Intelligent trend analysis for a solar thermal energy collector field

E K Juuso

Control Engineering, Faculty of Technology, 90014 University of Oulu, Finland

esko.juuso@oulu.fi

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 Acurex field, which consists of parabolic-trough collectors, supplies thermal energy (1 MW$_t$) 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 ºC 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

$$\left\| {}^{\tau}M_j^p \right\|_p = ({}^{\tau}M_j^p)^{1/p} = \left[\left(\frac{1}{N} \sum_{i=1}^{N} (x_j)_i^p \right) \right]^{1/p},$$

(1)

where the order of the norm $p \in \Re$ is non-zero. The analysis is based on consecutive equally sized samples. Duration of each sample is called sample time, denoted τ, 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

$$\alpha_j^- = \frac{(c_l)_j - \min(x_j)}{c_j - (c_l)_j} = \frac{(c_l)_j - \min(x_j)}{\Delta c_j^-}$$

(2)

and

$$\alpha_j^+ = \frac{\max(x_j) - (c_h)_j}{(c_h)_j - c_j} = \frac{\max(x_j) - (c_h)_j}{\Delta c_j^+}$$

(3)

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:

$$\Delta x_j^F(k) = \left\| {}^{K_s, \tau} M_j^{p_H} \right\|_{p_H} - \left\| {}^{K_s, \tau} M_j^{p_L} \right\|_{p_L}, \tag{4}$$

where the orders $p_H \in \Re$ and $p_L \in \Re$ 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 $\Delta x_j^F(k)$ 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 $I_j^T(k)$ is calculated from the scaled values with

$$I_j^T(k) = w_j \left[\frac{1}{(n_S)_j + 1} \sum_{i=k-(n_S)_j}^{k} X_j(k) - \frac{1}{(n_L)_j + 1} \sum_{i=k-(n_L)_j}^{k} X_j(k) \right], \tag{5}$$

which is based on the means obtained for a short and a long time period, defined by delays $(n_S)_j$ and $(n_L)_j$, 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 $I_j^T(k) > \varepsilon_1^+$. Correspondingly, $I_j^T(k) < \varepsilon_1^-$ for a decrease. The derivative of the index $I_j^T(k)$, denoted as $\Delta I_j^T(k)$, extends the analysis to nonlinear episodes. Trends are linear if the derivative is close to zero: $\varepsilon_2^- < \Delta I_j^T(k) < \varepsilon_2^+$. 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

$$I_j^D(k) = \frac{1}{3} \left(X_j(k) + I_j^T(k) + \Delta I_j^T(k) \right), \tag{6}$$

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 $(n_L)_j$ and $(n_S)_j$. The thresholds $\varepsilon_1^- = \varepsilon_1^+ = \varepsilon_2^- = \varepsilon_2^+ = 0.5$. Further fine-tuning can be done by adjusting the weight factors w_j^{T1} and w_j^{T2} used for the indices $I_j^T(k)$ and $\Delta I_j^T(k)$. The calculations are done with numerical values and the results are represented in natural language [17].

Figure 1. Intelligent trend analysis [24].
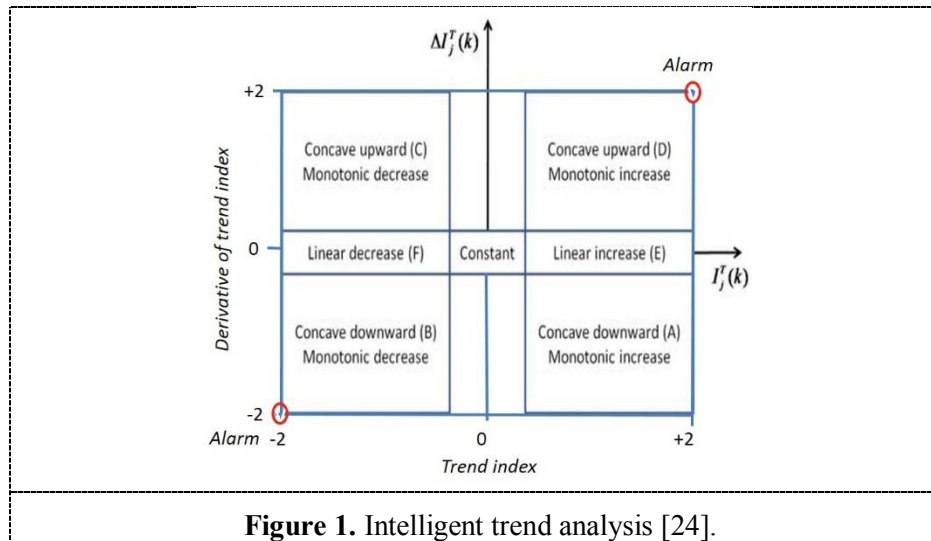
4. Intelligent trend analysis

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.
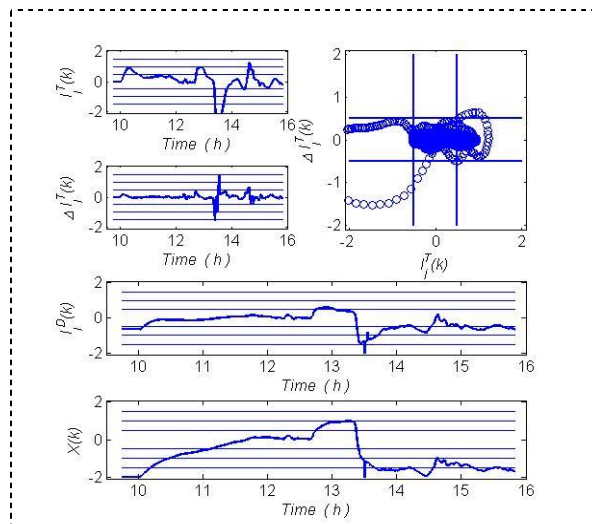
Figure 2. Trend analysis of outlet temperature T_{out} in normal start-up followed by a heavy cloudy period.
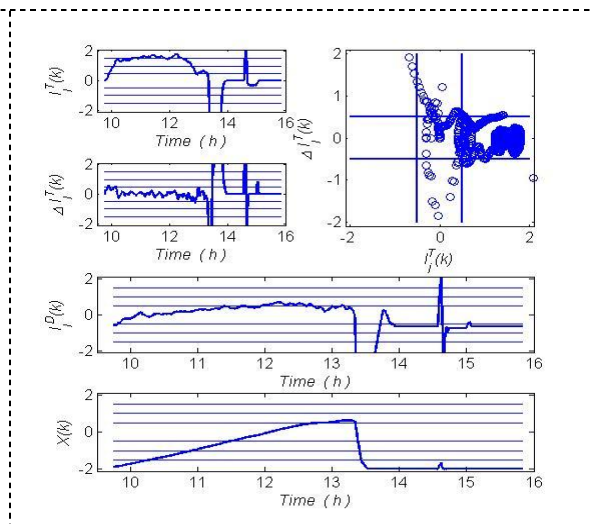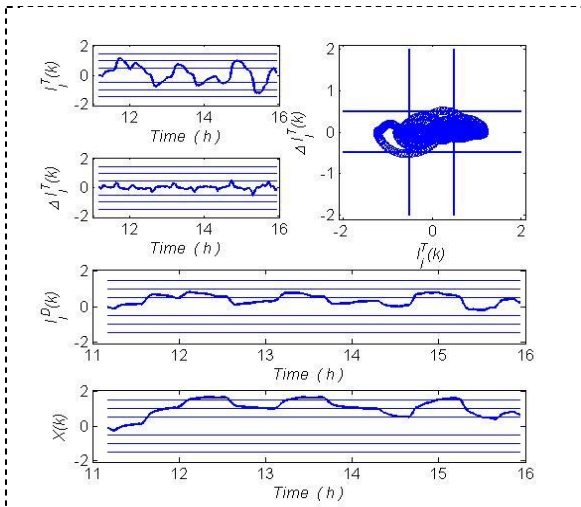
Figure 3. Trend analysis of average irradiation in normal operating conditions start-up followed by a heavy cloudy period.
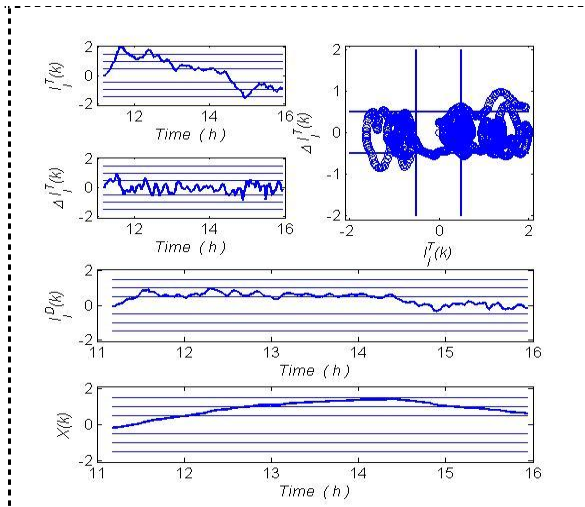
4.2. Normal operation

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.
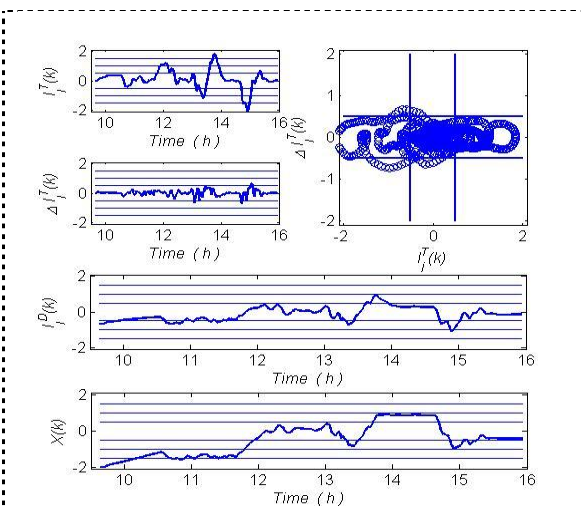

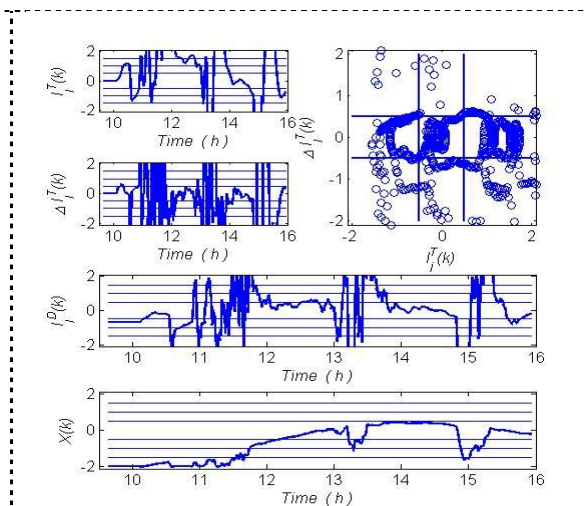**Figure 4.** Trend analysis of outlet temperature in normal operating conditions.

Figure 5. Trend analysis of average irradiation in normal operating conditions.

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).


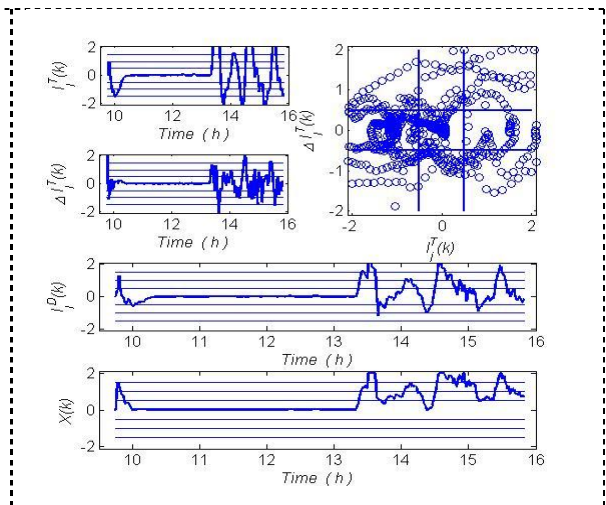**Figure 6.** Trend analysis of outlet temperature T_{out} in cloudy operating conditions.

Figure 7. Trend analysis of average irradiation in cloudy operating conditions.

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).
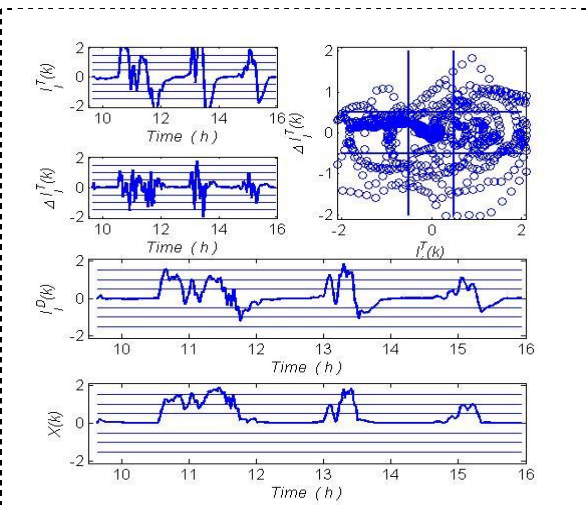
Figure 8. Trend analysis of total fluctuations in cloudy operating conditions.

Figure 9. Trend analysis of total fluctuations in heavy cloudy operating conditions.

4.4. Load disturbances

Load disturbance 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).
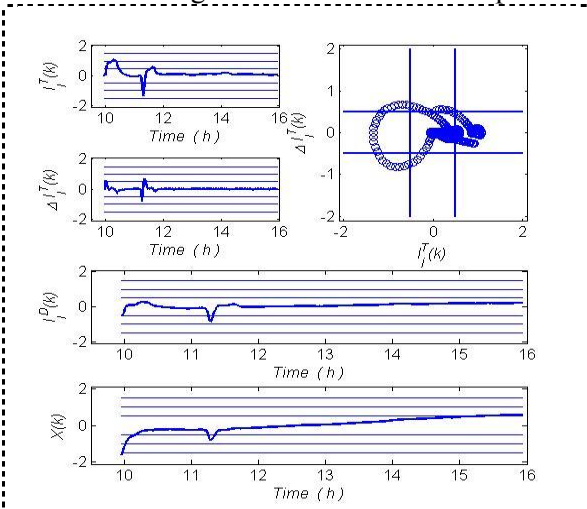
Figure 10. Trend analysis of inlet temperature with load disturbances.
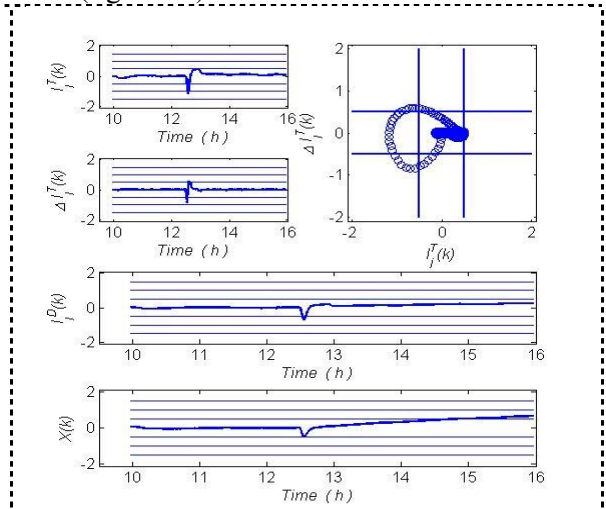
Figure 11. Trend analysis of inlet temperature with load disturbances.

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.

6. References

[1] Camacho E, Berenguel M and Rubio F R 1997 *Adaptive Control of Solar Plants* (Oxford: Springer).

[2] Juuso E K 1999 Fuzzy control in process industry: The linguistic equation approach, *Fuzzy Algorithms for Control, International Series in Intelligent Technologies (International Series in Intelligent Technologies)* ed H B Verbruggen, H-J Zimmermann and R Babuška (Boston: Kluwer) pp 243–300. doi: 10.1007/978-94-011-4405-6_10.

[3] Camacho E, Berenguel M, Rubio F R and Martinez D 2012 *Control of Solar Energy Systems, Advances in Industrial Control* (London: Springer). doi: 10.1007/978-0-85729-916-1.

[4] Cirre C M, Berenguel M, Valenzuela L and Camacho E 2007 Feedback linearization control for a distributed solar collector field *Control Engineering Practice* **15** 1533–1544. doi: 10.1016/j.conengprac.2007.03.002.

[5] Camacho E, Rubio F and Hughes F Self-tuning control of a solar power plant with a distributed collector field *IEEE System Control Magazine* **12** 72–78.

[6] Juuso E K, Balsa P and Valenzuela L 1998 Multilevel linguistic equation controller applied to a 1 MW solar power plant *Proc. ACC'98 Conf*, vol 6 (ACC) 3891–3895.

[7] Limon D, Alvarado I, Alamo T, Ruiz M and Camacho E F 2008 Robust control of the distributed solar collector field ACUREX using MPC for tracking *Proc. 17th IFAC World Congress*, vol 17, (IFAC) 958–963, http://www.ifac-papersonline.net/.

[8] Ayala C O, Roca L, Guzman J L, Normey-Rico J E, Berenguel M and Yebra L Local model predictive controller in a solar desalination plant collector field *Renewable Energy* **36** 3001–3012, doi: 10.1016/j.renene.2011.03.037.

[9] Farkas I and Vajk I 2002 Internal model-based controller for a solar plant *Proc. 15th Triennial World Congress* (IFAC) 49–54. http://www.ifac-papersonline.net/.

[10] E. K. Juuso and K. Leiviskä 1992 Adaptive expert systems for metallurgical processes *Expert Systems in Mineral and Metal Processing, IFAC Workshop*, *IFAC Workshop Series* no 2 ed S-L Jämsä-Jounela and A. J. Niemi (Oxford, UK: Pergamon) 119–124.

[11] Juuso E K 2004 Integration of intelligent systems in development of smart adaptive systems *International Journal of Approximate Reasoning* **35** 307–337. doi: 10.1016/j.ijar.2003.08.008.

[12] Juuso E K 2009 Tuning of large-scale linguistic equation (LE) models with genetic algorithms *Revised selected papers of the International Conference on Adaptive and Natural Computing Algorithms - ICANNGA 2009, Lecture Notes in Computer Science* ed M Kolehmainen (Heidelberg: Springer-Verlag) vol. LNCS 5495, 161–170. doi: 10.1007/978-3-642-04921-7 17.

[13] Juuso E and Lahdelma S 2010 Intelligent scaling of features in fault diagnosis *7th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM 2010 - MFPT 2010* vol 2, 1358–1372. [Online]. Available: www.scopus.com

[14] Juuso E K 2011 Recursive tuning of intelligent controllers of solar collector fields in changing operating conditions *Proceedings of the 18th World Congress The International Federation of Automatic Control* ed S Bittani, A Cenedese and S Zampieri (IFAC) 12282–12288. doi: 10.3182/20110828-6-IT-1002.03621.

[15] Juuso E and Lahdelma S 2011 Intelligent trend indices and recursive modelling in prognostics *8th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM 2011 - MFPT 2011*, vol 1, 440–450. [Online]. Available: www.scopus.com

[16] Juuso E K 2014 Intelligent methods in modelling and simulation of complex systems *Simulation Notes Europe SNE* **24** 1–10. doi: 10.11128/sne.24.on.102221.

[17] Juuso E K 2016 Informative process monitoring with a natural language interface *2016 UKSim-AMSS 18th International Conference on Modelling and Simulation* (IEEE Computer Society) 105-110. doi: 10.1109/UKSim.2016.37.

[18] Juuso E K and Yebra L 2013 Optimisation of solar energy collection with smart adaptive control *Proc. IECON 2013 - 39th Annual Conference of the IEEE Industrial Electronics Society* (IEEE) 7930–7935. doi: 10.1109/IECON.2013.6700459.

[19] Juuso E K 2011 Recursive tuning of intelligent controllers of solar collector fields in changing operating conditions, in Proc. 18th World Congress IFAC, 2011, IFAC, 2011, pp. 12282–12288, doi: 10.3182/20110828-6-IT-1002.03621.

[20] Juuso E K and Yebra L 2013 Model-based intelligent control of a solar energy collector field *Proc. 8th EUROSIM Congress on Modelling and Simulation* (IEEE) 513–518. doi:10.1109/EUROSIM.2013.92.

[21] Juuso E K 2017 Intelligent Control of a Solar Thermal Power Plant - Adaption in Varying Conditions *Jounal of Automation and Control Engineering* **5** 26-30. doi: 10.18178/joace.5.1.26-30

[22] Dash D, Rengaswamy R and Venkatasubramanian V 2003 Fuzzy-logic based trend classification for fault diagnosis of chemical processes *Computers and Chemical Engineering* **27** 347–362.

[23] Cheung J T-Y and Stephanopoulos G 1990 Representation of process trends - part I. A formal representation framework *Computers & Chemical Engineering* **14** 495–510.

[24] Juuso E K 2011 Intelligent Trend Indices in Detecting Changes of Operating Conditions *2011 UKSim 13th International Conference on Computer Modelling and Simulation (UKSim)* (IEEE Computer Society) 162-167. doi: 10.1109/UKSIM.2011.39.

[25] Lahdelma S and Juuso E 2011 Signal processing and feature extraction by using real order derivatives and generalised norms. Part 1: Methodology *The International Journal of Condition Monitoring* **1** 46-53. doi: 10.1784/204764211798303805.

[26] Lahdelma S and Juuso E 2011 Signal processing and feature extraction by using real order derivatives and generalised norms. Part 2: Applications *The International Journal of Condition Monitoring* **1** 54-66. doi: 10.1784/204764211798303814.

[27] Zimmermann H-J 1992 *Fuzzy set theory and its applications* (Kluwer Academic Publishers).

[28] Juuso E K 2012 Model-based adaptation of intelligent controllers of solar collector fields *7th Vienna Symposium on Mathematical Modelling* Part 1 (IFAC) 979–984, doi. 10.3182/20120215-3-AT-3016.00173.