# From Building Blocks to the Embedded Condition Monitoring System

**Pavel Ettler** *, **Kamil Dedecius** **, **Lenka Pavelková** **,
**Đani Juričić** ***, **Pavle Boškoski** ***, **Igor Steiner** ****

* *COMPUREG Plzeň, s.r.o., 306 34 Plzeň, Czech Republic*
*(e-mail: ettler@compureg.cz).*
** *Inst. of Inf. Theory and Automation AV ČR 182 08 Praha, Czech Republic*
*(e-mail: {dedecius,pavelkov}@utia.cas.cz)*
*** *Josef Stefan Institute, 1000 Ljubljana, Slovenia*
*(e-mail: {dani.juricic,pavle.boskoski}@ijs.si)*
**** *INEA d.o.o, 1000 Ljubljana, Slovenia*
*(e-mail: igor.steiner@inea.si)*

**Abstract:** Four partners – two SMEs and two research institutes – have united forces to elaborate principles and building blocks to be exploitable for the embedded condition monitoring system with advanced features. Existing novel kind of probabilistic logic was selected for propagation and compounding of information within the hierarchical distributed system, taking pervasive uncertainty of available data into account. Efficient algorithms were developed for teal-time quantification of uncertainty of measured signals. Significant effort is devoted to meaningful transformation of the probabilistic outputs into clear notifications for operators and maintenance personnel. Variety of particular solutions take advantage of the specific expertise of the involved partners and allow consideration of various future applications. Currently, the system is in the stage of testing in a metal-processing plant.

*Keywords:* Diagnostic programs; failure detection; probabilistic logic; maintenance engineering; programmable logic controllers

## 1. INTRODUCTION

Diagnostics and condition monitoring are becoming inherent constituents of modern control systems, at least for systems exceeding certain level of complexity. Their aim is obvious: effective maintenance as a prerequisite for the smooth production. Practical application of diagnostic features is often confronted with two main problems:

(1) Heterogeneity of components of a complex control system;
(2) Various credibility and importance of available incoming information.

The first case involves various types of incoming signals (analog, incremental, logical etc.), diversified ways of data acquisition (direct, remote with dedicated or shared communication means etc.), different technological platforms of system nodes (measurement units with embedded intelligence, Programmable Logic Controllers (PLC), industrial computers, office-floor computers etc.) and various types of networks.

The second case can be illustrated by a typical example: if certain sensor within the system stops to provide data due to, say, disconnected wiring, detection of the failure is mostly obvious and action to be done is straightforward. However, if the data are just affected by the impaired functionality of the sensor due to, say, its wear, the failure is much more difficult to detect and the action to be taken is less obvious. In fact, the operator has to make a binary decision based on uncertain information on the lowermost level while his decision influences operation of the whole machine or production line.

The paper presents outputs of the research project the aims of which are to overcome both groups of problems by introduction of an hierarchical (and possibly distributed) condition monitoring system which takes uncertainty of incoming and processed information systematically into account. Individual partners involved in the project have focussed on various aspects of the considered problem and have elaborated principles and building blocks which are at disposal for implementation of the system for a specific domain and in a given extent. Pilot application targets the metal processing industry.

The paper is organized as follows: the following section introduces an existing kind of probabilistic logic which was selected as the principal calculus for treatment of uncertain information. The next sections depict further principles and building blocks which were elaborated for the project's purpose. The application-oriented section is followed by the conclusion.

## 2. PRINCIPLES AND BUILDING BLOCKS

The system being built is schematically depicted in Fig. 1.

Measured signals and other quantities whose proper operation should be taken into account when evaluating *health*

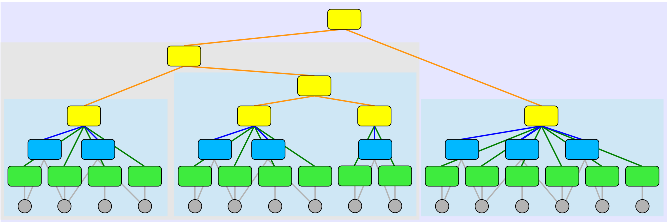

Fig. 1. Example of the structure of the hierarchical condition monitoring system. Green, blue and yellow blocks belong to single signals, relation between pairs of signals and probabilistic logic operations respectively.

of the system enter the hierarchical structure on the lowermost level. Particular green blocks evaluate health of single incoming signals while the blue blocks care about proper relation between pairs of signals. Yellow blocks realize probabilistic logic operations to asses health of functional or logical subsystem and – on the uppermost level – health of the system as the whole. Parts of the system *pyramid* can be distributed within a networked system.

Means used for the treatment of information and domain or application specific parts of the solution are summarized in the following sections.

### *2.1 From beta distributions to the Subjective logic*

Central idea of the project consists in using a kind of probabilistic logic for compounding of information about *health* of particular system components. Right from the beginning, the idea ran up against the problem of appropriate modeling of distribution of probabilities in question. As the key considered quantity – probability of health of a component – is naturally bounded, a group of suitable theoretical distributions with bounded support was thoroughly investigated, with the beta distribution as the obvious favorite (Dedecius and Ettler (2013)). Searching for a calculus which enables consistent logical operations with the beta distributions led to the engagement of the so called Subjective logic (SJ).

Subjective logic (Jøsang (2001), Jøsang (2009)) is a novel probabilistic logic theory for treatment of uncertain propositions. Appropriateness of its use for the purpose of the project was inferred by Ettler and Dedecius (2014a). Below we state the essentials of the calculus.

The theory of SJ is based on definition of a probabilistic opinion of a proposition about $h$ (health) 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

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

There exists a bijective mapping between an opinion $\omega_h$ and the corresponding beta probability density function for non-zero uncertainty $u$. 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 as counterparts to the binary logic and probabilistic logic operators including multiplication, addition, deduction, abduction, etc. Moreover, additional operators can be used for various types of fusion and unfusion and for the belief constraining.

The base rate $a$ represents the prior amount of belief and can be constructed from historical data or based on experience of the user. Bayesian approach can be beneficial for this purpose as was investigated by Dedecius and Ettler (2014).

### *2.2 Evaluation of uncertainty*

Quantification of the uncertainty $u$ is the crucial step of the whole approach. Several algorithms for evaluation of $u$ were developed within the project.

*Signal range*

Very basic evaluation of signal health is based on examination how the signal fits its allowed range. In the simplest case, the measured signal should lie within the specified interval: $x(t) \in [x_{\min}, x_{\max}]$. Measurements $x(t)$ are mostly corrupted by some kind of noise which can be expressed by the model

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

where $x^\star(t)$ is the real but unknown value of the signal in time $t$ and $e(t)$ is a zero-mean signal noise. In the neighborhood of signal boundaries, there is difficult to determine whether $x^\star(t)$ lies inside or outside the allowed range. Related uncertainty $u$ can be derived from statistical moments of $e(t)$ within the selected moving window. Detailed relations for evaluation of uncertainty $u$ and opinion $\omega_h$ for the model with normal noise can be found in Ettler and Dedecius (2014b). Fig. 2 illustrates a simulated situation where the measured signal traverses its allowed maximum (the upper plot) which is reflected by probability distribution of signal health $h(t)$ (the lower plot).

Pavelková and Jirsa (2014) consider two-level bounds $\underline{x}_{\mathrm{H}} < \underline{x}_{\mathrm{S}} < \bar{x}_{\mathrm{S}} < \bar{x}_{\mathrm{H}}$, where indices $H$ and $S$ stand for hard and soft boundaries, respectively. Under usual working conditions, the signal $x^\star(t)$ is expected to occur inside the soft bounds and it may not occur outside the hard bounds. Utilizing these bounds, the course of the opinion $\omega_h$ (1) of the health of $x^\star(t)$ can be constructed straightforwardly. Concerning $x(t)$, it is described here by the model (4) with uniformly distributed noise $e(t)$. Then, the resulting opinion $\omega_h$ depends on the mean value of $x(t)$ and its uncertainty $u$ is influenced by the interval given by the support of uniform distribution describing $x(t)$.

Signals the distribution of which is obviously not unimodal can be modeled by the mixture of normal distributions as explained by Jirsa and Pavelková (2014).

*Outliers*

Another type of uncertainty is connected with potential measurement outliers. Degradation of signal reliability

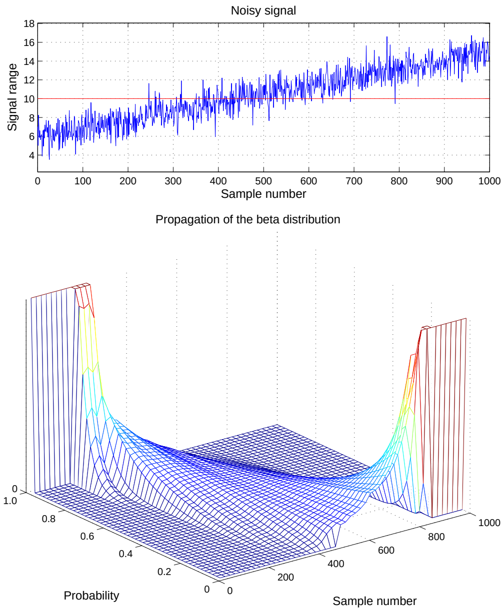


Fig. 2. Range-dependent proposition about signal health: The noisy signal is traversing its given positive boundary on the upper plot. Propagation of the beta distribution of probability of its health is depicted on the lower plot.

caused by occurrence of outliers can be appropriately expressed by non-zero uncertainty, relations for which were specified by Ettler and Dedecius (2014b).

*Monitoring in the frequency domain*

Some signals may suffer from harmonic disturbances. Utilization of the Fourier transform and analysis in the frequency domain is then commonplace. From the uncertainty evaluation point of view, undesired frequency peaks can be treated as outliers with similar consequences. More on the analysis in the frequency domain can be found in the following subsection.

*Monitoring and modeling of relationships between signals*

Relationships between signals can be monitored in two ways:

(1) Plain comparison of moving averages of signals and indication whether their difference exceeds given limit. Uncertainty of such comparison can be evaluated similarly as in the signal-to-range case.
(2) Simple modeling of signal relationship in the form
$$x_1(t) = p_1(t) * x_2(t) + p_2(t) + \epsilon(t)\,, \tag{5}$$
where $x_1(t)$, $x_2(t)$ stand for the two monitored signals, $p_1, p_2$ are time-varying model parameters, and $\epsilon(t)$ is a normally distributed, zero-mean noise. Comparison of parameter estimates $\hat{p}_1(t)$, $\hat{p}_2(t)$ and evaluation of its uncertainty is accomplished similarly as in preceding case. Again, details can be found in Ettler and Dedecius (2014b).

### *2.3 More on the monitoring in the frequency domain*

Data acquisition setup for the frequency analysis is explained in Figure 3. In certain cases it is not necessary to perform sampling all the time, but just in periodic sampling sessions while in other cases measurement sessions will immediately follow each other. Each session consists of $N$ samples taken at a sampling rate $f_s = \frac{1}{T_s}$. The first $N_{ref}$ sessions belong to the reference window and are taken while the inspected signal is in the healthy state. During the operation a sliding window with $N_{cur}$ recent sampling sessions is used to decide whether there is a change in the features statistics. For simplicity, let us assume that after each measurement session labeled $k$, a feature being the $m^{th}$ component of the Fourier spectrum is calculated as follows:

$$Z_{k,ref} = \sum_{t=0}^{N-1} y_k(t) e^{j2\pi \frac{mt}{N}} = X_{k,ref} + jY_{k,ref} \tag{6}$$
$$k = 1, ..., N_{ref}.$$

Since the Fourier transform (6) is a linear transformation of a normally distributed random signal (4), $Z_{k,ref}$ is also a normally distributed but complex random variable. Furthermore, the same applies also to the current condition:

$$Z_{l,cur} = \sum_{t=0}^{N-1} y_l(t) e^{j2\pi \frac{mt}{N}} = X_{l,cur} + jY_{l,cur} \tag{7}$$
$$l = 1, ..., N_{cur}.$$

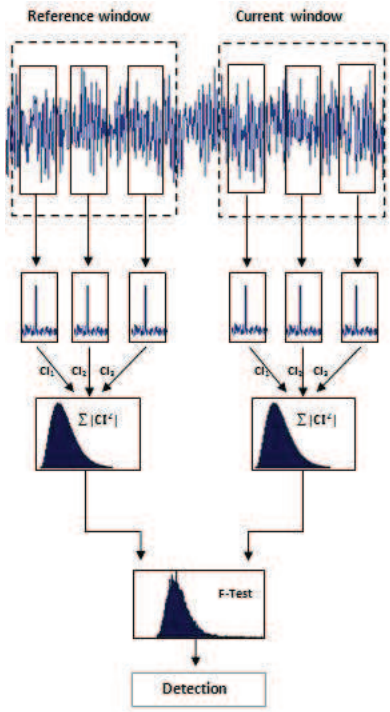


Fig. 3. Possible computational scheme for monitoring in the frequency domain.

After the sets of features are formed, a batch of $N_{ref}$ features obtained in nominal condition and a batch of $N_{cur}$ features obtained at current condition are subjected to centering by subtracting the average from nominal condition from both batches

$$Z_{k,ref} \leftarrow (X_{k,ref} - \overline{X}_{k,ref} + j(Y_{k,ref} - \overline{Y}_{k,ref}) \tag{8}$$

where $\overline{X}$ denotes the expected value of $X$.

*Failure detection*

A statistical hypothesis test is derived from the previously obtained centered reference and current sets of features $Z_{k,ref}$ , $k = 1, ..., N_{ref}$ and $Z_{l,cur}$ , $l = 1, ..., N_{cur}$. Let us now note that the sum of squared modules of $Z_{k,ref}$ is compliant with the central chi-squared distribution with $N_{ref}$ degrees of freedom.

$$CI_{ref} = \sum_{k=1}^{N_{ref}} Z_{k,ref}\, Z^*_{k,ref} = \sum_{k=1}^{N_{ref}} |Z_{k,ref}|^2 \qquad (9)$$

$$CI_{ref} \sim \chi^2(N_{ref})$$

This result is obtained by assumption that in nominal condition small changes in the mean occur between different sampling sessions. Actually we suppose that the healthy features are zero mean and their chi-square statistics are obtained by mathematical calculation (9). In general, when the component becomes faulty, the mean of the features is no longer zero, meaning that the features in current condition are

$$CI_{cur} = \sum_{l=1}^{N_{cur}} Z_{l,cur}\, Z^*_{l,cur} = \sum_{l=1}^{N_{cur}} |Z_{l,cur}|^2 \qquad (10)$$

$$CI_{cur} \sim \chi^2(N_{cur}, \lambda)$$

$$\lambda = \sum_{l=1}^{N_{cur}} \left(\frac{\mu_{l,cur}}{\sigma_{l,cur}}\right)^2, \qquad (11)$$

distributed according to the noncentral $\chi^2$ distribution with $N_{cur}$ degrees of freedom and noncentrality parameter $\lambda$. The noncentrality parameter is related to the means $\mu_{l,cur}$ and the variances $\sigma_{l,cur}^2$ of the random variables $CI_{cur}$. This is the case because of the non-zero mean features of $Z_{l,cur}$ (8). As a result of the changes, for example in the amplitude of a signal, the statistics of the features are changing, which is an indication that a fault has occurred. From here it is easy to distinguish between different faults. Changes in the signal will reflect in large increase in the mean of the signal and by the ratio between these CIs the decision could be made. If there is no change in the system condition, then the statistical properties of $|Z_{l,cur}|^2, l = 1, ..., N_{cur}$ should be equal to the statistical properties of $|Z_{k,ref}|^2, k = 1, ..., N_{ref}$, i.e. should share the same $\chi^2$ distribution. Let us assume $E|Z_{l,cur}|^2 = \sigma^2_{cur}$ and $E|Z_{k,ref}|^2 = \sigma^2_{ref}$ for all samples. If the signal health deteriorates, the statistical properties of the feature change, which normally affect the increase in feature variance. Since both sets of samples are independent, we can define the null hypothesis $H_0 : \sigma^2_{cur} = \sigma^2_{ref}$ versus the alternative hypothesis $H_1 : \sigma^2_{cur} > \sigma^2_{ref}$. We propose the test statistic

$$CI_F = \frac{CI_{cur}/N_{cur}}{CI_{ref}/N_{ref}} \sim F(N_{cur}, N_{ref}) \qquad (12)$$

which under $H_0$ complies with the central F-distribution with $N_{cur} - 1$ and $N_{ref} - 1$ degrees of freedom. So, given samples we reject $H_0$ if

$$CI_F \geq h = F_\alpha(N_{cur} - 1, N_{ref}) \qquad (13)$$

where the term on the right side denotes the critical value of the distribution at the level of significance $\alpha$. The level of significance $\alpha \cdot 100\%$ denotes the tolerated PFA. For example, in case of $N_{ref} = 400$ and $N_{cur} = 400$ and $PFA = 5\%$ from the table of low critical values for the F distribution it follows that the value of the threshold $h = 1, 2290$.

*An example:*

Let us take a two-component signal with additive white Gaussian noise

$$y(t) = A \cdot (sin(2\pi \cdot 20 \cdot t) + sin(2\pi \cdot 50 \cdot t)) + w(t). \quad (14)$$

Changes in amplitude $A$ simulate increase in a component of a vibrational signal due to a particular fault (e.g. unbalance). This change influences the current feature statistics. Let us take the referent set with $N_{ref} = 400$ sampling sessions and set the sliding window in on-line operation $N_{cur} = 100$. Each session contains $N = 1000$ samples. Prior to calculating the FFT of sampled record in a measurement session the record is multiplied by the Hamming window. From a batch of features collected in nominal condition and a batch corresponding to the current condition, a statistical hypothesis test is derived. Furthermore, noncentral F-test is performed where the resulting CIs are used for obtaining the threshold percentiles from the quantile function.

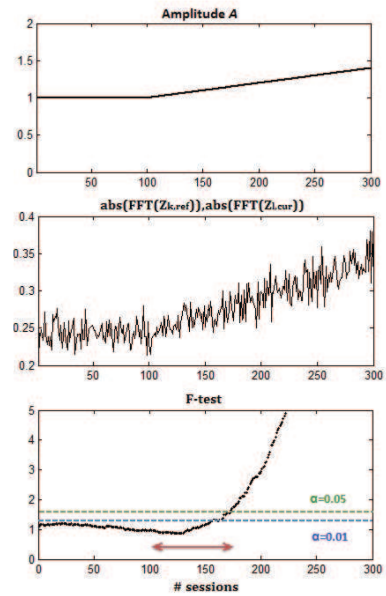


Fig. 4. An example of performance of the detection algorithm.

It can be seen in Fig. 6 that the test reliably detects change in the feature. However, the alarm is triggered with a delay, which depends on the window length.

## 2.4 Coherence with existing standards

Managing data processing and storing data on various levels of aggregation in condition based maintenance is rarely discussed in the publications as the bulk of interest of the community is on algorithms for feature extraction, diagnosis and recently prognosis. The most comprehensive approach to this issue seems to be provided by MIMOSA OSA-EAI (Mimosa (2013)) standard. The notable strength of MIMOSA comes from the completeness and consistency of the entities that constitute the system.

Condition monitoring is a multistage process. MIMOSA delivers a model of it, which consists of 6 modules, cf. Fig. 6. The first two modules take care of correct data acquisition and evaluation of the features. The next module checks the conformity of the pattern of features with the reference pattern and an alarm is triggered if discrepancy is detected. The health assessment module provides an estimate of the current health, i.e. indicating tentative faulty locations. From the historical trends of features as well as the available degradation models the remaining useful life of the machine can be estimated (Gasperin et al. (2012)). Based on the assessed current health and expected machine lifetime the last module generates guidelines for the operators and maintenance personnel.

The state detection module is based on various algorithms for detecting changes in trends of the features evolution over time. Simple thresholding techniques are also utilized for large changes. Prognostic assessment (PA) is a notoriously difficult task and is not addressed here.

Our system schematically depicted in Fig. 1 can be considered as a subset of the above mentioned standard scheme realizing blocks Data acquisition (DA), Data manipulation (DM) and Health assessment (HA).

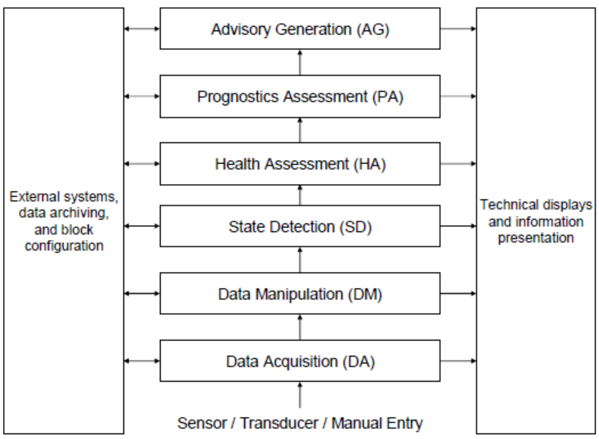


Fig. 5. MIMOSA standard: Data processing and information flow blocks.

### *2.5 Presentation of outputs*

Although the theory behind the control system health evaluation is complex, the system operators should be confronted with as simple and comprehensible information as possible. Therefore, it is necessary to 'translate' the outputs from the hierarchical monitoring system to a format allowing quick understanding. Furthermore, the presented information must be stable in the sense that any changes must be sufficiently smooth.

The situation is illustrated in Fig. 7: uncertain information is consistently processed up to the uppermost block, the outputs of which are presented in the form of the three-state semaphore and textual messages for the operator. Detailed probabilistic information is still available for the qualified inspection.

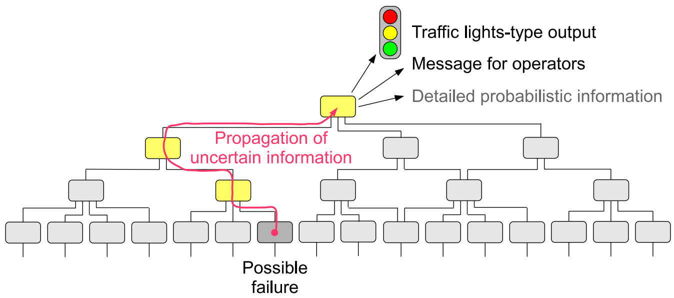


Fig. 6. Propagation of uncertain information upwards the hierarchical system and its simplification on the uppermost level.

A possible way towards smooth information for operators is to model the time between events – the semaphore states – as an exponentially distributed random variable (denoted $X_t$) with an unknown rate parameter $\lambda > 0$. The Bayesian estimation of this parameter, accompanied by an exponential discounting (setting the smoothness of transitions among states), exploits the probability density function of $X_t$ of the form

$$p(x_t|\lambda) = H(x_t)\lambda \exp(\lambda x_t),$$

where the Heaviside step function

$$H(x_t) = \begin{cases} 0 & \text{if } x_t < 0 \\ 1 & \text{otherwise.} \end{cases}$$

From now on, we assume $\lambda$ time-variable and denote it $\lambda_t$. The conjugate prior distribution allowing fast sequential estimation is the gamma distribution. It has two non-negative prior hyperparameters $\alpha_{t-1}$ and $\beta_{t-1}$ and the probability density function

$$\pi(\lambda|\alpha_{t-1}, \beta_{t-1}) = \frac{\beta_{t-1}^{\alpha_{t-1}}}{\Gamma(\alpha_{t-1})} \lambda^{\alpha_{t-1}-1} \exp(-\lambda\beta_{t-1}).$$

The prior hyperparameters summarize the available statistical knowledge about $\lambda_t$, whose mean, variance and mode read

$$\mathbb{E}[\lambda] = \frac{\alpha_{t-1}}{\beta_{t-1}}, \quad \operatorname{var} \lambda = \frac{\alpha_{t-1}}{\beta_{t-1}^2}, \quad \text{and} \quad \tilde{\lambda} = \frac{\alpha_{t-1} - 1}{\beta_{t-1}}.$$

The posterior density is proportional to the product of the exponentially discounted prior and the model,

$$\pi(\lambda|\alpha_t, \beta_t) \propto [\pi(\lambda|\alpha_{t-1}, \beta_{t-1})]^{\gamma} \, p(X_t = x_t|\lambda),$$

where $\gamma \leq 1$ is a discounting factor slightly smaller than one and $x_t$ a measurement of the time between events. The posterior is fully characterized by the hyperparameters

$$\alpha_t^+ = \gamma\alpha_{t-1} + 1, \quad \text{and} \quad \beta_t^+ = \gamma\beta_{t-1} + x_t.$$

## 3. APPLICATION

The main feature of the proposed condition monitoring system is its hierarchical structure, allowing distribution of its parts over a network of interconnected processing nodes. System components or the system as the whole can be embedded into the nodes of the monitored system. The last possibility is suitable mainly in situations where the control and condition monitoring systems are developed and commissioned together, i.e. for new systems. When the monitoring functionality is to be added to an existing control system, using of dedicated nodes may be more suitable.

Such solution has been used for the experimental system which is now being tested in a metal-processing plant. Single nodes are realized by industrial computers as in Fig. 8. MS Windows Embedded are used as the operating system in this case while Linux with the real-time kernel extension is considered as an alternative.


Fig. 7. A node of the ProDisMon condition monitoring system.

The experimental system monitors functionality of the control system of the four-high cold rolling mill which processes copper and brass strips. Four groups of quantities are supervised:

(1) Measured analog signals (hydraulic pressures, slide-valve positions of proportional valves, strip thicknesses and electric currents of the mill drives);
(2) Digitally measured signals (positions of the roll positioning system, revolutions of working rolls and coilers and strip speeds);
(3) Information about computer hardware (processor temperatures and revolutions of fans);
(4) Information about software functionality (load of processor cores and execution times of particular real-time tasks/threads).

The input signals are accessed via the industrial network. The software solution is based on the OOP (Object Oriented Programming) principles. Outputs and internal states of each block are recorded continuously to allow subsequent detailed inspection. Developed visualization tools provide on-line information about operation of the system together with simplified outputs intended for the operators.

## 4. CONCLUSION

Several principles were adopted or elaborated and number of building blocks were developed to be ready for implementation of the probabilistic condition monitoring system. Subjective logic – a kind of probabilistic logic taking information uncertainty systematically into account – was adopted as the principal calculus for compounding and propagation of information within the system. This approach enables consistent treatment of uncertain propositions about health of particular components, parts of the system and health of system as the whole. Thus, a better decisions support is placed at disposal of operators and/or maintenance personnel.

Bulk of the developed building blocks were used for configuration of the experimental condition monitoring system the testing of which has been commenced for a cold rolling mill. Enlargement of the system for monitoring other aggregates within the metal processing plant is envisaged after evaluation of long-term testing.

## ACKNOWLEDGEMENTS

The research is accomplished in the framework of the Eurostars project E!7262 ProDisMon and is supported by the Czech grant MŠMT 7D12004 and the Slovene grant MVZT 2130-13-090007.

## REFERENCES

Dedecius, K., Ettler, P., 2013. Overview of bounded support distributions and methods for Bayesian treatment of industrial data. In: Proceedings of the 10th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2013). Reykjavík, Iceland, pp. 380–387.

Dedecius, K., Ettler, P., 2014. 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.

Ettler, P., Dedecius, K., 2014a. 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.

Ettler, P., Dedecius, K., 2014b. 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.

Gasperin, M., Juricic, D., Boskoski, P., 2012. Prediction of the remaining useful life: an integrated framework for the model estimation and failure prognostics. In: Proc. IEEE International Conference on Prognostics and Health Management. Denver, Colorado.

Jirsa, L., Pavelková, L., 2014. 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.

Jøsang, A., 2001. A logic for uncertain probabilities. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 9 (3), 279–312.

Jøsang, A., 2009. Conditional reasoning with subjective logic. Journal of Multiple-Valued Logic and Soft Computing 15 (1), 5–38.

Mimosa, 2013. MIMOSA OSA-EAI v3.2.2. URL `http://www.mimosa.org/`

Pavelková, L., Jirsa, L., 2014. 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.