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# A method to improve human prognosis in supervision of complex systems

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**Abstract:** Human-machine supervision is a fundamental research and applicative axis to contribute to the dependability of complex systems. A recent and promising way to optimize means and performances of supervision is to provide human operators with prognosis activity support tools. Many methods are currently developed or adapted. This paper focuses on the fuzzy treatment and read-out of residuals. After their specification, their application for benchmark supervision provides experimental results which are analyzed in order to discuss on their real impact for human prognosis.

## 1. INTRODUCTION

Human has the ability to anticipate events and dysfunctions evolution (Hoc *et al.*, 94). This ability is a keystone to prevent problems and plan solutions. In context of supervision, human-machine practices centered on anticipation allow the prognosis activity to be carried out (Gentil, 07). Our integration and evaluation work show that favour prognosis enhances human-machine performances of supervision (Delépine, 07). With regards to a development methodology of anticipatory supervision environment, many methods have been searched, adapted and/or developed. In this paper, one of these is highlighted. It concerns fuzzy treatment and read-out of residuals.

Before describe this method, a survey of prognosis activity provides the reasons of its choice. In a next part, it is applied to assist human operator in supervision of a hydraulic two-tank benchmark. Finally, based on experimental results we discuss of its applicability and efficiency to improve human prognosis.

## 2. PROGNOSIS ACTIVITY

Prognosis is to anticipate and predict the evolution of a system in all its states so as to maintain over time its smooth functioning (Mathur, 01). Find precursors of failures or fault symptoms, envisage their causes and consequences, and support decision making process constitute prognosis roles in supervision (Propes *et al.*, 02, Qiu *et al.*, 05, Delépine, 07). Whatever the integration approaches and the prediction goals, prognosis activity follows the cyclic process of hypotheses generation, Fig. 1.

The process begins with the generation of hypotheses, and then allocates certainty degree to each hypothesis. Afterwards according to requirements, the plausible hypotheses are selected and used as predictions for future exploitations.

Based on the **perception** and **interpretation** of past, present, and future data which are recorded and/or predicted during its process, prognosis activity must provide results on the future in a dynamic context. This context is obviously incomplete, imprecise, and uncertain. Indeed, principal vector of the process, the generated hypotheses imply uncertain knowledge that evolves related to the process evolution and to the available information on the dynamic system.

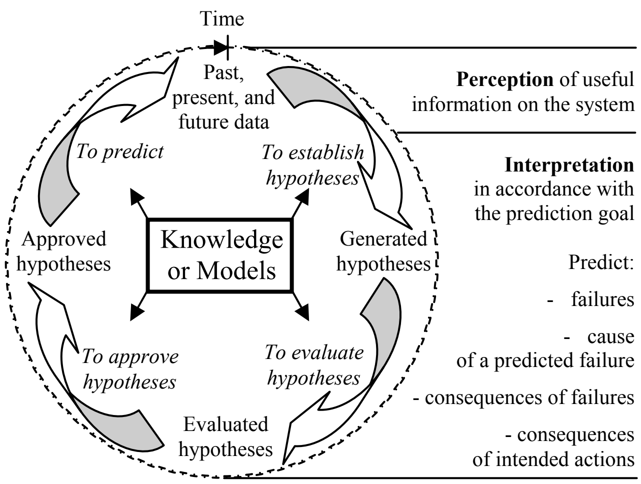


Fig. 1. Process and tasks linked to the prognosis activity

When temporal and cognitive resources are available, anticipatory supervision of complex systems can be applied. If human operators aim at predicting the future behaviour of a given system by perceiving pertinent information, they have to manage the research of these information and to focus on the evolution of non-optimal parameters. By interpreting the perceived information, they generate hypotheses on possible future state and evolution of the controlled system. Finally, they evaluate hypotheses in order to identify and venture the more relevant predictions.

In situation of smooth functioning, predictions concern mainly the duration of such a situation or, in a dual way, a possible future failure. On the additional basis of perception of parameters near to nominal values, the role of the human operators usually is the refining of the ins and the outs of the predicted failure. Related to the knowledge they have on the

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system, human operators manage prognosis on the future consequences of their actions on the system before their execution. As part of decision/action function, the exploitation of the various predictions opens the possibility for planning actions to be proceeded.

As a system keeps very seldom the nominal conditions, it is necessary to assess continually system performances in order to predict its future state. Success of such a process relies essentially on the relevance and the representation of available information on the system. In relation with human task for prognosis, it seems useful to provide human operators with **supports on the information perception process.** The development of adapted support tools requires methods to **elaborate and present salient data** for generation of human hypotheses (Endsley, 98). Both the fuzzy treatment and the read-out of residuals are considered in order to develop support tool for prognosis and to test it in experimental context (Delépine, 07).

## 3. METHOD

The fuzzy treatment and the read-out of residuals combine several information in order to elaborate operating indicators. The basis of this method is a dynamic model of smooth functioning and the fuzzy logic. This method involves implementing the elaboration chain of Fig. 2 **appropriately with system conditions and demands of supervision designer**. Keys of this method are detailed in three parts.

### *3.1 Model and residuals*

According to residuals as a pertinent support for assessing performances system, the fuzzy treatment and the read-out of residuals require a model that can be simulated in real-time (Delépine *et al.*, 05). Thus, as shown in Fig. 2, u(t) are both the system and the model inputs ; y(t) are the outputs measurements of the system submitted to noise ; ŷ(t) are the system outputs estimated by the dynamic model ; residuals are differences between y(t) and ŷ(t). These residuals show the system drift. More accurately, if the model represents reliably the correct functioning of the dynamic system, residuals reflect disturbances and fault effects.

An interesting approach to generate useful residuals relates to the assessment of elementary residual $r_i(t)$ in accordance with $\forall i \in 1$ to $n$, $n =$ number of measured variables:

$$r_i(t) = y_i(t) - \hat{y}_i(t) \quad (1)$$

In order to generate complementary residuals, a structural analysis of elementary residuals should be done. This consists in identifying each variable directly related to each residual. Automatically, the first variable to list is the measured variable $y_i(t)$. The next identified variables are the ones implicated in relations used to estimate $\hat{y}_i(t)$ from the model.

Making the structural analysis in-depth needs a temporal survey of all variables that can be incriminated by dysfunction propagation when a residual diverges from zero and indicates a failure.

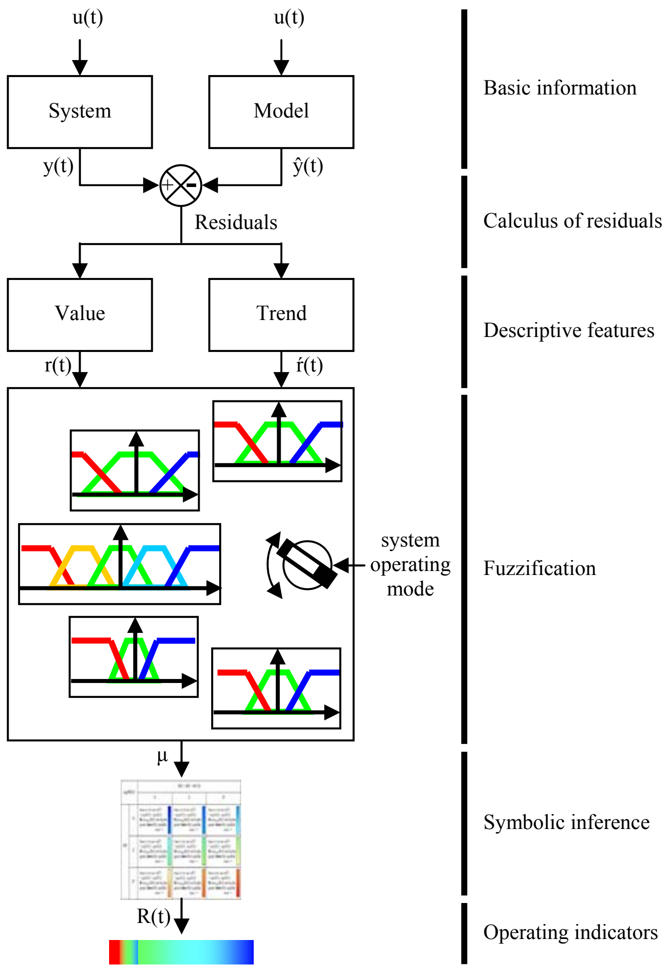


Fig. 2. Elaboration chain of operating indicator

Based on this analysis, last step of the approach can be carried out. The goal of this final step is to generate residuals that complete elementary residuals. This generation requires attempting mathematical combinations of measured variables to simplify relations, provide a new group of incriminated variables and so make useful residuals founded on these combinations. The more the residuals implying different groups of variables are, the more residuals allow faults to be distinguished.

### *3.2 Fuzzification and symbolic inference*

In process control, uncertainties from measurements or models for instance are most often inevitable and so must not be ignored. Indeed, uncertainty intervenes in reasoning activities and affects results of decision making process. Reliability and stability of process control depend on how to manage this uncertainty. A solution is to integrate and to control uncertainty longer as possible in control methods. Thus, final decisions remain based on information significantly near of perceived real. Properly, the fuzzy logic allows such a purpose.

Introduced by Zadeh (Zadeh, 68), fuzzy subsets express partial membership of an element to a symbolic attribute. As work carried out in monitoring framework (Evsukoff *et al.*, 05), or in supervised control (Neves *et al.*, 99), it is possible to organize a fuzzy treatment for different domains of application. Even if parametric techniques exist, calibration of fuzzy treatment is usually done by expert of the system. Based on him knowledge, expert attempts to find the best compromise between number and representativeness of attributes, calculation and conceptual cost of membership functions in order to obtain membership rates of element to these attributes that provide significative information.

Fig. 3 illustrates a fuzzification example of residual values to prepare prognosis process. According to trapezoid functions associated to **P**, **Z**, and **N** subsets, a dynamic membership degree for each attribute ($\mu N(r(t))$, $\mu Z(r(t))$ and $\mu P(r(t))$) qualifies r(t). **P**, **Z**, and **N** mean respectively **P**ositive, normal **Z**one (near to zero), and **N**egative. These attributes are representative of the conformity or of the deviation types concerning residual values.

To acquire results more refined, the calibration of fuzzy treatment can be made in order to adapt treatment parameters according to the system operating mode. For example, in a system operating mode wherein model reliability is satisfactory, subsets domains are decreased so as to benefit from a higher sensibility.

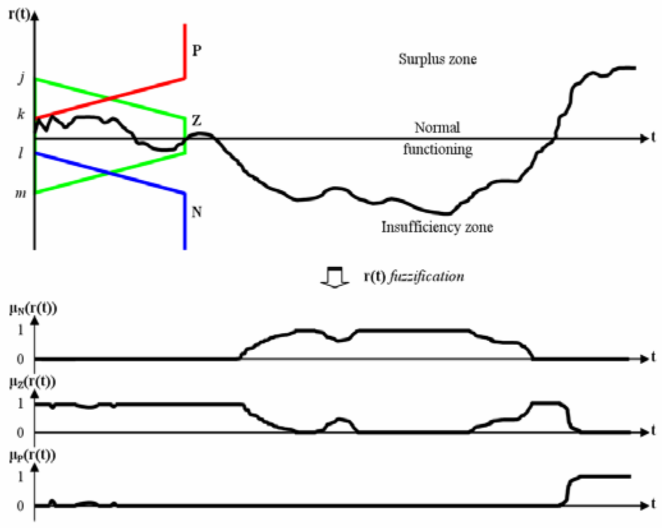


Fig. 3. Example of residual fuzzification

The evolution of residual trends allows the assessment of system situation and the prediction of dynamics of the propagation for a given deviation. Therefore, it seems interesting to make a fuzzification of trends residual ($\mu N(\acute{r}(t))$, $\mu Z(\acute{r}(t))$ and $\mu P(\acute{r}(t))$), then to combine results with those obtained by the fuzzification of residual values in order to obtain a R(t) salient information. Each membership degree $\mu_{state}(R(t))$ of all possible situations is calculated according to the symbolic rules presented on Fig. 4 and synthesized by this expression:

$$\begin{aligned} \mu_{stateGH}(R(t)) &= \top(\mu_{(r(t) \in G \text{ AND } \acute{r}(t) \in H)}(t)) \\ \mu_{stateGH}(R(t)) &= \mu_G(r(t)) \times \mu_H(\acute{r}(t)) \end{aligned} \tag{2}$$

with G and H represent attributes index from fuzzy treatment of the residual amplitude and its trend. The product operator corresponds to a useful probability T-norm. Indeed, it allows all combined memberships to be dissociated and compared. Thus, as human practices, this method highlights the most probable situation. At every time, the biggest degree $\mu_{stateGH}(R(t))$ symbolises the predominant situation so it is selected to characterize R(t) information.

| $\mu_\Omega(R(t))$ | | $\acute{r}(t) = r(t) - r(t\text{-}\Delta)$, $\Delta$ = temporal window of trend calculation | | |
|---|---|---|---|---|
| | | N | Z | P |
| r(t) | N | $\mu_{stateNN}(R(t)) =$<br>$\mu_N(r(t)) \times \mu_N(\acute{r}(t))$<br>**If** $\mu_{stateNN}(R(t))$ is the biggest **Then** R(t) qualified and presented with => | $\mu_{stateNZ}(R(t)) =$<br>$\mu_N(r(t)) \times \mu_Z(\acute{r}(t))$<br>**If** $\mu_{stateNZ}(R(t))$ is the biggest **Then** R(t) qualified and presented with => | $\mu_{stateNP}(R(t)) =$<br>$\mu_N(r(t)) \times \mu_P(\acute{r}(t))$<br>**If** $\mu_{stateNP}(R(t))$ is the biggest **Then** R(t) qualified and presented with => |
| | Z | $\mu_{stateZN}(R(t)) =$<br>$\mu_Z(r(t)) \times \mu_N(\acute{r}(t))$<br>**If** $\mu_{stateZN}(R(t))$ is the biggest **Then** R(t) qualified and presented with => | $\mu_{stateZZ}(R(t)) =$<br>$\mu_Z(r(t)) \times \mu_Z(\acute{r}(t))$<br>**If** $\mu_{stateZZ}(R(t))$ is the biggest **Then** R(t) qualified and presented with => | $\mu_{stateZP}(R(t)) =$<br>$\mu_Z(r(t)) \times \mu_P(\acute{r}(t))$<br>**If** $\mu_{stateZP}(R(t))$ is the biggest **Then** R(t) qualified and presented with => |
| | P | $\mu_{statePN}(R(t)) =$<br>$\mu_P(r(t)) \times \mu_N(\acute{r}(t))$<br>**If** $\mu_{statePN}(R(t))$ is the biggest **Then** R(t) qualified and presented with => | $\mu_{statePZ}(R(t)) =$<br>$\mu_P(r(t)) \times \mu_Z(\acute{r}(t))$<br>**If** $\mu_{statePZ}(R(t))$ is the biggest **Then** R(t) qualified and presented with => | $\mu_{statePP}(R(t)) =$<br>$\mu_P(r(t)) \times \mu_P(\acute{r}(t))$<br>**If** $\mu_{statePP}(R(t))$ is the biggest **Then** R(t) qualified and presented with => |

Fig. 4. Base for symbolic inference process of residuals

Concretely, this inference process gives from two descriptive features (value and trend) of a residual, a representative information of system situation. The case of residual for which the value is located essentially in N and its trend in P, represents by means of R(t) a less critical situation than in case of respective way N-N or even than P-P. In other words, N-P case characterizes a low residual value but that seems to recover nominal conditions. The N-N case signifies also a low residual value that will probably get worse. Finally, the P-P case corresponds with a high residual value that continues to raise. However, N-P case specifies a less reassuring situation than in Z-N, Z-Z and Z-P cases.

### *3.3 Operating indicators*

The fuzzy values of R(t) can be used on this numeric form for automated techniques of supervision. However, assimilation and use of R(t) by human operators needs to favour reachable, synthetic and appropriate read-out principle that allows them to perceive and assess quickly the system performances. For this reason, the base of symbolic rules provides a specific range of colors according to the predominant online situation. Range of colors and means of colors assignment have been determine by experts, supervision designers and end users.

In the end, R(t) represents on the form of colorful signal, the evolution of salient information that synthesizes trend and value for behaviour of a measured variable in relation to its referent variable. This information turns out an extremely valuable operating indicator. Indeed, it is analogous to the interpretation of perceived signals made by the human operators.

Range of colors should be wisely antisymmetric because the R(t) sign is a relevant and useful information. For example, with the residual of a liquid level, the R(t) sign makes possible to distinguish a case of liquid leak (negative residual) with a liquid obstruction (positive residual). These operating indicators contribute to establish a reliable and relevant informational framework. Presumably, this framework must stimulate and improve spontaneous generation of human operator hypotheses.

## 4. APPLICATION

In order to evaluate the method of fuzzy treatment and read-out of residuals, the integration of such a method is made to supervise a benchmark and presented in this section. The benchmark is firstly described.

### *4.1 Benchmark description*

The benchmark is a hydraulic system composed of two tanks. It is the benchmark for the 193 Specific Action of CNRS "Diagnosis of Hybrid Systems" (AS, 04). Illustrated on Fig. 5, the selected configuration is equipped of two control valves V1 and V3 that are constantly opened, a manual control valve V2 and a controlled pump P1 in order to maintain the fluid level $h_2$ between $h_2^H$ and $h_2^B$.

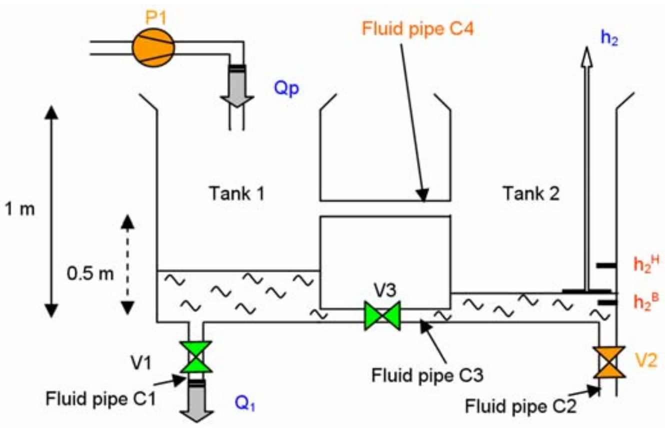


Fig. 5. Hydraulic two-tank benchmark

System instrumentation is made up of three sensors that measure $Q_p$, $h_2$ and $Q_1$. The presence of fluid pipe C4 at mid-height provides further evolution conditions for system operating mode. This feature highlights the complex dynamics of the benchmark for which fluid volume evolutions in each tank are equal to the sum of inputs and outputs fluid flows. Finally, system parameters are:

| | |
|---|---|
| $A = 3{,}6.10^{-5}$ m$^2$: | Section surface of fluid pipes |
| $S = 0{,}0154$ m$^2$: | Section surface of tanks |
| $g = 9{,}81$ m/s$^2$: | Gravity constant |
| $Qcp_1$: | P1 pump flow = 0,0002 m$^3$/s |
| $ucp_1\{0,1\}$: | Discrete control of P1 pump |
| $uc_2\{0,1\}$: | Discrete control of valve V2 |

The Toricelli's law completes the description with variables and relations that control the system. These variables and relations are:

| | |
|---|---|
| $Q_p = ucp_1 . Qcp_1$ | Effective flow of P1 pump |
| $Q_1 = A.\sqrt{(2g.h_1)}$ | Effective flow of fluid pipe C1 |
| $Q_2 = uc_2 . A.\sqrt{(2g.h_2)}$ | Effective flow of fluid pipe C2 |
| $Q_3 = A.\text{sign}(h_1 - h_2)\sqrt{(2g.\lvert h_1 - h_2\rvert)}$ | Effective flow of fluid pipe C3 |
| $Q_4 = A.\text{sign}(h_1 - h_2)\sqrt{(2g.\lvert\max(h_1;0{,}5) - \max(h_2;0{,}5)\rvert)}$ | Effective flow of fluid pipe C4 |
| $h_i$ | Fluid level in tank i |

So the system can be modelled by:

$$\sum_{NL}:\begin{cases}\dot{h}_1 = \dfrac{1}{S}(Q_p - Q_1 - Q_3 - Q_4)\\ \dot{h}_2 = \dfrac{1}{S}(Q_3 + Q_4 - Q_2)\end{cases} \tag{3}$$

In the next section, the studied method is implemented.

### *4.2 Implementation*

In order to be able to generate residuals, a dynamic model of the benchmark is available. According to the method and system instrumentation three first residuals are generated:

$r_1 = Q_p - \hat{Q}_p$ $\quad r_2 = h_2 - \hat{h}_2$ $\quad r_3 = Q_1 - \hat{Q}_1$

The values from the dynamic model are provided depending on physical and simulated relations, so:

$\hat{Q}_p$ is deduced from $Q_p = ucp_1 . Qcp1$ relation. Therefore, through $r_1$ residual, this variable gives information to suspect beyond the sensor measuring $Q_p$, elements related to $Q_p$, $ucp_1$, and $Qcp_1$ variables, i.e. actuator, fluid supply pipe, pump P1 and its control ;

$\hat{h}_2$ is deduced from (3). Therefore, through $r_2$ residual, this variable gives information to suspect beyond the sensor measuring $h_2$, elements related to $h_2$, $Q_2$, $Q_3$, and $Q_4$ variables ;

$\hat{Q}_1$ is deduced from $Q_1 = A.\sqrt{(2g.h_1)}$ relation. Therefore, through $r_3$ residual, this variable gives information to suspect beyond the sensor measuring $Q_1$, elements related to $Q_1$ and $h_1$.

By mathematical combination, an other residual is generated. This last residual is more abstract for human operator. It is about making-up of fluid levels:

$r_4 = (h_{1d} + h_2) - (\hat{h}_1 + \hat{h}_2)$ with $h_{1d}$ deduced value from $Q_1$ measurement and $Q_1 = A.\sqrt{(2g.h_1)}$ relation

As $\dot{h}_1 + \dot{h}_2 = \frac{1}{S}(Q_p - Q_1 - Q_2)$, $r_4$ residual allows $Q_3$ and $Q_4$ variables to be not incriminated during a short-term investigation.

Finally, regarding to the method, a supervision tool is developed to apply the fuzzy treatment and symbolic inference to the four residuals. The supervision framework is completed with a human-machine interface to display all results of the elaboration chain and final operating indicators, Fig. 6. Related to the indicators displayed on the interface, red color symbolizes a situation which becomes worse through surplus deviation, green color reflects a stable situation or a return to nominal conditions, and at last, blue nuances translate an aggravation in a dysfunctional zone of an insufficiency.

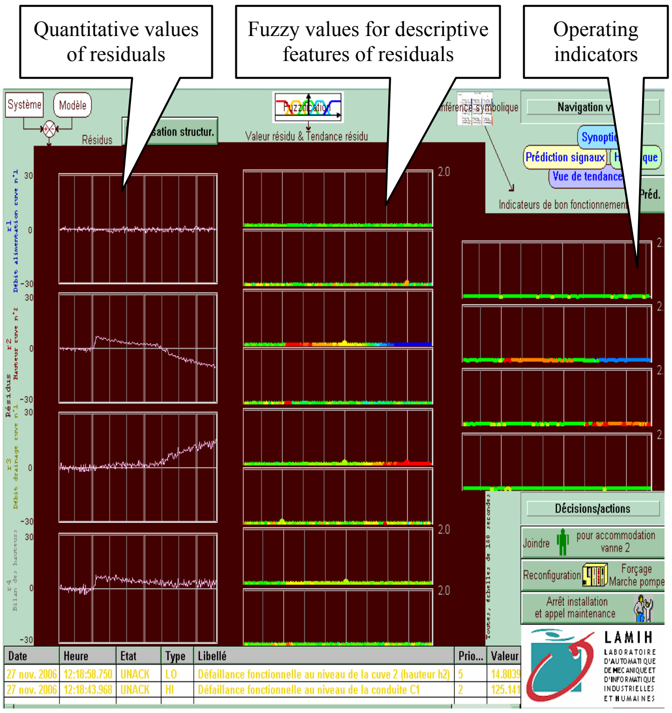


Fig. 6. View of operating indicators

These method, tool and interface related to operating indicators refer to one of the subjects of an experimental campaign for which experimental parameters are detailed in (Delépine, 07). These parameters have been defined to relativize learning phenomena.

## 5. EXPERIMENTAL RESULTS

The campaign concerns eleven human operators which supervise the benchmark. Two supervision frameworks are tested. The first is a basic supervision configuration, and the second is completed by tool and interface related to operating indicators described on section 4 following the proposed and detailed method in section 3. For each configuration, all human operators must control six scenarios of dysfunction.

In a first part, human operator appreciations on interests of operating indicators are communicated. Then experimental data concerning prognosis and supervision performances are analyzed.

### 5.1 Human operators judgments

Subjectively, human operators have given their opinion on operating indicators utility for their prognosis activity. First of all, human operators highlight that operating indicators are more helpful than traditional alarms. According to their observations, indicators report **every dynamic variation** which is significative of a dysfunction. Sometimes deteriorations are elusive due to physical and temporary compensation and so measurements seem objectively register in values intervals of smooth functioning. Even in these cases, thanks to the dynamic model these deteriorations are reported by operating indicators.

Human operators note that, individually, each operating indicator represents functional state of the system at the measured variable level. For this system, this means that if one of operating indicators $R_1$, $R_2$, $R_3$, and $R_4$ undergoes a deviation then it traduces a functional impairment respectively at the $Q_p$, $h_2$, $Q_1$, and $h_1$ or $h_2$ level.

However, when operating indicators are used together, human operators can manage a structural and temporal investigation to process a prognosis on ins and outs of a predicted failure. Regarding to their judgments, the operating indicators facilitate the perception of abnormal situation and its conditions. Next results give information to assess if this facilitation favours effectively the human prognosis activity.

### 5.2 Prognosis and supervision performances

Based on subjective data coming from human operators explanations and from their monitoring, it is possible to count proceeded prognosis and to assess the quality of the predictions of the human operators. When at least one prediction is incorrect or missing according to conditions of the moment, the prognosis is respectively imprecise or incomplete. In Fig.7, these results manifest that human prognosis is more undertaken with the second configuration. So, **operating indicators supply a major benefit focusing on human prognosis stimulation.**

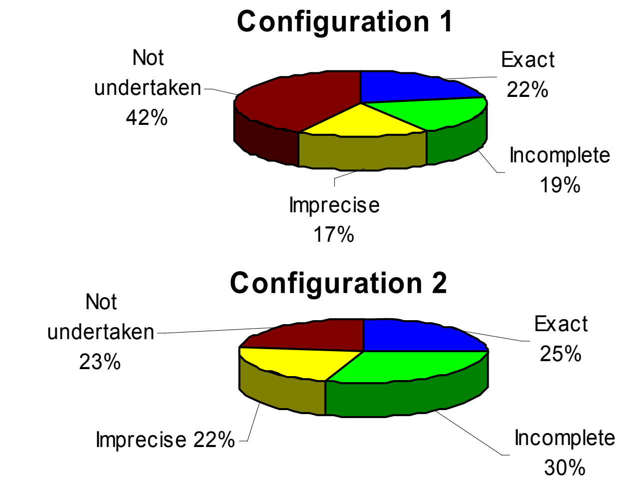


Fig.7. Human prognosis for dysfunction management

Nevertheless, a low progression is noticed for the prediction quality. The stimulation of the human prognosis and the enhancement of prediction quality are satisfactory but it is convenient to relate them with the performances of supervision. There are two interesting types of performances:

- the distribution of the success of the problems resolution that constitutes the dysfunction management ;
- the time durations used to carry out this investigation.

Results on Fig. 8 show that a more frequent and best-managed prognosis brings about a significative benefit on the quality of human decisions. Moreover a great progression of the human operator predictivity is observed according to Table 1. Indeed, fault presence is suspected earlier with the second configuration.

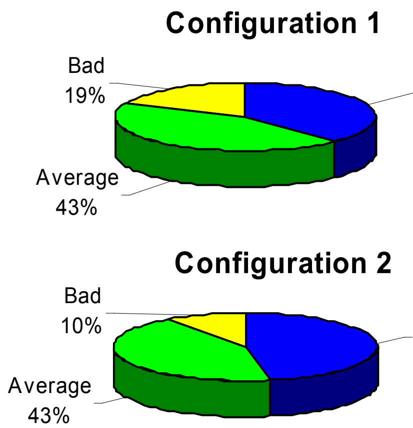


Fig. 8. Quality distribution of human operator decisions

In relation with duration between the initial human suspicions and the first human decision/action, the predictivity progression is capitalised by operators to investigate with a greater temporal interval. However, this greater duration to take action can be interpreted as a decrease of operator reactivity. The interpretation of operating indicators in order to decide and take action with certainty requires a high-attention. This attention demand and the temporal cost remain acceptable in relation to a best decision making.

**Table 1. Objective results**

| Temporal indicators of human investigation dynamics | Configuration 1 | Configuration 2 |
|---|---|---|
| Duration (s) between fault insertion and first human suspicions | 86 | 29 |
| Duration (s) between first human suspicions and human decision/action | 121 | 195 |
| Duration (s) between fault insertion and first traditional alarm | 92 | |

Based on this group of results, it is validated that tool and human-machine interface related to operating indicators stimulate effectively the human prognosis and cause a best dysfunction management.

## 6. CONCLUSION

The quality of the human operator decisions, the affluence of proceeded prognosis, the human predictivity are acceptable and **confirm adequacy, applicability, and efficiency of the fuzzy treatment and the read-out of residuals to improve prognosis activity**. Nevertheless, it seems that this method applied to perception support can be insufficient in case of the presence of a great number of operating indicators. Future work will focus on the development of extended method to provide human operator with interpretation support tools for prognosis activity.

## ACKNOWLEDGEMENTS

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