Intelligent trend analysis for a solar thermal energy collector field

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Abstract. Solar thermal power plants collect available solar energy in a usable form at a temperature range which is adapted to the irradiation levels and seasonal variations. Solar energy can be collected only when the irradiation is high enough to produce the required temperatures. During the operation, a trade-off of the temperature and the flow is needed to achieve a good level for the collected power. The scaling approach brings temporal analysis to all measurements and features: trend indices are calculated by comparing the averages in the long and short time windows, a weighted sum of the trend index and its derivative detects the trend episodes and severity of the trend is estimated by including also the variable level in the sum. The trend index, trend episodes and especially, the deviation index reveal early evolving changes in the operating conditions, including cloudiness and load disturbances. The solution is highly compact: all variables, features and indices are transformed to the range [-2, 2] and represented in natural language which is important in integrating data-driven solutions with domain expertise. The special situations detected during the test campaigns are explained well.

1. Introduction
Solar thermal power plants should collect any available energy in a usable form at the desired temperature range. In addition to seasonal and daily cyclic variations, the intensity depends also on atmospheric conditions such as cloud cover, humidity, and air transparency. The Acrex field, which consists of parabolic-trough collectors, supplies thermal energy (1 MWt) in form of hot oil to an electricity generation system or a multi-effect desalination plant. Control is done by means of varying the flow pumped through the pipes in the field during the operation. The collector field status must be monitored to prevent potentially hazardous situations, e.g. oil temperatures greater than 300 °C or too temperature increase. A fast start-up and efficient operation in varying cloudy conditions is important. Unnecessary shutdowns and start-ups of the collector field are both wasteful and time consuming. The field is a good test platform for control methodologies [1, 2, 3], including basic feedforward [4, 5] and PID schemes, adaptive control [6], model-based predictive control [7, 8], frequency domain and robust optimal control and fuzzy logic control [6]. On a clear day, nonlinear effect can be handled with model-based feedforward controllers with additional feedback controllers to remove offsets [9].

Linguistic equation (LE) approach combines data-driven methodologies with linguistic meanings. The LE approach originates from fuzzy set systems [10]: rule sets are replaced with equations, and meanings of the variables are handled with scaling functions which have close connections to membership functions [2]. The nonlinear scaling technique is needed in constructing nonlinear models with linear interactions [11]. Constraints handling [12] and data-based analysis [13] are important in the recursive scaling [14, 15]. Combined fuzzy systems can include fuzzy arithmetic and inequalities [16] and the operation can be expressed with natural language [17].
Linguistic equation (LE) control includes solutions also for cloudy conditions and varying load situations [18, 19, 20, 21]. The main challenge is to handle harmful situations efficiently to reach an unattended operation as a part of a smart grid. The control system based on intelligent analysers and predefined adaptation techniques activates special features when needed. Fast start-up, smooth operation and efficient energy collection is achieved even in variable operating condition. The smart working point control improves the efficiency of the energy collection. A trade-off of the temperature and the flow is needed to achieve a good level for the collected power.

Trend analysis systems have three components: a language to represent the trends, a technique to identify the trends, and mapping from trends to operational conditions [22]. The fundamental elements are modelled as triangles to describe local temporal patterns. The elements are defined by the signs of the first and second derivative, respectively. They are also known as triangular episodic representations [23]. The fuzzy rule-based solution has been transformed to an equation-based solution by the LE based trend analysis introduced in [24].

In this paper, the earlier developed trend analysis method is applied in the real data collected at a solar collector field. The method is shortly summarized and analysis results are presented for different operating conditions.

2. Data analysis
Normalisation or scaling of the data is needed since measurements with considerably different magnitudes cause problems in modelling. The nonlinear scaling extends modelling to various statistical distributions and allows recursive tuning. Data analysis includes feature extraction and nonlinear scaling.

2.1. Features
Arithmetic mean and standards deviation are special cases of generalized norms

\[
\|\mathbf{M}_p\|_p = \left(\mathbf{M}_p^T \mathbf{M}_p\right)^{1/p} = \left(\frac{1}{N} \sum_{j=1}^{N} (x_j)^p\right)^{1/p},
\]

where the order of the norm \( p \in \mathbb{N} \) is non-zero. The analysis is based on consecutive equally sized samples. Duration of each sample is called sample time, denoted \( \tau \), and \( N \) is the number values in the sample. The norm (1) has the same dimensions as the variable \( x_j \). The generalized norms were introduced for condition monitoring [25, 26]. The norm values increase monotonously with increasing order if all the signals are not equal. The computation of the norms can be divided into the computation of equal sized sub-blocks, i.e. the norm for several samples can be obtained as the norm for the norms of individual samples. The same result is obtained using the norms of the sub-blocks. Each sample has \( N \) variable values. As the aggregation can be continued to longer and longer time periods, this generalizes the practice used automation systems for the arithmetic means.

2.2. Intelligent indices
Intelligent indices are obtained from measurements and features by a nonlinear scaling approach which extends the z-score based linear scaling functions to asymmetric nonlinear scaling functions defined by two second order polynomials. The parameters of the polynomials are defined with five parameters corresponding the operating point \( c_j \) and four corner points of the feasible range [11]. The feasible range is defined as a trapezoidal membership function defined by support and core areas, see [27]. The scaling functions are monotonously increasing throughout the feasible range, see [12, 16]. This is satisfied if the coefficients

\[
a_i^x = \frac{(c_i) - \min(x_j)}{c_j - (c_i)} = \frac{(c_i) - \min(x_j)}{\Delta c_j}
\]

and

\[
a_i^y = \frac{\max(x_j) - (c_i)}{(c_i) - c_j} = \frac{\max(x_j) - (c_i)}{\Delta c_j}
\]
are restricted to the range $\left[ \frac{1}{3}, 3 \right]$.

The scaled values are obtained by means of the inverse functions of the second order polynomials. Data-based tuning by using generalized norms and skewness was introduced in [13]. The constraints are taken into account by moving the corner points or the upper and lower limits if needed. The parameters of the functions can be tuned with genetic algorithms [12].

### 3. Temporal analysis

Fluctuations, trends and models are used in temporal analysis for all types of measurements, features and indices. Recursive updates of the parameters are needed in prognostics.

#### 3.1. Fluctuations

The fluctuations are evaluated as the difference of the high and the low values as a difference of two moving generalized norms:

$$\Delta x^f_j(k) = \left| M^F_{p} - M^F_{p}\right|,$$

where the orders $p_l \in \mathbb{N}$ and $p_u \in \mathbb{N}$ are large positive and negative, respectively. The norms are calculated from the latest $K_s+1$ values, and an average of several latest values of $\Delta x^f_j(k)$ is used as the feature of fluctuation. The feature, which was originally developed for control [28], is easy to calculate and more robust than using the difference between the actual maximum and minimum. The fluctuation indices are calculated from features (4) by the nonlinear scaling. Similar calculations can be done for intelligent indices if the variations close to the normal conditions are important.

#### 3.2. Trend analysis

For any variable $x_j$, a trend index $I^T_j(k)$ is calculated from the scaled values with

$$I^T_j(k) = w_j \left[ \frac{1}{n_x_j + 1} \sum_{i=1}^{n_x_j} X^s_j(k) - \frac{1}{n_x_j + 1} \sum_{i=1}^{n_x_j} X^l_j(k) \right],$$

which is based on the means obtained for a short and a long time period, defined by delays $(n_x_j)_j$ and $(n_x)_j$, respectively. The weight $w_j$ is variable specific. The index value is in the linguistic range $[-2, 2]$ representing the strength of both the decrease and increase of the variable $x_j$. [24]

Episode alternatives are shown in figure 1. An increase is detected if the trend index exceed a threshold $I^T_j(k) > \varepsilon^+_i$. Correspondingly, $I^T_j(k) < \varepsilon^-_i$ for a decrease. The derivative of the index $I^T_j(k)$, denoted as $\Delta I^T_j(k)$, extends the analysis to nonlinear episodes. Trends are linear if the derivative is close to zero: $\varepsilon^- < \Delta I^T_j(k) < \varepsilon^+$. The concave upward monotonic increase (D) and the concave downward monotonic decrease (B) are dangerous situations, which introduce warnings and alarms. The concave downward monotonic increase (A) and the concave upward monotonic decrease (C) mean that a harmful trend is stopping.

Severity of the situation can be evaluated by a deviation index

$$I^D_j(k) = \frac{1}{3} \left( X^s_j(k) + I^T_j(k) + \Delta I^T_j(k) \right),$$

whose absolute values are the highest when the difference to the set point is very large and is getting still larger with a fast increasing speed.

The trend analysis is tuned to applications by selecting variable specific the time periods $(n_x_j)_j$ and $(n_x)_j$. The thresholds $\varepsilon^- = \varepsilon^+_i = \varepsilon^- = \varepsilon^+_2 = 0.5$. Further fine-tuning can be done by adjusting the weight factors $w_1^{T1}$ and $w_2^{T2}$ used for the indices $I^T_j(k)$ and $\Delta I^T_j(k)$. The calculations are done with numerical values and the results are represented in natural language [17].
4. Intelligent trend analysis
The intelligent trend analysis is here presented for the scaled values of temperatures and irradiation in different operating conditions. Fluctuations are included in the analysis to detect different cloudy conditions and load disturbances.

4.1. Start-up
On a clear day, the start-up operation is very smooth (figure 2) with increasing irradiation (figure 3). The trend index is steadily increasing when the control is based on the working point. In the beginning, there are faster changes followed by stopping of the increase and a new increase. These are resulting from the setpoint changes. Changes of trend indices are all the time very small and there are no considerable fluctuations. The effects of the heavy clouds are discussed in section 4.3.

4.2. Normal operation
Smooth operation is continued in the normal operation; for the outlet temperature $T_{out}$, trend indices are in the range [-1, 1] and follow the setpoint changes (figure 4). Changes of trend indices are in the range [-0.5, 0.5], also related to setpoint changes. The irradiation increases steadily before solar noon.
and starts to decrease after that (figure 5). The concave parts are very short. There are no sever changes nor fluctuations. According to the trend analysis, everything is operating fine.

4.3. Cloudy conditions

The outlet temperature is kept low (below level 1) to avoid heavy oscillations (figure 6). The operation is fairly smooth although there drastic changes in the irradiation (figure 7). For the outlet temperature, the trend index reaches both the maximum and minimum but the change of the trend index is varying only slightly. The irradiation is varying between sever high and low levels (figure 7).

The deviation indices react early to the starting cloudiness (figures 2 and 3). Early reactions are seen in fluctuations, which are very heavy in cloudy conditions and modify the acceptable range of the working point (figure 8 and 9). Both the starting of the cloudy period and the clearing the sky are seen early in the deviation indices. The trend indices vary between -2 and 2 and the change of indices is fairly high. The operation is very different from the smooth start-up (figure 9).
4.4. Load disturbances
Load disturbances come to the field through the variations of the inlet. Therefore, the trend analysis of inlet temperature is informative (figures 10 and 11). Depending on the flow, there is time to react to the drastic changes: some working point changes improve the operation (figure 11) when compared with the running of the field without compensating actions (figure 10).

5. Conclusions
The intelligent trend analysis provides useful information from the real data collected at a solar collector field. According to the analysis results, the trend analysis is an efficient tool for early detection of evolving problems. Start-ups and normal operation with increasing and decreasing irradiation operate smoothly and the effects of the setpoint changes are seen as modest changes which do not cause false alarms. The analysis focuses on the problematic situations: early warnings are introduced before the changes in the average irradiation are seen and the analysis of fluctuations further improves this detection. The early detection of the changes in the inlet temperature is valuable in reducing the effects of load disturbances.
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