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EXPERT SYSTEM FOR DAM ASSESSMENT AND EMERGENCY DETECTION

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ABSTRACT: This work presents an intelligent system integrated to Cemig's (which is one of the most solid and important groups in the electric energy segment in Brazil) corporate software and data environment. The intent of the expert system presented in this work is to provide a core model that is able to flag the state for each of Cemig's dams given a set of field data. Since the state of a dam could be flagged as being either green, yellow, orange or red, the proposed model was calibrated to be able to process as many inputs as necessary. To accomplish this task, the proposed methodology uses a fuzzy rule-based approach to compute the state of the system. However, under some circumstances, those rules might not be available or might be incomplete for some dams, hence the proposed methodology not only uses fuzzy rules to compute the state of the system, but also proposes an approach for auto-generating the rule database when they are absent or incomplete. Therefore, the proposed methodology not only innovates when using expert systems for dam assessment in the Brazilian scope (this technique has been proved to be effective by a couple of researchers worldwide, however, such approach has never been evaluated in the Brazilian river basins and its dams), but also innovates when proposing a totally new concept of auto-generated fuzzy rules. Moreover, the proposed innovative model was designed to be the core element of a software package, which is still under development in the Cemig's corporate information technology environment and is called "PAE-WEB". This system is a big framework that intends to create a unique solution to cover the whole spectrum of dam safety management.

Key Words: Dam Assessment, Dam management, Flood Risk, Intelligent Systems, Fuzzy Inference Systems.

1. INTRODUCTION

Recently, the dam state and risk assessment (DSRA) topic has being drawing community and researchers attention due to dam aging and, also, due to new technology emergence for dam inspection (hardware) and assessment (software). Hence, in order to provide a better understanding of the DSRA problem, many studies have already being published. In Brazil, Ladeira carried out an outstanding study (Ladeira, 2007) in which he developed a risk assessment methodology for the dam located at the "Sao Simao" hydropower plant in Brazil. The proposed methodology was based on the study of Fault Tree Analysis (FTA)[1] in conjunction with field observations to try to evaluate the dam failure risk probability.

[1] The FTA is a technique, which was first introduced in 1962 by HA Watson who worked at Bell Laboratories, which was at first contracted by the United States Air Force (USAF) to be used in a launching control system for the "Intercontinental Ballistic Missile (ICBM)" project (Ericson & LI, 2000).

Moreover, there many other studies which provide a basic framework for the DSRA problem, such as Balbi's master thesis (Balbi, 2008).

Brazil is specially interested in the DSRA problem since there are many dams in Brazil, which, in many cases, are associated with hydropower facilities. Despite this fact, there are many interesting researches that were or are being conducted around the world to deal with the DSRA problem. As an example, in Australia, Mark Foster and his team have being working for a long time in this subject. Thus, one of their papers describes a method for estimating the relative likelihood of failure of embankment dams by piping (Foster, Fell, & Spannagle, 2000a). This method evolved from historical failure analysis of embankment dam analysis and, with that, the failure probability was estimated by adjusting the historical frequency of failures taking into account factors such as the age of the dam, the dam performance, and monitoring and surveillance. Hence, with such a basic framework, they were able to detect accidents caused by piping in advance, what enabled them to schedule proper maintenance or even to draw the reservoir down. Furthermore, there are many other papers that discuss the DSRA problem, such as the work carried out by Wan and Fell, in which the embankment erosion ratio was investigated in order to provide predictive maintenance (Wan & Fell, 2004), the study carried out by Foster and his team to raise detailed statistical analysis to understand dam failures (Foster, Fell, & Spannagle, 2000b) and one other work in which the piping evolution time was analyzed (Fell, Wan, Cyganiewicz, & Foster, 2003).

Also, since most critical problems that arise from the monitoring process are related to degenerated information that travels from the monitoring site to the crisis managers (such as communication issues originated from anxiety), there are many studies that propose an integrated and automated system to deal with assessment and communication (Curt, Talon, & Mauris, 2011) (Rodrigues, Santos, Santos, & Rocha, 2002) (de Almeida, 1997).

1.1 Expert Systems

In the artificial intelligence field, expert systems are those that simulate the capabilities of a human expert to make decisions under multiple decision variables and uncertainty levels. Expert systems are designed to solve complex problems regarding knowledge reasoning issues that are generally represented using consequence rules such as "IF-THEN". However, expert systems are designed to be much more flexible than classical procedural programming, which make them a very useful tool to deal with more realistic decision-making problems.

The expert systems were first conceived in the 1970 decade and got very popular during the 1980 decade (Leondes, 2002). Nowadays, they are scatter all around the world, not only as part of many reasearches but also embed in many apliances and electronics used by everyone. Eventhough, when it comes to dealing with the DSRA problem, there are many authors that use classical statistical tools to help in the decision-making process. However, since there might be measurements, data or observation failures, many tools that were developed under the big umbrella of the computational intelligence may be much more suitable to deal with such problems.

To make it more clear, in many cases, one human expert is not able to perfectly quantify, for instance, the safe range of readings of a piezometer (or a set of piezometers) so that the overall dam state would be considered safe. Also, it is not always suitable to calculate probabilities values associated to the dam state, since probability values are hard to decode in terms of everyday linguistic such as "low likelihood" or "extremely likely". Moreover, it is important to emphasize that this dilema is faced by many studies that were already developed (Foster, Fell, & Spannagle, 2000a) (Ladeira, 2007) to deterministically deal with the DSRA problem.

In order to overcome those difficulties, the utilization of expert systems built upon, for instance, fuzzy rules, is very common. In this context, one of the oldest studies is the work conducted by Franck and Krauthammer in which they have studied the knowledge domain regarding the experts knowledge about the DSRA problem and, with that, an expert system built was is used to monitor concrete dams (Franck & Krauthammer, 1988). Later on, Franck and Krauthammer continued their work and published two papers (Franck & Krauthammer, 1989a) (Franck & Krauthammer, 1989b) describing the details on how the original expert systems was implemented. It is important, though, to emphasize that their algorithm was developed using the MYCIN framework which was developed by Buchanan and Shortliffe (Buchanan & Shortliffe, 1984).

Furthermore, more recently, many other papers were published over the same research topic. Those papers, in fact, resemble a lot the Franck and Krauthammer methodology that, essecially, use expert systems, with or without fuzzy rules to build a dam state monitoring system (Curt, Peyras and Boissier 2010), (Portela and Bento 2001).

2. PROPOSED MODEL

Cemig's DSRA problem looks very similar to those presented by many authors in the literature and, in general, reservoir level, flood forecasting and data from piezometers (and many other sensors) are monitored at real-time. However, one of the most important data that helps guiding Cemig's managers are field reports (which might also add a set of subjective data that might be hard to map to real numbers) that should be filed also at real time, in order to compute the state of the system (the output of the expert model) as being one of these four states: green, yellow, orange and red.

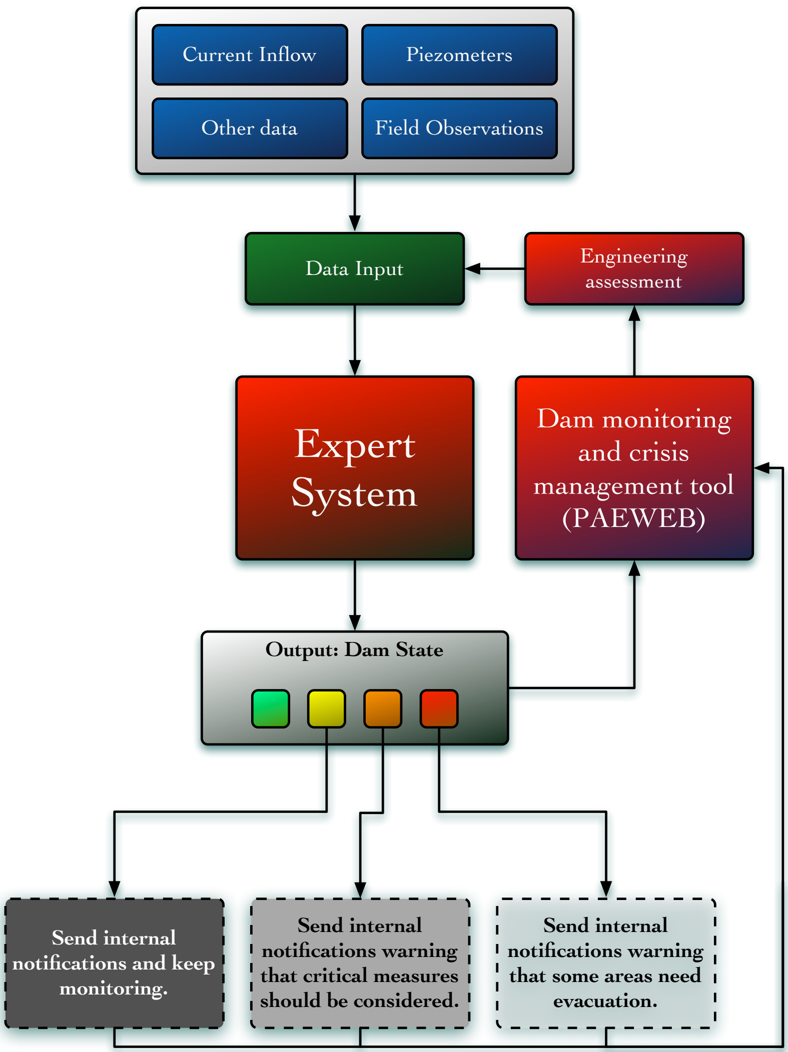


Figure 1: Proposed Expert System Workflow

Thus, Figure 1 shows schematically how the information flow works and how the expert system is situated in this context. Basically, input data is retrieved from a centralized database (where instrumentation data is stored) and also from a data monitoring and crisis management tool (which is called PAEWEB. PAEWEB is a tool capable of displaying the state of the system, sending notifications to users and also interacting with field team, engineers and managers), processed by the expert system which, then, computes the state of the system.

In order to achieve this goal of computing the state of the system, the expert system was built in a way that each information, that might be related to output state, is preprocessed by fuzzy rules, combined and defuzzified which, finally, generates the state of the system. Figure 2 illustrates this concept.

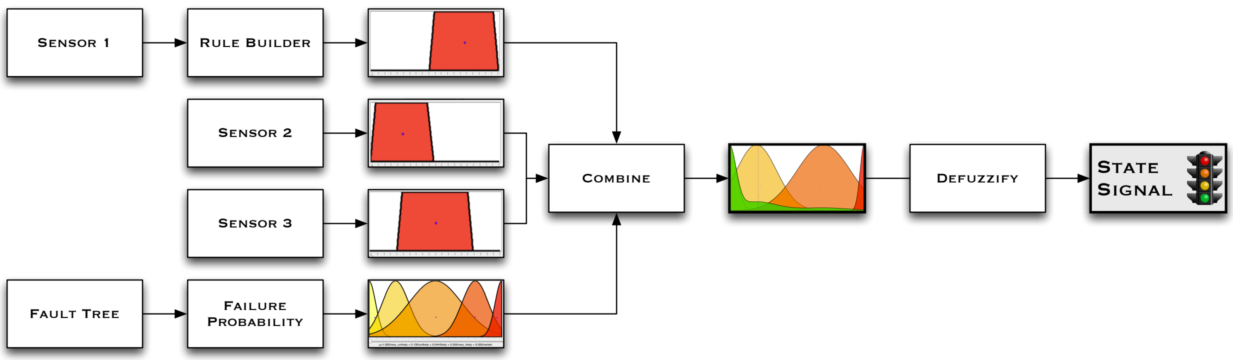


Figure 2: Fuzzy Inference System Architecture.

Additionally, Figure 2 also shows two aspects that are not peculiar in a fuzzy inference system: the "rule builder" and the "fault tree".

To begin with, the "rule builder" is a simple methodology that was conceived in order to build fuzzy rules that would represent a real sensor or an instrument that is not yet represented by a fuzzy rule, hence factors like precision, reliability and range of normal operation had to be taken into account. Thus, the precision σ is a characteristic of each instrument that, in general, is calculated by specialists when an instrument is calibrated; the reliability ρ $(0 < \rho < 1)$ is calculated as a function of the instrument aging α (in months: $\alpha > 1$):

$$\rho = \frac{1}{\sqrt[4]{\alpha}}$$

And the range of normal operation is generally determined by the original dam design (which might also be reviewed by engineers):

$$\gamma^{min} \leq x \leq \gamma^{max}$$

Now, since the goal of this methodology is to represent an instrument as a fuzzy rule, many tests were conducted which revealed that the most suitable shape of fuzzy rules to be used for instruments was the trapezoid, hence the most important terms to be defined for a trapezoid are "a", "b", "c" and "d":

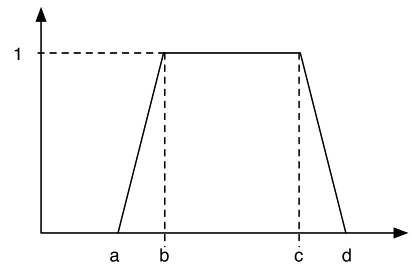


Figure 3: Trapezoid terms definition.

Where:

$$a = \gamma^{min} - \frac{\sigma}{\rho}$$

$$b = \gamma^{min}$$

$$c = \gamma^{max}$$

$$d = \gamma^{max} + \frac{\sigma}{\rho}$$

With that, the "rule builder" is defined as a trapezoid fuzzy rule with terms "a", "b", "c" and "d" as show above.

Secondly, the "fault trees" in Figure 2 are available for each of Cemig's dams and they are used in FTA (discussed in previous section), though the FTA is always done by experts and individually analyzed based on field reports of possible issues regarding Cemig's dams. However, this scenario is, in general, impractical, since Cemig has to monitor many dams at the same time. Hence, one module was built to perform semantic analysis in each field report submitted using PAEWEB in order to estimate the fault tree state of each dam, although this module itself is subject of one other research that will be published in the future. Nevertheless, fuzzy rules were designed to express the most important linguistic variables associated with any FTA:

- Failure is very unlikely;
- Failure is unlikely;
- Failure is likely;
- Failure is very likely;
- Failure is certain.

Thus, Gaussian curves were designed to express these linguistic variables (see Figure 4), which together formed the set of fuzzy rules that were responsible to map any given fault probability (x axis in Figure 4) that would arise from the FTA

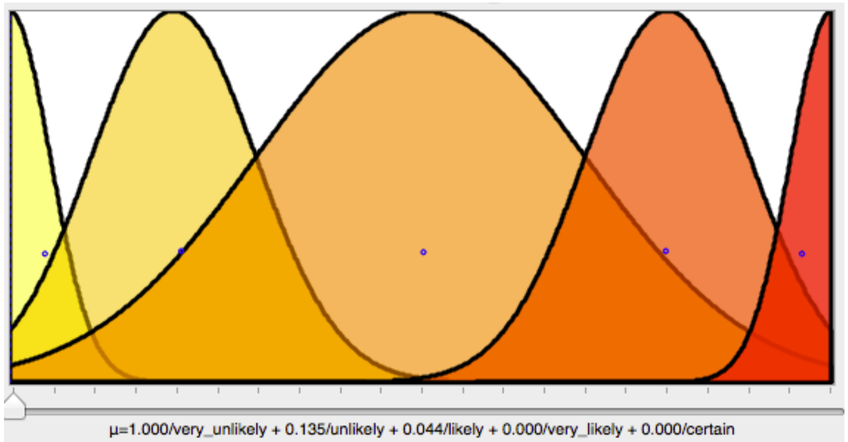


Figure 4: Fuzzy failure rules to map the FTA.

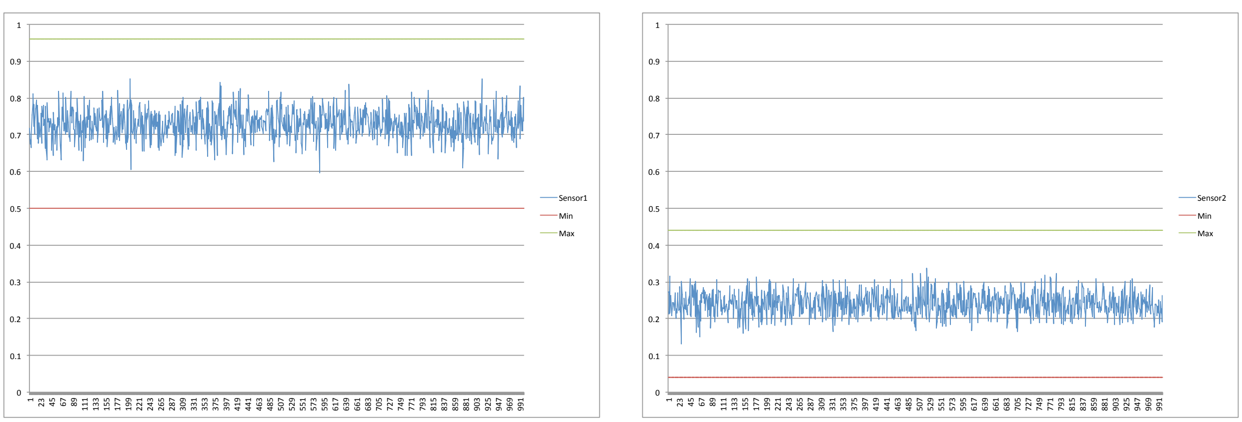
With that, the inputs were combined using the following inference rules (using Einstein product for conjunction and activation and Einstein sum for disjunction):

1. If sensor1 is not normal or sensor2 is not normal or sensor3 is not normal then signal is yellow;
2. If failure is very_unlikely then signal is green;
3. If failure is unlikely then signal is yellow;
4. If failure is likely then signal is orange;
5. If failure is certain then signal is red.

Finally, using this methodology on top of FuzzyLite library (Rada-Vilela, 2014), many tests were carried out and the results are discussed in the next section.

3. RESULTS

In order to calibrate the proposed model, synthetic series were generated to be used as inputs for the model (sensor data and failure probabilities). As for the goal of calibrating the model, all sensor data was generated within their allowed bounds and only FTA probability was left a little bit loose. The intent of this approach was to evaluate if the proposed model was effective in triggering critical events related to FTA and, with that, it was expected that the dam would be green most of the time with occasional yellow signs. Hence, at first, Figure 5 show the data used for model calibration.



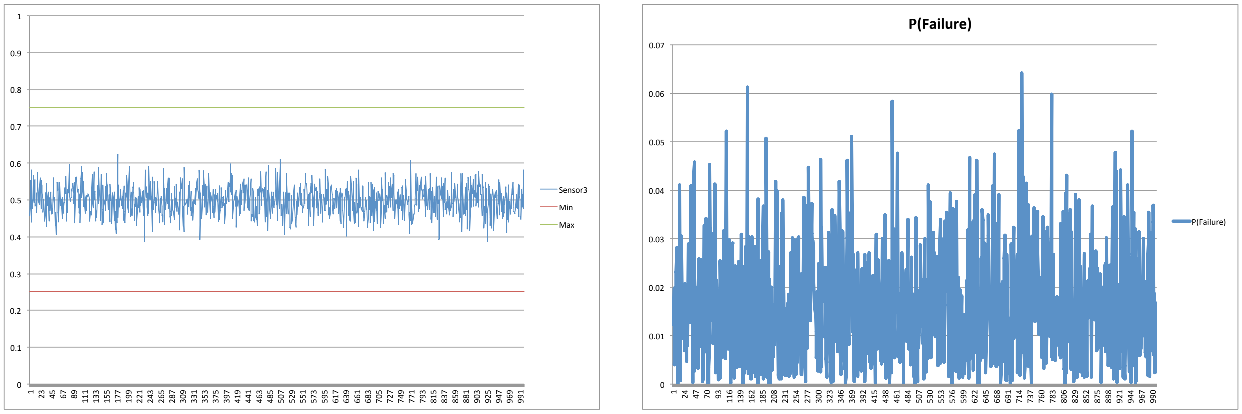


Figure 5: Synthetic series utilized for model calibration.

In Figure 6, each line in the graph represents the activation value of each of the five inference rules previously described and the state signal switch colors when the most critical rule is (more critical inference rules are those associated with more hazardous state signal color), at least, 30% activated. Accordingly, Figure 6 shows that the initial hypothesis turned out to be true, since seldom yellow signs (represented by the yellow ellipses in Figure 6) are triggered when failure probability reach the neighborhood of 4% (compare with P(failure) in the fourth graph of Figure 5).

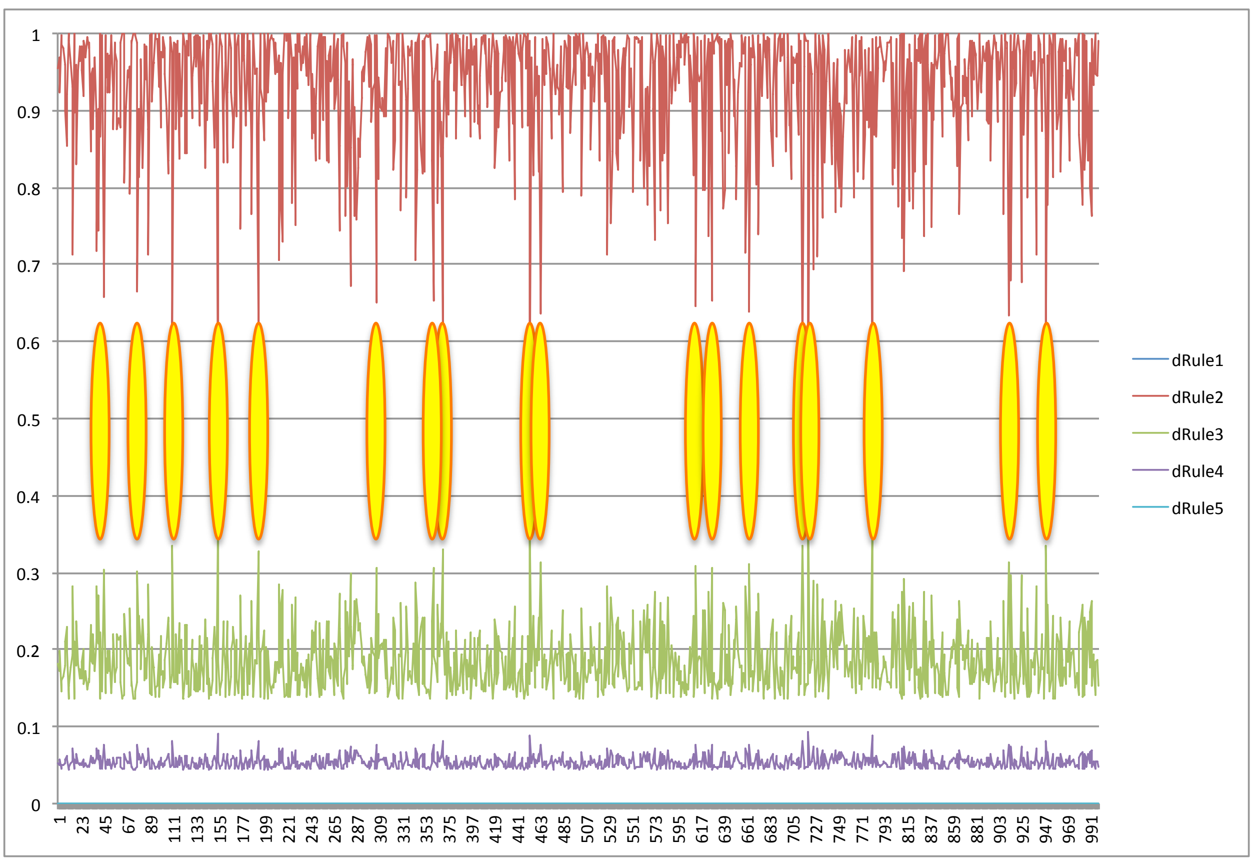


Figure 6: Rules activation for model calibration.

Next, real data was evaluated together with arbitrary bounds (those bounds were positioned in such a way that, occasionally, sensor data would be out of bounds - this was necessary since real data had no issues) to assess the expert system performance. Figure 7 illustrates the input data used in the proposed methodology. Here is not difficult to perceive that all initial data and some other spurious outliers from the sensors are not within the desired bounds what makes one infers that the fuzzy inference system will flag all those cases as problematic.

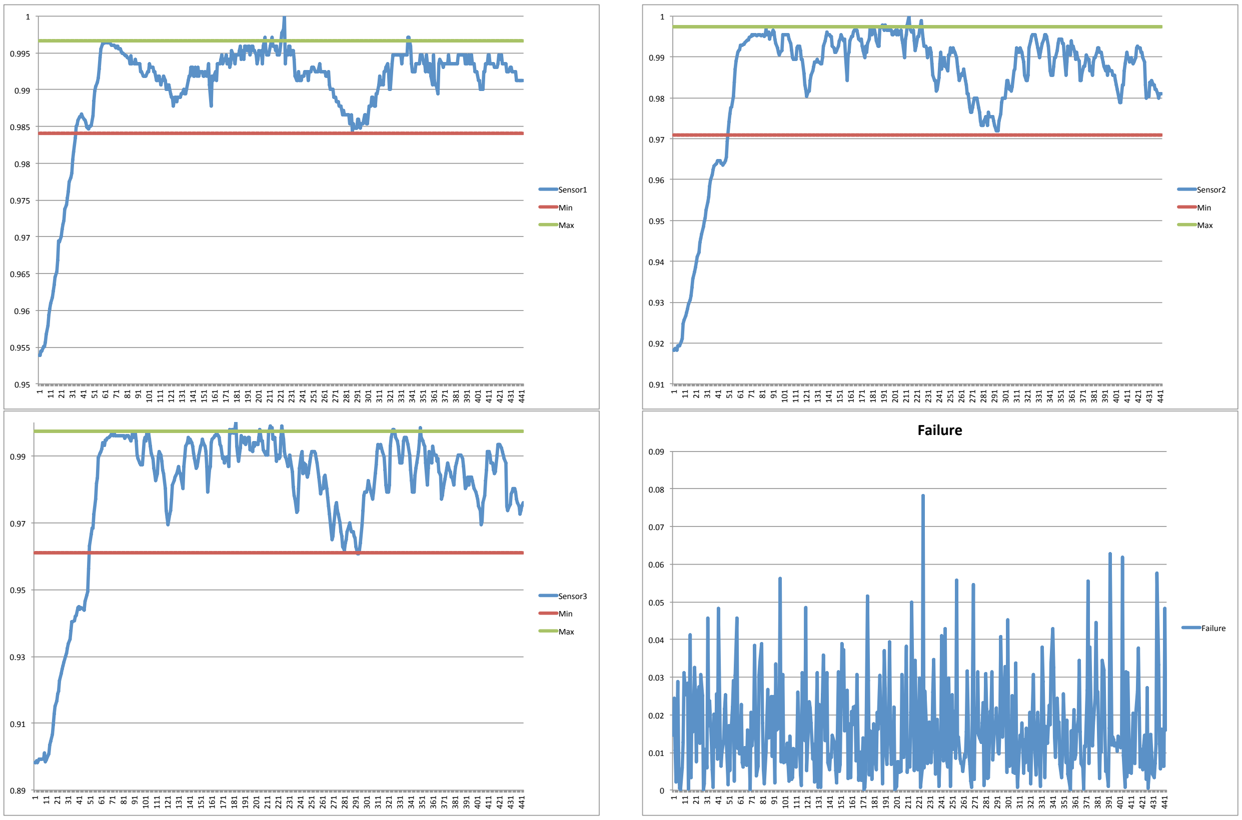


Figure 7: Real piezometer data used to evaluate methodology performance.

On the other hand, Figure 8 reveals that this logic is not always true. In some cases (more specifically, five times), the fuzzy inference system triggered the yellow sign when some kind of issue was detected from the sensors (see the rectangular yellow shapes in Figure 8), whereas in all other cases, the yellow sign was only triggered due to the increase in the failure probability (the yellow ellipses in Figure 8).

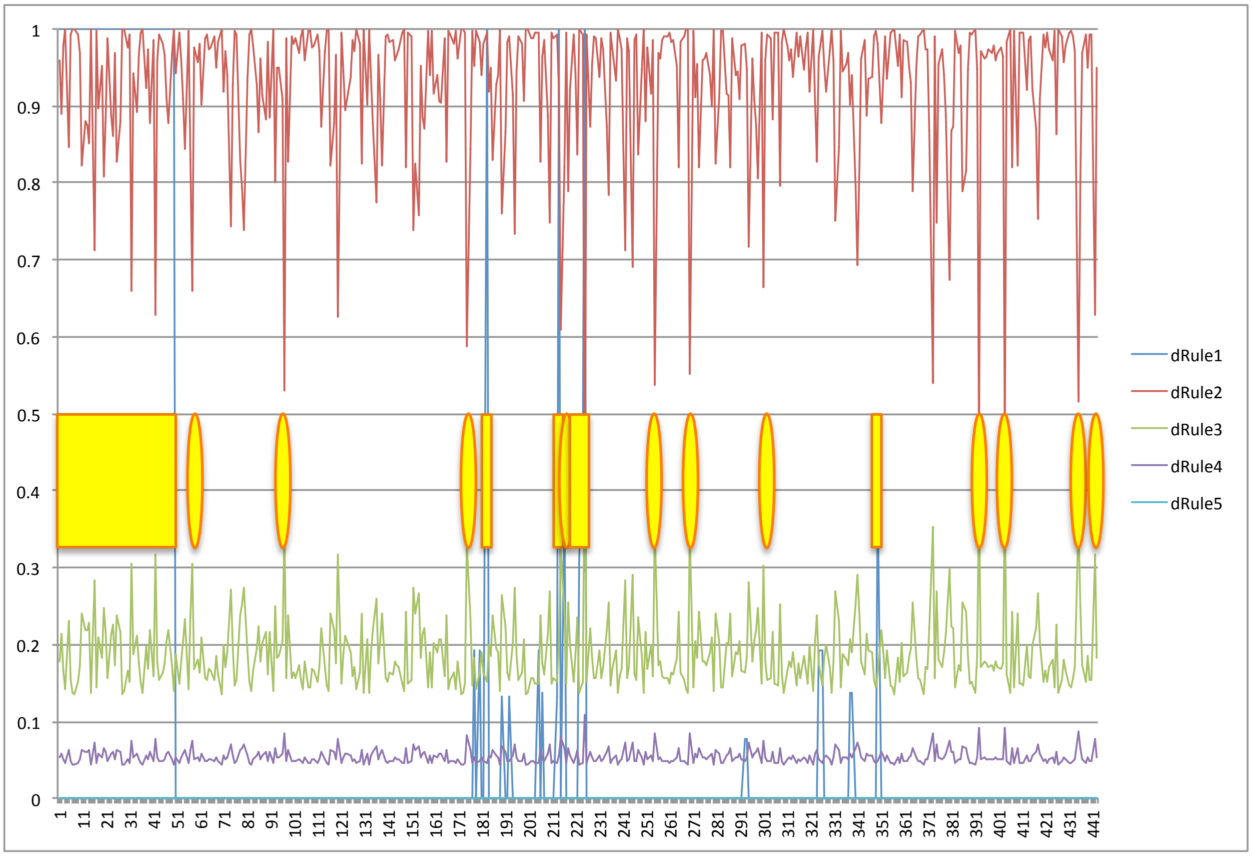


Figure 8: Rules activation for model evaluation.

4. CONCLUSIONS

These results revealed that the proposed methodology was able to smartly calculate the dam state not only by flagging the adequate state when it needed to, but also being wise enough not to overestimate the dam state using biased information or not to analyze multiple dimensions at the same time. Hence, the proposed methodology proved to be flexible enough to be used in everyday dam assessment routines.

Finally, it is important to mention again that this expert system is the core model of a broader decision support system, the PAEWEB, and many other interesting results will still be drawn from this model, what means that some tuning might still be needed in the future in order to take full advantage of the proposed methodology.

5. ACKNOWLEDGEMENTS

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