Measurement	Sources
volume flow hot water	(Knabl, et al., 2012; Fischer, 2008)
volume flow chilled water	(Knabl, et al., 2012; Fischer, 2008)

³ As explained in the corresponding chapter it is recommended to use more than three sensors in the heat storage tank if a large-scale system is considered.

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volume flow cooling water	(Knabl, et al., 2012; Fischer, 2008)
return temperature cooling	(Knabl, et al., 2012; Fischer, 2008)
flow temperature hot water	(Knabl, et al., 2012; Fischer, 2008)
flow temperature chilled water	(Knabl, et al., 2012; Fischer, 2008)
electricity meter hot water pump ⁴	(Knabl, et al., 2012; Fischer, 2008)
electricity meter chilled water pump	(Knabl, et al., 2012; Fischer, 2008)
electricity meter cooling water pump	(Knabl, et al., 2012; Fischer, 2008)
electricity meter cooling tower fans	(Knabl, et al., 2012; Fischer, 2008)
electricity meter chiller	(Knabl, et al., 2012; Fischer, 2008)
relative humidity (at cooling tower)	(Knabl, et al., 2012)

Table 9: Recommended Measurements at consumer circuit.

Consumer (District Heating, Domestic Hot Water)	
Recommended Measurement	Sources
volume flow	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
flow temperature	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)
return temperature	(Knabl, et al., 2012; Fischer, 2008; Faure, et al., 2020)

⁴ Even though (Knabl, et al., 2012; Fischer, 2008) recommend using electricity meters, for pumps the electric consumption can be calculated quite easily and accurately using the affinity law 1c.