UNCECOMP 2015
1st ECCOMAS Thematic Conference on
Uncertainty Quantification in Computational Sciences and Engineering
M. Papadrakakis, V. Papadopoulos, G. Stefanou (eds.)
Crete Island, Greece, 25–27 May 2015

PROBABILISTIC CONDITION MONITORING COUNTING WITH INFORMATION UNCERTAINTY

Pavel Ettler[1] **and Kamil Dedecius**[2]

[1]COMPUREG Plzeň, s.r.o.
306 34 Plzeň, Czech Republic
e-mail: ettler@compureg.cz

[2] Institute of Information Theory and Automation, Czech Academy of Sciences
182 08 Prague, Czech Republic
e-mail: dedecius@utia.cas.cz

Keywords: Uncertainty Quantification, Condition Monitoring, Fault Detection, Probabilistic Logic.

Abstract. *Industrial condition monitoring and fault detection rely first of all on measured signals which are – like all information coming from the real world – burdened by pervasive uncertainty. A small international consortium is developing a hierarchical condition monitoring framework, which takes this uncertainty into account at any level of the observed control system hierarchy: from individual components up to the entire system. The framework adopts the so-called subjective logic - a kind of probabilistic logic enhanced by the notion of uncertainty. The main question is how to evaluate condition of every piece of input information using this theory. There were developed several methods of quantification of uncertainty for this purpose, based on relation between allowed signal range and noise of the signal, occurrence of outliers and investigation of spectral density, respectively. A specific method based on model switching was developed for piecewise stable signals which change their working points more or less abruptly. The system entered the phase of its validation in a pilot metal processing plant.*

1 INTRODUCTION

This paper aims to illustrate several methods for quantification of uncertainty which are usable for real-time applications. Starting point for these results was the need to build an industrial hierarchical condition monitoring system which would provide continuous report of health of both the system components and of the system as the whole. Obviously, there may exist elements of a complex industrial system which do not work perfectly but still allow satisfactory operation of the whole system. Therefore the use of the binary logic operators for such purpose was considered as inadequate from the beginning. Probabilistic logic, on the other hand, enables to evaluate health of a unit in the whole scale from zero to one which reflects the reality much closely. However, even such approximation is lacking the possibility to express how uncertain the processed information is. The problem can be illustrated on a simple statistical evaluation of an event: if the event resulted in the state 0 for 40 cases and in the state 1 for 60 cases, than we may expect the next state to be 1 with probability 0.6. However, the question is how certain we are about the evaluation of particular cases and thus with the resulting probability. Subjective logic – a generalization of the probabilistic logic – takes uncertainty systematically into account. Once every piece of the "input" uncertainty is quantified, subjective logic operators allow to treat it consistently. Several methods for such quantification are introduced.

The paper is organized as follows: The next section sketches the system being built, introduces the calculus of subjective logic and defines the problem of the interface. Subsequent section summarizes previously developed means for uncertainty quantification, and is followed by a section devoted to the pure noise-based uncertainty. Summary of the work concludes the paper.

2 PROBABILISTIC CONDITION MONITORING

2.1 Hierarchical system

Following deliberation is based on the considered hierarchical condition monitoring system [1] an example of which is depicted in Fig. 1. The system uses measured signals and other data at disposal as its inputs which enter the system from the bottom. Block structure which reflects inner relations within the inspected system enables to evaluate health/condition of both any particular functional block or the entire system purveyed by the uppermost block.

2.2 Probabilistic calculus

The calculus used for compounding of information within the condition monitoring system should cope with the uncertainty inherent in every piece of information being at disposal. Subjective logic – a kind of the probabilistic logic – turned out to be the suitable choice [2]. The theory [3] is based on definition of a probabilistic opinion about a proposition h in the form of a quadruplet

$$\omega_h = (b, d, u, a) \;, \tag{1}$$

where the components b, d, u, a are belief (amount of h-supporting information), disbelief (the opposite), uncertainty (amount of information insufficiency) and base rate (prior information) respectively. It must hold

$$b + d + u = 1 \;, \qquad b, d, u, a \in [0, 1] \tag{2}$$

and the expected value can be expressed as

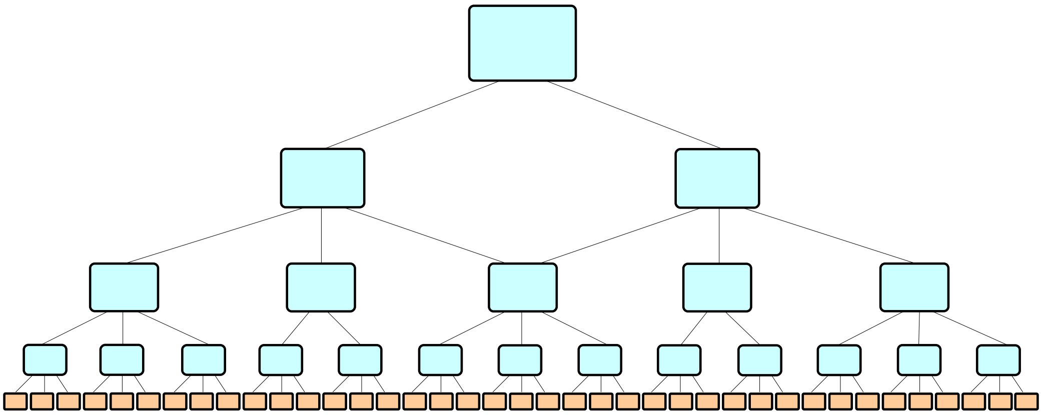

Figure 1: Example of the structure of a hierarchical condition monitoring system.

$$E_h = b + au \; . \tag{3}$$

In case of non-zero uncertainty u, there exists direct relation between an opinion ω_h and the corresponding beta probability density function. For $u = 0$, the function degenerates to the Dirac pdf concentrated at a point between 0 and 1 given by the belief b. There exists a full set of operators [4] as counterparts to the binary logic and probabilistic logic operators including deduction, abduction, etc.

The base rate a represents the prior amount of belief and can be constructed from historical data or based on experience of the user.

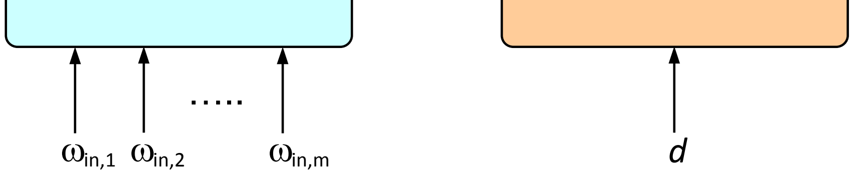

Figure 2: Two types of nodes of the hierarchical condition monitoring system.

A common block of the monitoring system which combines information from the adjacent lower blocks to provide compounded information for the next upper block is depicted on the left side of Fig. 2. The right block in the same figure which transforms incoming data into information of the suitable form constitutes the lowermost level of the pyramid in Fig. 1.

2.3 Problem: interface towards the real world

Although the Subjective logic constitutes the consistent and comprehensive theory, an obvious problem arises on its boundary with the real world: how to evaluate particular opinion ω_h and namely its component u representing uncertainty for information entering the system in Fig. 1 from below. Thus creation of an interface between the real world and the condition monitoring system in question means implementation of the right block in Fig. 2 which reads a particular data input d and provides opinion about its health ω_h. The following sections concern ω's most questionable component – the uncertainty.

3 QUANTIFICATION OF UNCERTAINTY

Several methods for quantification of uncertainty for the purpose of the monitoring system in question were already developed. They are briefly quoted in the following. A novel method representing signal inspection based on model switching is described in an extra section.

3.1 Signal vs. its allowed range

Quantification of uncertainty based on inspection of a noisy signal within its allowed range is depicted in [5] and [6]. While [5] considers the signal corrupted by a uniformly distributed noise, [6] takes possible multimodal signal distribution into account and approximates it by Gaussian mixtures. Roughly speaking, uncertainty of signal health evaluation increases when signal mean within the moving window come near to its given upper or lower boundaries. The uncertainty culminates when the mean equals to the either boundaries – one is the most uncertain whether the real signal value lies inside or outside the allowed region.

3.2 Signal quality – outliers

Another cause of an increased uncertainty lies in irregular occurrence of signal outliers as investigated in [7]. The signal is certainly unhealthy at the moment of the detected outlier. However, right after recovery of the signal, possibility of the next outlier causes high level of uncertainty which diminishes if further progress of the signal stays undisturbed.

3.3 Frequency domain analysis

The above mentioned approach can be used in the frequency domain as well. Output of the FFT (Fast Fourier Transform) is inspected for undesired peaks. These are treated similarly as outliers in the time domain: their occurrence indicates decreased health of the signal. Information uncertainty remains non-zero after their dissipation and is gradually decreased using linear or exponential forgetting. Details of the method can be found in [7].

3.4 Signal noise

Uncertainty quantification based on the signal noise itself belongs to rather different viewpoint to the condition monitoring. While all of the above mentioned methods count with the possibility of zero uncertainty in well-determined situations, non zero noise-based uncertainty is inherent for some types of signals, eg. for analog ones. Therefore the next separate section is devoted to this approach.

4 NOISE-BASED UNCERTAINTY

Let us consider an additive model of measurement of a general signal

$$y(t) = x(t) + e(t) \ , \tag{4}$$

where $y(t)$ is the measured value of the signal at time instant t, $x(t)$ is signal's true but unknown value and $e(t)$ represents the measurement noise. Particularly in case of an analog signal, the noise can hardly be neglected. Thus, signal changes less than a certain threshold can be hardly distinguished from effects of the noise which can be considered as an uncertainty of its kind. Now the root of the trouble is its quantification.

4.1 A slowly varying signal

A starting point for evaluation of uncertainty can be the signal-to-noise ratio expressed by the relation

$$\mathrm{SNR} = \frac{\sigma_x^2}{\sigma_e^2} \ , \tag{5}$$

where σ_x^2 and σ_e^2 stand for signal and noise variances respectively. The problem is that these variances cannot be distinguished without a pointed experiment the accomplishment of which is often unfeasible.

A simple alternative consists in computation of variance of the measured signal σ_y^2 and using of the 3-σ rule for comparison with the given or estimated signal range.

$$u = \min\left(1, \frac{3\sigma_y}{r_y}\right) \tag{6}$$

where $r_y = r_{\max} - r_{\min}$ is range of the signal. Tracking of slow variations of the signal can be enabled by the use the moving windows.

A step towards the ideal solution can be to elaborate the model into the form

$$y(t) = \vartheta + e(t) \ , \tag{7}$$

where ϑ is an unknown parameter and $e(t) \sim \mathcal{N}(0, \sigma_e^2)$ is the zero-mean Gaussian noise. Again, application of forgetting allows the estimate $\hat{\vartheta}$ to track smooth changes of the signal and the momentary uncertainty can be quantified as

$$u(t) = \min\left(1, \frac{3\hat{\sigma}_e(t)}{r_y}\right) \ . \tag{8}$$

4.2 An abruptly changing signal

Problem with the abruptly changing signal consists in temporarily increased variance at the moment of change whether it concerns σ_y^2 for the moving window computation or $\hat{\sigma}_e^2$ for the parameter estimation. The trouble can be solved by introduction of model switching, at least for a piecewise stable signal.

Model switching [8] assumes that the observed system generates outputs driven by more than a single *parametric* model, i.e.

$$y(t) \sim \mathcal{M}_j(\Theta_j(t), x(t)), \qquad j > 1, \tag{9}$$

where Θ is a possibly multivariate model parameter and $x(t)$, if present, is a system input driving the observation $y(t)$. The models $\mathcal{M}_j$ need not have the same structure. For instance, $\mathcal{M}_1$ may be a state-space model active when the system of interest performs operations, while $\mathcal{M}_2$ is a pure noise model suitable for standby mode.

In our case, we assume another model switching realm: the models $\mathcal{M}_j$ have identical structure (concretely, they are linear regressive models) but they differ in values of a priori *unknown* parameters $\Theta_j(t)$. Moreover, in the adopted framework the models count is unknown, as the system dynamics changes over time and is unlikely to repeat. The models are generated whenever a switch occurs and forgotten with another switch.

In the considered setting, the task of detection of model switch reduces to a hypotheses testing procedure. Each new input $y(t)$ is confronted with the model active up to time instant $t-1$ and a fit is assessed. If there is enough evidence that $y(t) \sim \mathcal{M}_j(\Theta_j(t-1), x(t))$, the hypothesis of model switch is rejected, model M_j is preserved and the statistical knowledge of its parameters $\Theta_j(t-1)$ is updated to $\Theta_j(t)$. Otherwise a new model with a reasonably preset variance estimates is generated and inferred.

The evidence supporting or rejecting the hypothesis that $y(t) \sim \mathcal{M}_j(\Theta_j(t-1), x(t))$ can be obtained in different ways. If $\mathcal{M}_j$s are statistical or probabilistic models, it is possible to decide whether $y(t)$ lies in their respective high-confidence regions of the induced predictive distributions or the models with parameters plugged in [9].

An example of model switching in estimation of cold sheet rolling mill hydraulic pressure is depicted in Fig. 3.

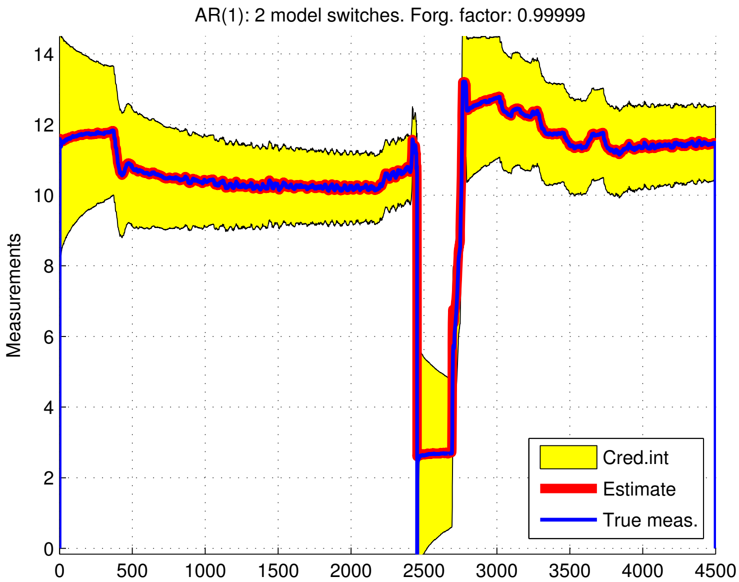

Figure 3: Evolution of true measurements (red), their estimated value (blue) and the $\pm 3\sigma$ credibility interval band. Apparently, the estimation is very stable and quickly recognises model switches. The estimation of AR(1) model employed very small forgetting.

5 PROJECT DEVELOPMENT

Algorithms for quantification of uncertainty and for the condition monitoring as the whole have been developed within the Matlab environment, using a large set of recorded process data for testing and validation. The OOP (Object Oriented Programming) features of current Matlab versions help to make the development transparent and effective. Validated algorithms have been re-programmed in C++ and tailored for execution within the multithreading application under the Windows embedded operating system. Currently, the project is in the stage of validation by the experimental pilot application in the metal processing plant.

6 CONCLUSIONS

The contribution dealt with the issue of hierarchical monitoring of control system condition using the subjective logic theory. Signals from each part of the control system are independently checked and their health is evaluated together with the information about the related uncertainty. The possible ways towards identification of this uncertainty are indicated in the paper. The subjective logic then fuses all the obtained information into the final report about the condition of the whole monitored system.

The system is currently being tested in the industrial environment.

ACKNOWLEDGEMENTS

The research project is supported by the grant MŠMT 7D12004 (E!7262 ProDisMon).

REFERENCES

[1] K. Dedecius and P. Ettler, “Hierarchical modelling of industrial system reliability with probabilistic logic,” in *Proceedings of the 11th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2014)*, (Vienna, Austria), 2014.

[2] P. Ettler and K. Dedecius, “Probabilistic reasoning in service of condition monitoring,” in *Proceedings of the 11th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies CM2014/MFPT2014*, (Manchester, UK), 2014.

[3] A. Jøsang, “Conditional reasoning with subjective logic,” *Journal of Multiple-Valued Logic and Soft Computing*, vol. 15, no. 1, pp. 5–38, 2009.

[4] A. Jøsang and D. McAnally, “Multiplication and comultiplication of beliefs,” *International Journal of Approximate Reasoning*, vol. 38, pp. 19–51, Jan. 2005.

[5] L. Pavelková and L. Jirsa, “Evaluation of sensor signal health using model with uniform noise,” in *Proceedings of the 11th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2014)*, (Vienna, Austria), 2014.

[6] L. Jirsa and L. Pavelková, “Testing of sensor condition using gaussian mixture model,” in *Proceedings of the 11th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2014)*, (Vienna, Austria), 2014.

[7] P. Ettler and K. Dedecius, “Quantification of information uncertainty for the purpose of condition monitoring,” in *Proceedings of the 11th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2014)*, (Vienna, Austria), 2014.

[8] S. Frühwirth-Schnatter, *Finite Mixture and Markov Switching Models*. Springer, Aug. 2006.

[9] L. Held and D. Sabanés Bové, *Applied Statistical Inference*. Berlin: Springer, 2013.