Integration of Knowledge-based Information in Intelligent Condition Monitoring

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Abstract

A consistent representation is needed to use knowledge-based information together with measurements. Generalised norms and moments are used together to obtain informative features from measurements and signals processed by real-order derivatives. Intelligent condition and stress indices in the range [-2, 2], denoted as linguistic range, are obtained by using the norms and moments in nonlinear scaling. The procedure is in principle the same as in representing fuzzy rule-based systems in linguistic equation (LE) systems: linguistic labels are replaced with membership locations defined in the range [-2, 2]. Although knowledge-based information does not necessarily contain numerical values, the linguistic labels can be defined by membership functions in the linguistic range. For example, labels {very low, low, normal, high, very high} or {fast decrease, decrease, constant, increase, fast increase} have clearly defined locations in the linguistic range. These terms are represented by equally spaced membership functions, which can be further refined in the chosen part of the range [-2, 2]. The linguistic terms are fuzzy numbers, which can be made sharper or wider with powering modifiers 'extremely', 'very', 'more or less' and 'roughly', and then processed with conjunction, disjunction and negation. The methodology is used in the analysis of the event data: the information represented with these numbers produces a real-valued relation base to be used to analyse interactions. Known relationships can also be handled with the fuzzy calculus and the extension principle to keep the uncertainty in the calculation.

Keywords: Knowledge-based systems, nonlinear scaling, intelligent indices, fuzzy set systems, event data, condition monitoring

1. Introduction

Process control systems, like those used in oil & gas industry, pulp & paper industry, or other processes, typically include one or more centralized or decentralized process controllers communicatively coupled to at least one host or operator workstation and to one or more process control and instrumentation devices, such as field devices. Process control operators who generally oversee the day to day operation of the process and who are primarily responsible for assuring the quality and continuity of the process operation typically affect the process by setting and changing set points within the process, tuning loops of the process, scheduling process operations, etc. Typically, maintenance interfaces and maintenance personnel form a really huge of data network, which is located apart from process control operators (Figure 1). In some process plants, process control operators may perform the duties of maintenance people or vice versa, or the different people responsible for these functions may use the same interface. (1)

Advanced signal processing methods and intelligent fault diagnosis have been developed to detect different types of machine faults reliably at an early stage. Dimensionless indices, which are obtained by comparing each feature value with the corresponding value in normal operation, provide useful information on different faults, and even more sensitive solutions can be obtained by selecting suitable features.[2] Generalised moments and norms include many well-known statistical features as special cases and provide compact new features capable of detecting faulty situations [3,4,5]. Intelligent models extend the idea of dimensionless indices to nonlinear systems.

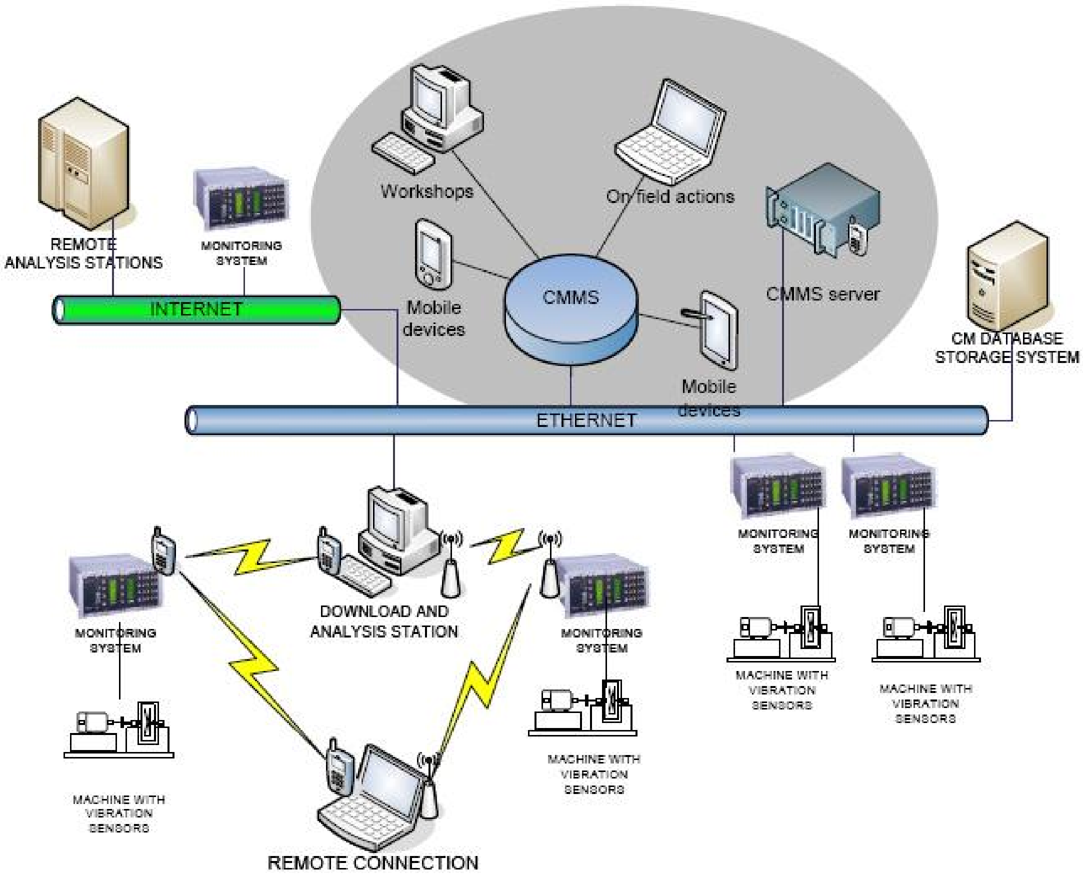

Figure 1. Typical architecture of maintenance information system [1].

Smart adaptive applications combine expertise and data (Figure 2). Expert systems have been a long time a feasible channel for introducing expertise to the applications, and the main benefit of fuzzy logic is that it provides additional tools for using expertise in these systems. Neural computing started from data-driven modelling. Both fuzzy set systems and neural networks are coming closer: data-driven techniques have use in fuzzy set systems, and utilisation of expertise is also an important topic in neural computing. Various neuro-fuzzy systems are examples of these synergy effects. Top-down and bottom-up approaches are combined also in Bayesian networks (BN), i.e. prior knowledge and data. Hyperplane methods also combine data and expertise: e.g. support vector machine (SVM) approach is based on statistical methods. [6]

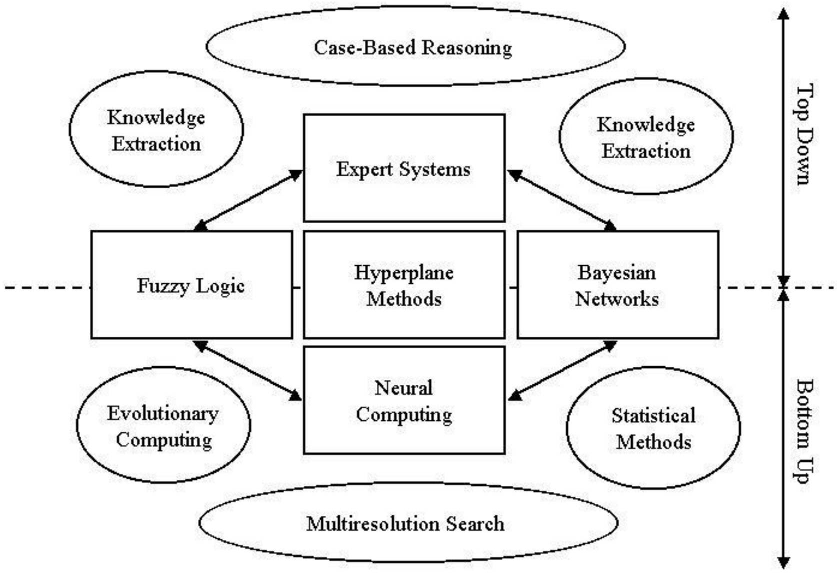

Figure 2. Methodologies of smart adaptive systems [(6)].

The linguistic equation approach can be understood as a hyperplane method, which resembles the idea of fuzzy set systems: the rule sets of fuzzy systems are replaced by equations, and instead of membership functions nonlinear scaling is used.[(7)] Operating conditions can be detected by means of a Case-Based Reasoning (CBR) type application with linguistic equation (LE) models and fuzzy logic [(8,9)]. The basic idea is nonlinear scaling, which was developed to extract the meanings of variables from measurement signals [(10)]. The basic scaling approach presented in [(9)] has been improved by introducing new methods for constraint handling [(11)] and extracting parameters from data [(12)].

This paper addresses combining data and expertise in integrated control and condition based maintenance by means of intelligent methods. The nonlinear scaling approach is taken as a basis for the interaction.

2. Maintenance information

Maintenance information is collected from various sources (Figure 1). For condition monitoring measurements, advanced signal processing and feature extraction is combined with nonlinear scaling to obtain condition and stress indices [(12)]. The nonlinear scaling has also been used for performance indicators, including harmonised indicators (Table 1), key performance indicators and overall equipment effectiveness (OEE). More information can be collected with reliability-centered maintenance (RCM), and finally, all this can be monitored with statistical process control (SPC) [(13)]. The nonlinear scaling approach is an integrating part of this analysis.

The maintenance systems include a huge amount of event information, which is not necessarily in a numeric form. However, the linguistic labels of this knowledge-based information can be defined by membership functions in the linguistic range. For example, labels {very low, low, normal, high, very high} or {fast decrease, decrease, constant, increase, fast increase} have clearly defined locations in the linguistic range. The linguistic labels are fuzzy numbers, which can be made sharper or wider with modifiers “very”, “more or less” etc.

Table 1. Examples of harmonised indicators [13].

Harmonised indicators		
Indicator	**Nominator**	**Denominator**
Cost	Maintenance cost Internal personnel Contractor cost Corrective maintenance Condition-based maintenance	Asset replacement value Quantity of output Total maintenance cost
Inventory value	Maintenance materials	Asset replacement value
Time	Operating time Time to restore	Number of failures
Systems	Covered by criticality analysis	Total number
Work orders	As scheduled	Total number
Man-hours	Training	Total internal man-hours
Spare parts	Supplied as requested	Total number

3. Fuzzy set systems

Fuzzy logic emerged from approximate reasoning, and the connection of fuzzy rule-based systems and expert systems is clear, e.g. the vocabulary of AI is kept in fuzzy logic [14]. Fuzzy set theory was first presented by [15] to form a conceptual framework for linguistically represented knowledge. Extension principle is the basic generalisation of the arithmetic operations if the inductive mapping is a monotonously increasing function of the variable. The interval arithmetic presented by [16] can be used together with the extension principle on several membership α-cuts of the fuzzy number for evaluating fuzzy expressions [17,18,19]. Type-2 fuzzy models introduced by Zadeh in 1975 take into account uncertainty about the membership function [20]. Most systems are based on interval type-2 fuzzy sets, which are reduced to an interval-valued type-1 fuzzy set.

Linguistic fuzzy models [21], where both the antecedent and consequent are fuzzy propositions, suit very well to the qualitative description of the process as they can be interpreted by using natural language, heuristics and common sense knowledge. The key idea is to use membership functions for both the inputs and the outputs, each rule can have several inputs and outputs. Membership functions can be defined by expert knowledge or by experimentation. The input-output mapping is realized by the fuzzy inference mechanism equipped with conversion interfaces, fuzzification and defuzzification. Fuzzy set systems can also handle contradictory data [22,23].

Takagi-Sugeno (TS) fuzzy models [24], where each consequent is a crisp function of the antecedent variables can be interpreted in terms of local models. The consequent is a parameterized function, whose structure remains constant and only the parameters vary. For linear functions, the standard weighted mean inference must be extended with a smoothing technique [25]. TS fuzzy models are suitable for identification of nonlinear systems. Singleton models, where the consequents are crisp values, can be regarded as special cases of both the linguistic fuzzy models and the TS fuzzy models. Defuzzification reduces to the fuzzy-mean of the singleton values.

Fuzzy relational models [26], which allow one particular antecedent proposition to be associated with several different consequent propositions, can be regarded as generalizations of the linguistic fuzzy models. Each element of the relation represents the degree of association between the individual reference fuzzy sets defined in the input and output domains, i.e. all the antecedents are tied to all the consequents with different weights.

The increasing complexity of the application requires more and more combined approaches classified to the upper right corner of Figure 3. Selecting a suitable number of modelling areas is the key issue. In the knowledge-based approach, understanding the rules is important, and the number of rules is tried to keep in minimum. The knowledge-based approach is based on nonlinear sets of membership functions and a fairly simple set of rules. This approach, which is usually based on linguistic fuzzy models, is well suited to human input, and the operation of the system can be improved by tuning of the membership functions.

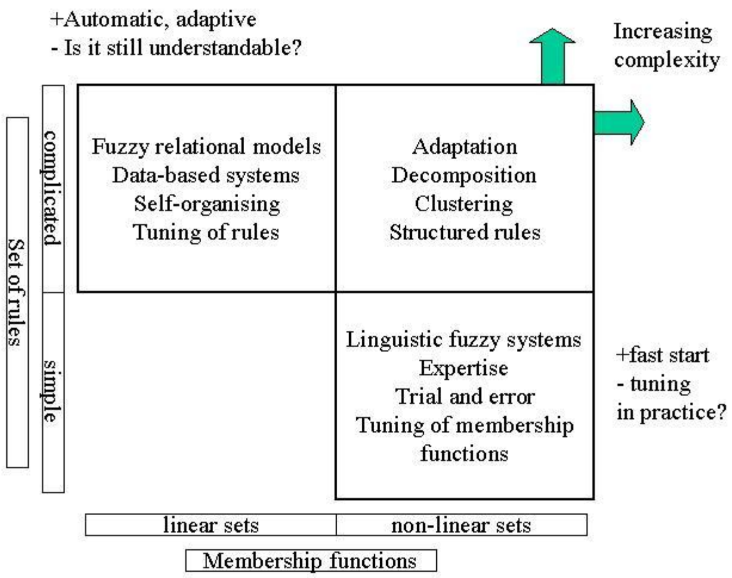

Figure 3. Classification of fuzzy set systems [9].

The membership functions are often based on domain expertise. Nonlinear behaviour should be included as much as possible in the distribution of the membership functions.

The basic idea of the nonparametric models explains the decomposition level: a weighted average of neighbouring values, i.e. singletons in fuzzy set systems. Membership functions and approximate reasoning extend this to partially overlapping submodels. Crisp levels and rules are useful for special cases with abrupt changes. Simple models classified to the lower right corner contain only the decomposition level.

The fuzzy set scan be modified by fuzzy modifiers, which are used as intensifying adverbs (‘very’, ‘extremely’) or weakening adverbs (‘more or less’, ‘roughly’). The resulting terms,

$$extremely\, A \subseteq very\, A \subseteq A \subseteq more\, or\, less\, A \subseteq roughly\, A, \quad \text{.................(1)}$$

correspond to powers {4, 2, 1, ½, ¼} of the membership in the powering modifiers. The vocabulary can also be chosen in a different way, e.g. ‘highly’, ‘fairly’, ‘quite’. Only the sequence of the labels is important. Linguistic variables can be processed with conjunction ‘and’, disjunction ‘or’ and negation ‘not’. More examples can be found in [27].

4. Linguistic equation (LE) systems

The linguistic equation (LE) models are linear equations

$$\sum_{j=1}^{m} A_{ij} X_j + B_i = 0, \quad \text{..(2)}$$

where X_j is the linguistic level for the variable j, $j = 1...m$. Each equation i has its own set of interaction coefficients A_{ij}, $j = 1...m$. The bias term B_i was introduced for fault diagnosis systems. Various fuzzy models can be represented by means of LE models, and neural networks and evolutionary computing can be used in tuning. The first LE application in condition monitoring was presented in [28]. The condition monitoring applications are similar to the applications intended for detecting operating conditions in the process industry [29].

Both expertise and data can be used in developing the mapping functions (membership definitions). The basic idea is to extract the meanings of variables from measurement signals. The scaling function scales the real values of variables to the range of [-2, +2] which combines normal operation [-1, +1] with the handling of warnings and alarms. The scaling function contains two monotonously increasing functions: one for the values between -2 and 0, and one for the values between 0 and 2. [9] The membership definition f consists of two second-order polynomials, i.e. the scaled values, which are called linguistic levels X_j, are obtained by means of the inverse function f^{-1}. The coefficients of the polynomials are defined by points

$$\left\{ (\min(x_j), -2), ((c_l)_j, -1), (c_j, 0), ((c_h)_j, 1), (\max(x_j), 2) \right\}, \quad \text{.............(3)}$$

where $[(c_l)_j, (c_h)_j]$ is the core (Figure 4). Additional constraints can be taken into account for derivatives, e.g. locally linear function results if continuous derivative is chosen at the centre point. [11]

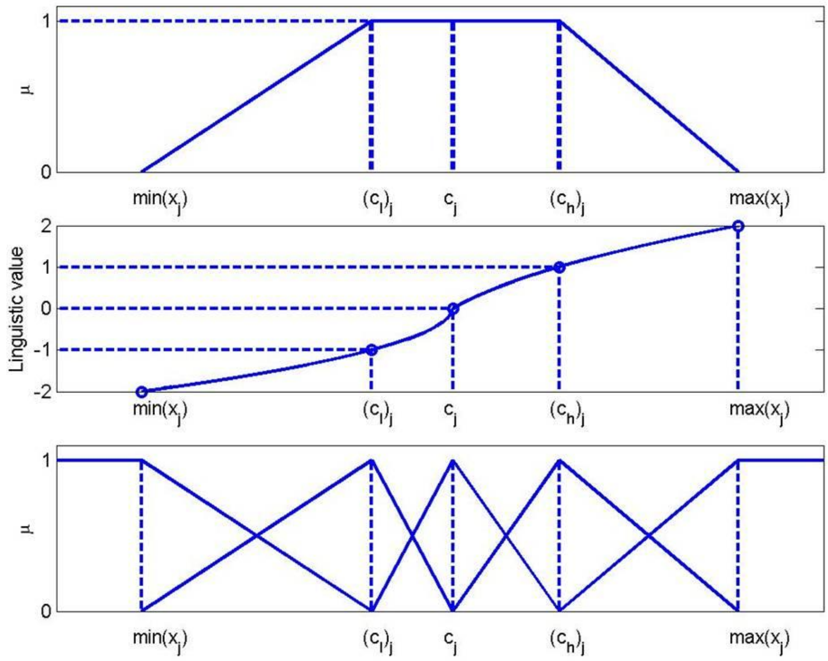

Figure 4. Feasible range, membership definitions and membership functions [9].

In the analysis of the corner points, the value range of x_j is divided into two parts by the central tendency value c_j and the core area, $[(c_l)_j, (c_h)_j]$, is limited by the central tendency values of the lower and upper part. There are problems when the value range is very wide or the distribution is very concentrated. The central tendency value is chosen by the point where the skewness changes from negative to positive, i.e. $\gamma_3 = 0$. Then the data set is divided into two parts: a lower part and an upper part. The same analysis is done for these two data sets. The estimates of the corner points, $(c_l)_j$ and $(c_h)_j$, are the points where the direction of the skewness changes. The iteration is performed with generalised norms. Then the ratios α_j^- and α_j^+ are restricted to the range $\left[\frac{1}{3}, 3\right]$ moving the corner points $(c_l)_j$ and $(c_h)_j$ or the upper and lower limits $\min(x_j)$ and/or $\max(x_j)$. The linearity requirement (10) is taken into account, if possible. [12]

The membership definitions of each variable are configured with five parameters, including the centre point c_j and three consistent sets:

- corner points $\{\min(x_j), (c_l)_j, (c_h)_j, \max(x_j)\}$ are good for visualisation,
- parameters $\{\alpha_j^-, \Delta c_j^-, \alpha_j^+, \Delta c_j^+\}$ are suitable for tuning, and
- the coefficients of the polynomials are used in the calculations.

5. Applications

Knowledge-based information obtained from natural language is translated to the same value range [-2, 2] with the indices and indicators calculated from numerical values.

5.1 Knowledge-based information

The labels {very low, low, normal, high, very high} or {fast decrease, decrease, constant, increase, fast increase} can be represented by number {-2, -1, 0, 1, 2}. In the real scale, the membership functions are similar to ones shown in Figure 4. Different shapes of membership definitions result different sets of default membership functions: the locations depend on the core, the support and the centre point. However, the linguistic data can be understood as scaled values, whose membership functions are equally spaced, i.e. {-2, -1, 0, 1, 2}. The overlap between adjacent linguistic terms expresses a smooth transition from one term to the other.

The number of membership functions is not limited to five. A gradually refining set can be formed by inserting new membership functions between the existing ones, see [JuBeSi93]. The set of membership functions can be refined in a different way for each area of linguistic values: more labels may be needed close to the centre point or to the high and/or low values of the support. The resulting set is represented by a domain specific set of labels to explain the system operation. The calculations are based on the corresponding number, which are positive integer numbers in fuzzy set systems and real numbers in the range [-2, 2] in the LE systems.

The fuzzy labels are extracted from linguistic information given by humans. Therefore, the resulting fuzzy numbers may contain vagueness and uncertainty. To take this into account, the membership functions are made sharper or wider with modifiers 'extremely', 'very', 'more or less' and 'roughly'. The powering modifier should reflect the reliability of the piece of information, or of the source of information. Several linguistic terms can be combined or further modified with 'and', 'or' and 'not'.

Interactions of the linguistic variables can be handled with linguistic equations (2), where the levels X_j can originate from numeric data or linguistic information. When the methodology is used in the analysis of the event data, the information represented with these numbers produces a real-valued relation base to be used to analyse interactions. Known relationships can also be handled with the fuzzy calculus and the extension principle to keep the uncertainty in the calculation.

5.2 Condition and stress indices

Cavitation indices obtained from the scaled values [12] provide an indication of the severity of the cavitation. The index shown was calculated by using the generalised norms $\left\| {}^{3}M_{4}^{2.75} \right\|$ and the nonlinear scaling based on skewness. The indices are calculated with problem-specific sample times, and variation with time is handled as uncertainty by presenting the indices as time-varying fuzzy numbers. The classification limits can also be considered fuzzy. Practical long-term tests have been performed e.g. for diagnosing faults in bearings, in supporting rolls of lime kilns and for the cavitation of water turbines [12]. The indices obtained from short samples are aimed for use in the same way as the process measurements in process control. The new indices are consistent with the measurement and health indices developed for condition monitoring. [30] The cavitation index is an example of a stress index: $I_S = -2$ when the stress in negligible, and levels {-1, 0, 1} are analogue to the lower limits of the vibration severity ranges {usable, still acceptable, not acceptable} defined in the VDI 2056 [31,32].

Table 2. Cavitation index and vibration severity criteria [12].

Cavitation index	Cavitation level	Severity
$I_C^{(4)} < -1$	Cavitation-free	Good
$-1 \le I_C^{(4)} < 0$	Short periods of weak cavitation	Usable
$0 \le I_C^{(4)} < 1$	Short periods of cavitation	Still acceptable
$I_C^{(4)} \ge 1$	Cavitation	Not acceptable

5.3 Performance measures

Performance measures can be handled with nonlinear scaling to produce information in natural language, e.g. the improvements of overall equipment effectiveness (OEE) shown in Table 3 can be based on following classification: [0.25,\: 0.75) slight, [0.75,\: 1.25) good, [1.25,\:1.75) very good, and ≥ 1.75 excellent improvement [13]. The feasible range defined by 48.0%, 62.6%, 76.4%, 86.6% and 95.0% was analysed from the OEE values presented in [33].

Table 3. Examples of Overall equipment effectiveness (OEE) [13].

	From	To	From	To	Improvement		From	To
Steel Plant	74 %	90 %	-0.18	1.38	1.56	Very good	Good	Very good
White Goods	79 %	88 %	0.24	1.15	0.91	Good	Good	Very good
Automotive	48 %	75 %	-2.00	-0.11	1.89	Excellent	Poor	Good
Flour Mill	86 %	93 %	0.93	1.74	0.81	Good	Very good	Excellent
Chemical Plant	82 %	95 %	0.52	2.00	1.48	Very good	Very good	Excellent
Filling Line 1	55 %	85 %	-1.53	0.83	2.36	Excellent	Poor	Very good
Filling Line 2)	68 %	80 %	-0.62	0.33	0.95	Good	Acceptable	Good
Packing Line 1	66 %	87 %	-0.76	1.04	1.80	Excellent	Acceptable	Very good
Packing Line 2	50 %	75 %	-1.87	-0.11	1.76	Excellent	Poor	Good

Statistical process control (SPC), which is used for monitoring variability, can also be extended to monitor harmonised indicators, KPIs, RAMS data and the OEE. In addition, SPC can be used to compare the results of improvements when developing best practices. Also trend indices can be monitored with SPC.

5.4 Integrated control and condition-based maintenance

New numerical values facilitate the deeper analysis of relationships between intelligent indices, harmonised indicators, KPIs and OEEs (Figure 5). The analysis can be further deepened with LE modelling. Performance improvement is taken as the primary goal in the asset management: efficient monitoring with intelligent indices provide a good basis for control and condition-based maintenance. The losses are analysed with OEE and actions are in the following sequence: first accept reduced quality, if possible, then decrease speed, if necessary, to anyway plan the maintenance actions. The feedback loops in the integrated operation and maintenance function reduce the operational uncertainty and risks of unexpected problems ensuring better safety and reliability.

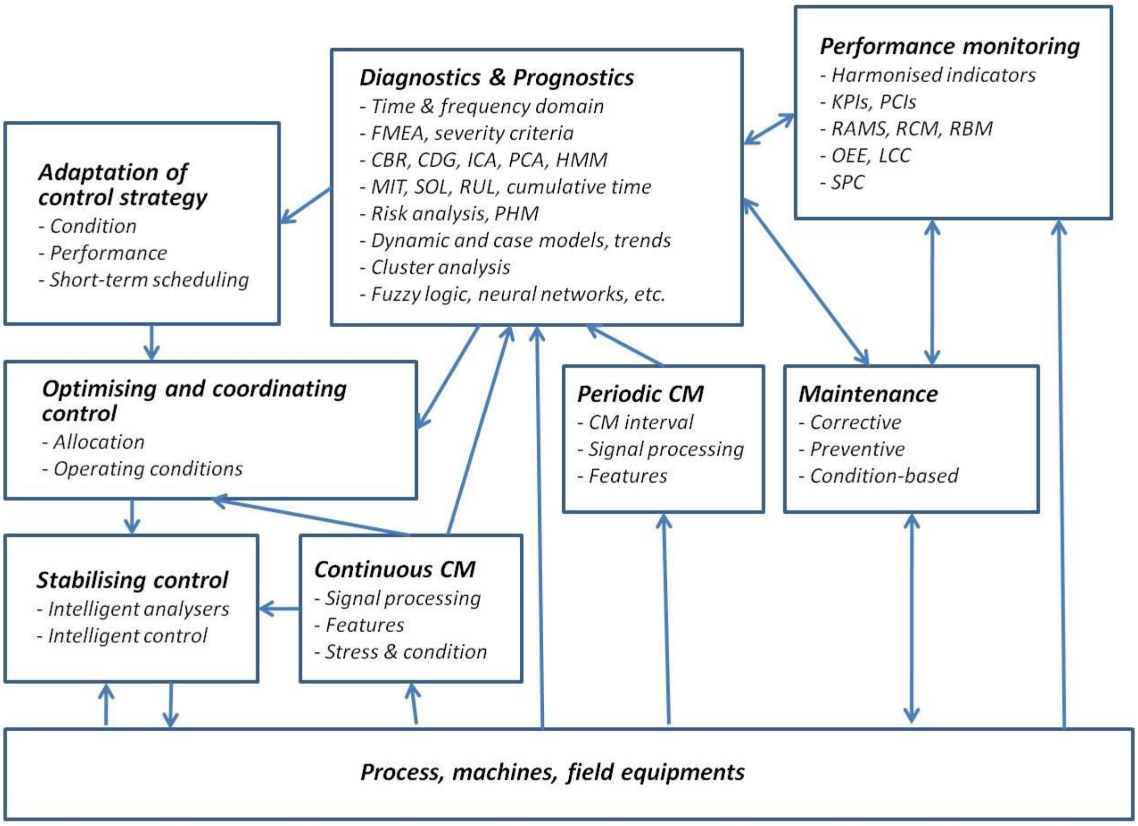

Figure 5. Integrated control and condition-based maintenance [13].

6. Conclusions

Knowledge-based information obtained from natural language is translated to the same value range [-2, 2] with the indices and indicators calculated from numerical values. Reliability of the information can be handled with the powering modifiers, and the resulting linguistic terms can be further modified with ‘and’, ‘or’ and ‘not’ to be used in fuzzy calculus and the extension principle. The information represented with these numbers produces a real-valued relation base to be used to analyse interactions. The uncertainty of the knowledge-based information is kept in the calculation.

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