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TREND-WEIGHTED RULE-BASED EXPERT SYSTEM WITH APPLICATION TO INDUSTRIAL PROCESS MONITORING

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Abstract. *This paper presents a novel technique – referred to as trend-weighted rule-based expert system (TWRBES) – grounded in the integration of two existing tools of the artificial intelligence field, expert systems (ES) and qualitative trend analysis (QTA). Main goal of this approach is to benefit from the major advantages associated with each of the techniques used, such as the ability to represent knowledge through rules and the capability to extract the behaviour and the trends of a continuous signal. Such integration allows a direct purpose in industrial environment applications, especially in the intelligent automation field. The features of the proposed algorithm, particularly in terms of industrial process monitoring, are supported by simulations and experimental results based on industrial benchmark known as Tennessee Eastman process.*
Keywords: Process monitoring, Expert system, Qualitative trend analysis, Tennessee Eastman process

1. **Introduction.** In today's modern industries, size and complexity of involved processes make intelligent monitoring a task of extreme importance. The goal of maintaining process operational flows within its normal operating range brings immediate benefits from promoting productivity and efficiency as well to avoid incidents with more serious consequences. Other factors, such as the incorporation of more restrictive standards for emissions, less waste of raw material and energy consumption and even the emergence of new technological challenges – such as those existing for exploration and production of oil and gas in petrochemical industry – are also aspects that promote the need to avoid oscillations and operational deviations through a preventive monitoring.

In present-day industries, there are several important issues of interest, such as process safety and quality enhancement. In order to achieve those objectives, process monitoring and fault diagnosis have been an active research field in the intelligent automation community during the past several decades.

Generally, process monitoring can be classified into three different categories: quantitative model-based methods [1], qualitative model-based methods [2], and process history-based methods [3].

Model-based methods are the most traditional ones, and it has been successfully applied on plenty of processes for industrial electronics and automatic control systems. There are also several papers dedicated to reviewing and analyzing the state-of-the-art model-based process monitoring and fault diagnosis techniques [4, 5, 6, 7].

Compared to the data-driven techniques, such as the history-based methods, the model-based method is based on exact process models, which rely on physical models from first principles [8]. As a result, they usually give more accurate results than data-driven methods (as long as the system model is reliable). However, for the large-scale industries like some chemical processes, requirements of physical and mathematical knowledge of the process become much more difficult, costly and sometimes are even impossible to obtain.

On the other hand, data-based process monitoring methods have no requirement of the process model and can also be associated with expert knowledge to obtain more complex and detailed information from the raw data. It has become more popular in recent years, especially because of the wide utilization of the distributed control system (DCS) in modern industrial processes, which results in large amounts of data being collected and recorded.

Several data-based systems are constantly being published in different areas of application in the industrial field. Li et al. [9] describe a process monitoring technique based on principal component analysis. Yin and Wang [10] and Hao et al. [11] describe data-driven fault detection methods. It is worthy to note that all the described methods do not take account of qualitative aspects of the analyzed data. Other areas of applications include process modeling [12, 13, 14] and controller design and tuning [15, 16, 17]. Articles dedicated to reviewing and analyzing the state-of-the-art model-free (or data-driven) process monitoring and fault diagnosis techniques are easily found in the literature, such as in [8, 18, 19, 20, 21].

Therefore, industrial branch companies increasingly invest in new technologies aiming to boost the performance, productivity, efficiency, quality, and operational safety of its processes. The adoption of computational solutions that are able to assist the human operator in the decision-making process minimizes the risk of human errors, failures that are promoted by several factors, such as stress, fatigue, distraction and lack of experience. The incorporation of information technology for process monitoring also allows the industry to meet the new requirements to obtain quick and intelligent responses from the used systems.

Aiming at an increase in operational security and efficiency in the industrial sector, new computational methods and techniques are constantly being developed by the scientific community. In that sense, promoting possible real applications with the aid of those proposed methodologies bring considerable benefits for all those who adopt it.

The main objective of this paper is to present an innovative technique based on two methods widely used and already consolidated by the scientific community: expert systems and qualitative trend analysis. By integrating these techniques, it is possible to extract the main advantages of both methodologies. The proposed technique is referred to as trend-weighted rule-based expert system, or simply TWRBES. The primary application of the approached technique in this paper is monitoring of industrial processes.

The rest of this paper is organized as follows. The method known as trend-weighted rule-based expert system is reviewed in Section 2, while its application and results in the process monitoring field will be addressed in detail in Section 3. The conclusions and discussions are given in the last section.

2. The Proposed Method.

In order to merge the efficient process of inference and the ease to represent knowledge through *if-then* rules – remarkable features of expert systems – along the symbolic representation approach of data from qualitative trend analysis, this paper is mainly aimed at presenting a technique characterized as a scientific contribution, referred by the authors as trend-weighted rule-based expert systems (TWRBES).

The main purpose of trend-weighted rule-based expert systems is, from real-time data collection and a previously modeled set of rules, to carry out an inference process capable of extracting the degree of accuracy of these rules at that instant. This degree of accuracy is expressed between the range of 0 and 1, unlike classical expert systems, in which the outputs are discrete (true or false).

TWRBES allows rule conditions to make use of continuous or discrete variables. Thus, its contributions are better noticed when rules are associated with continuous inputs, since these allow an uninterrupted analysis of the monitored situation. The idea then is to analyze continuous variables present in rules stored in the knowledge base – which are basically summarized in relational expressions including upper and/or lower thresholds – and conclude the effectiveness of the concerned rule in a value between 0.0 and 1.0, which are simply referred as *certainty factor*.

The methodology of the proposed approach consists of four successive steps, completed on-line:

1) on-line polynomial fitting of the last segment
2) classification of the last segment into seven different shapes (primitives)
3) calculation of the reinforcement/penalty function
4) definition of the rule's certainty factor

These steps are required to each of the continuous variables present in at least one rule condition of the knowledge base. If a given rule has more than one variable in its condition, it is necessary to run the method for each one of its conditions, and the certainty factor of the rule is calculated subsequently.

Each of those four steps is briefly described in the following Subsections (2.1, 2.2, 2.3 and 2.4). Fluxogram of required stages, highlighting each of the inputs and outputs, is shown in Figure 1.

2.1. **On-line polynomial fitting of the last segment.** Given the measurements (data points) available from a sensor, the first step taken by the proposed method is based on fitting the monitored continuous signals into a sequence of unimodal segments. This stage is done on-line, by trying to construct a curve that has the best fit to the current segment with a polynomial of at most second order.

There are several different techniques that could be applied for curve fitting. Due to simplicity and efficiency, the method known as polynomial regression adjusted by the

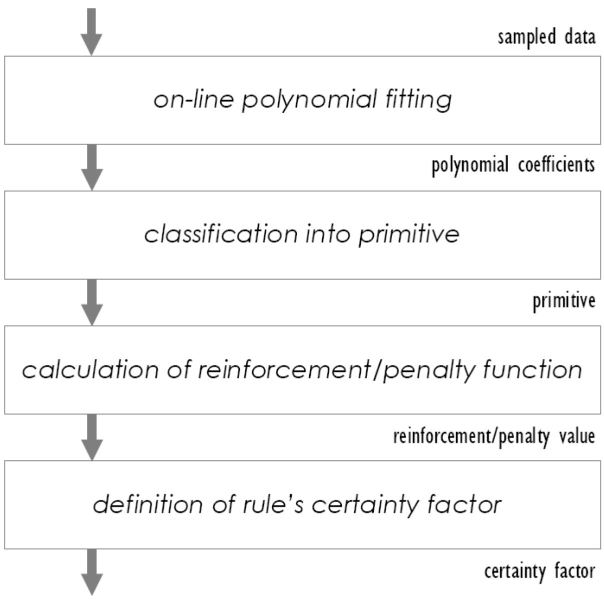

Figure 1. Stages fluxogram of the proposed method

method of least squares was chosen. As previously mentioned, polynomials in the proposed method are limited to at most second order, so the polynomial regression model is simplified to a quadratic model as shown in Equation (1), where a_i (a_0, a_1 and a_2) are the polynomial coefficients necessary to calculate the expected value of y in terms of the value of an independent variable (or vector of independent variables) x.

$$y = a_0 + a_1 x + a_2 x^2 \tag{1}$$

Essentially this methodology is characterized as a sliding window method, since the algorithm initializes its windows with unitary length and as new data arrives it is added to the segment until the approximation error exceeds a predefined threshold. If its tolerance is transgressed, a new window with unitary length is created.

One of the main advantages of this stage is filtering undesired outliers and providing easy and quick calculation of numerical derivatives required for the next stage.

2.2. **Classification of the last segment into a primitive.** Given the polynomial coefficients obtained from the last step, it is possible to classify it according to a predefined limited set of shape primitives.

Each primitive consists of the sign of first derivative and the sign of second derivative (or zero). In other words, each primitive brings information about whether that segment is positive or negative, increasing, decreasing, or not changing, and concavity. This set of seven basic shapes called primitives was first proposed by [22], as part of a method that generates qualitative descriptions of signals trends, and it is shown in Figure 2.

These primitives are identified according to the values of the first and second derivatives, which are calculated by numerical differentiation given the current polynomial (at most second order). In the case of a change of concavity of the unimodal polynomial, splitting the segment may be required to its proper classification into a valid primitive. This is simply done by identifying the inflection point of the current segment and splitting into two. Figure 3 illustrates the second stage, as the previously obtained polynomial is split in its inflection point and classified according to its first and second derivatives.

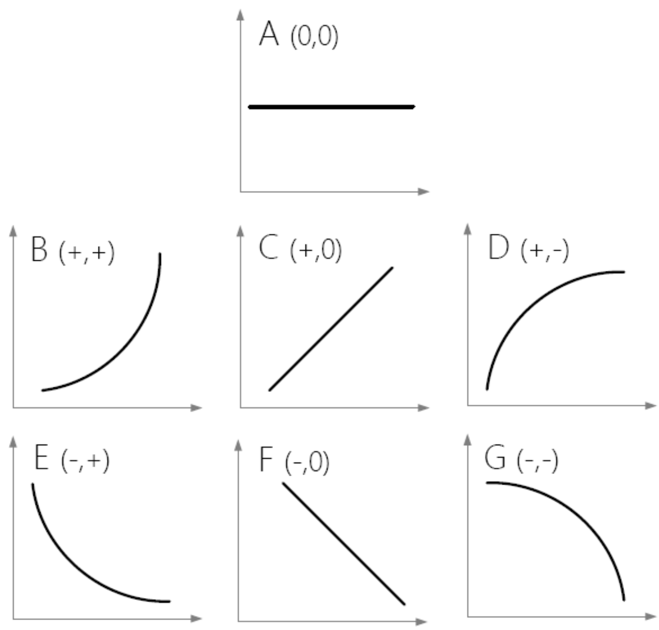

FIGURE 2. Set of primitives proposed by Janusz and Venkatasubramanian [22] (the signs are that of the first and second derivatives, respectively)

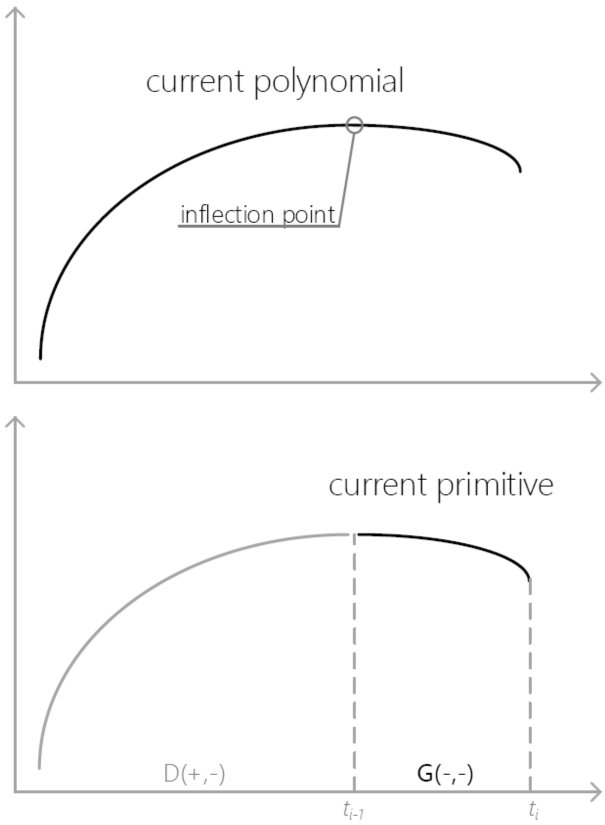

FIGURE 3. Current polynomial obtained in stage 1 is split in its inflection point and the last segment is identified as being primitive G due to the signs of its first and second derivatives.

By the end of this stage, the required data to store is the current primitive p, as well as the time interval Δt that the corresponding behaviour goes on without changes.

There are several advantages of qualitative analysis using a pre-defined set of primitives. One of them is the significant compaction of large amounts of numerical data generated every few seconds that is stored in modern computer-controlled process environments. If extracting the behaviour (analyzing qualitatively) from the available monitored sampled data is enough for the considered analysis, there is no more need to store the raw data. A second advantage of a qualitative approach is abnormality detection. Process trends often offer valuable clues about faults and operational deviations in the monitored process.

An algorithm represented in the form of a flowchart is shown in Figure 4. It describes steps from stages 1 and 2, on-line polynomial fitting of the last segment and classification of the last segment into a primitive, respectively.

2.3. **Calculation of the reinforcement/penalty function.** Given the current primitive obtained in the last stage, the algorithm is then responsible to calculate a value resulting from a reinforcement/penalty function based on its quantitative and also qualitative information. The reinforcement/penalty value is required to calculate the certainty factor to the defined thresholds (upper and lower) of a given rule.

In order to ease the explanation of this stage, this section assumes a problem concerning a single upper boundary rule, in which a monitored signal of average μ is required to operate below the upper threshold θ. Problems concerning lower boundaries are similar, with a few minor adjustments.

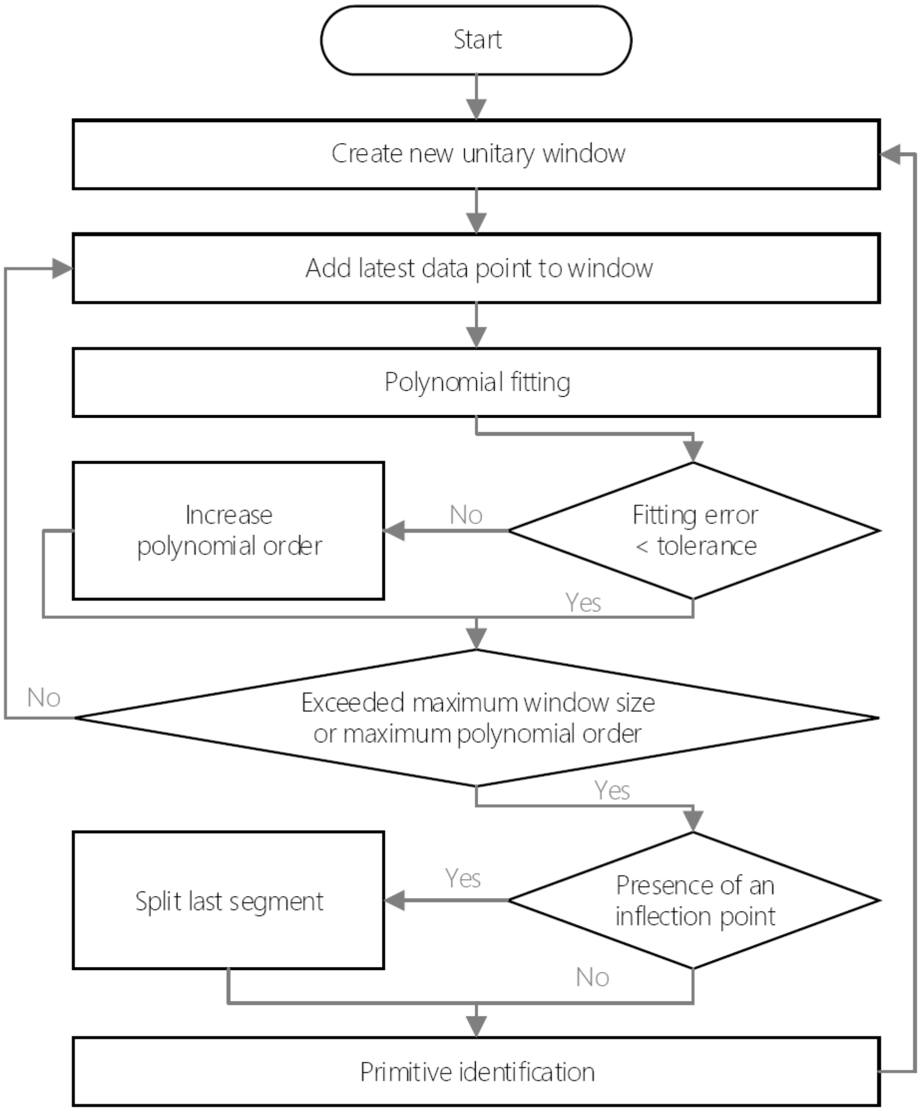

FIGURE 4. Flowchart for on-line primitive extraction

Consider the case of a signal represented by a continuous variable whose current value is y. Calculation of how close (P) this variable is relative to its upper threshold (θ) is shown in Equation (2), taking account of the normal operation average of that variable (μ).

$$P = \begin{cases} 1 & \text{if } y > \theta \\ \dfrac{y-\mu}{\theta-\mu} & \text{if } \theta \geq y \geq \mu \\ 0 & \text{if } y < \mu \end{cases} \tag{2}$$

Equivalently, the relative distance (δ) related to the threshold (θ) is given by the complement of the previous equation, as shown in Equation (3).

$$\delta = 1 - P \tag{3}$$

The relationship between the current value (y), the threshold (θ) and its average (μ) is shown in Figure 5. In this example, at t_1, t_2 and t_3 the relative distance δ has a value of 1.0, 0.55 and 0.1, respectively.

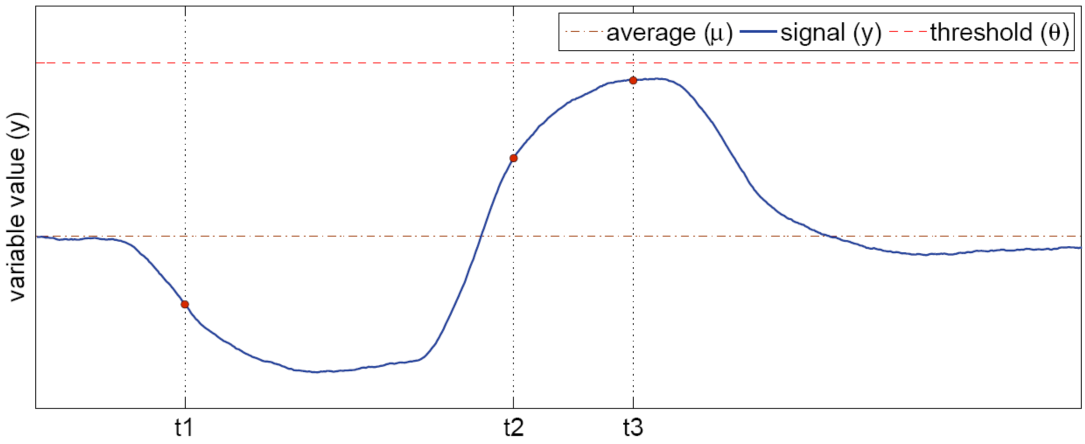

FIGURE 5. Relationship between the variable value (y), the threshold (θ) and the variable mean value (μ)

Result of this equation quantitatively reflects the percentage of how close the current measurement of the variable is relative to its upper limit (taking account of the average value of the signal). Note that, qualitative information, such as the behaviour and trend of this variable, is not taken into consideration. Regardless of the variable with current value of y assuming an increasing or decreasing behaviour, the value of P will remain the same.

The main objective of this stage is – from the available measured data – to calculate a reinforcement or penalty value to be added to the proximity index P, resulting in a numeric value that reflects both quantitative and qualitative aspects of the monitored signal. The function that has this responsibility, called reinforcement/penalty function ($F_{r/p}$), is given by:

$$F_{r/p}(p, \Delta t, \delta) = A(p) * W(\Delta t) * \delta \tag{4}$$

Value of $A(p)$ is defined according to pre-existing boundaries that reflects the maximum contribution each of the primitives will result in the reinforcement/penalty function. Those values were chosen empirically, considering that steeper trends (like primitives B and G) should contribute more than steadier behaviours (like primitives C and F). According to the primitive (p) detected in the previous stage (classification of the last segment into a primitive), $A(p)$ will be determined according to Equation (5). Note that the higher the growth rate of the primitive is, the greater the value of $A(p)$ is (reinforcement), and analogously, the higher the rate of decrease is, the smaller the value of $A(p)$ is (penalty).

$$A(p) = \begin{cases} 1 & \text{if } \; p = (+,+) \\ 2/3 & \text{if } \; p = (+,0) \\ 1/3 & \text{if } \; p = (+,-) \\ 0 & \text{if } \; p = (0,0) \\ -1/3 & \text{if } \; p = (-,+) \\ -2/3 & \text{if } \; p = (-,0) \\ -1 & \text{if } \; p = (-,-) \end{cases} \tag{5}$$

Calculation of $W(\Delta t)$ is performed by a natural exponential function given by $1 - e^{-\Delta t}$. In other words, $W(\Delta t)$ is a weighting factor based on the continuity of a similar behaviour. The longer a certain detected primitive remains unchanged, the greater its addition will be to the reinforcement/penalty function.

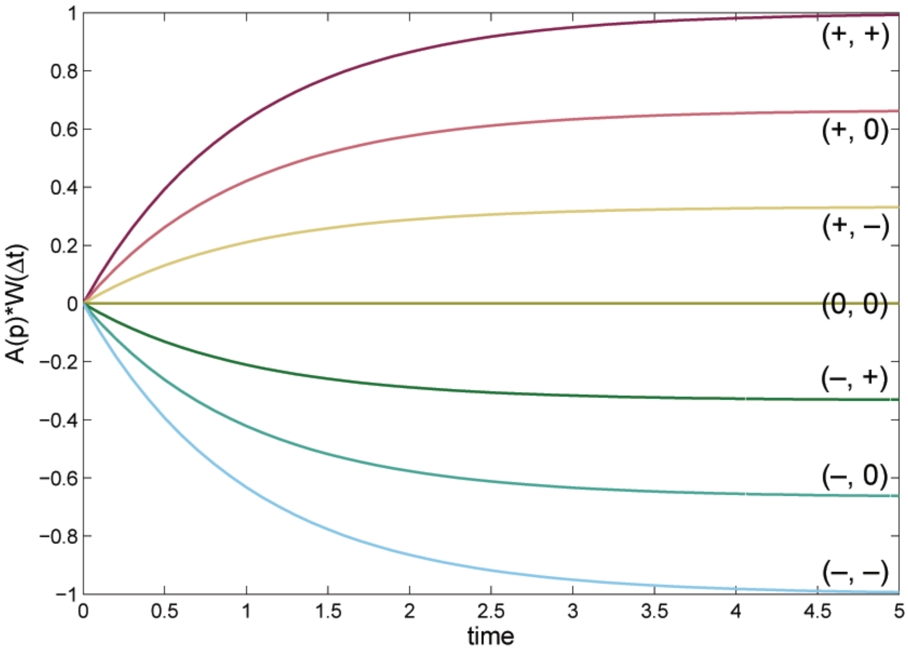

Figure 6. Possible combinations between $A(p)$ and $W(\Delta t)$

By multiplying $A(p)$ and $W(\Delta t)$, it is obtained of the relative weighting that will be applied to the relative distance δ according to Equation (4). Figure 6 illustrates all possible combinations of the weighting factor, along time, based on the identified primitive p and the time interval Δt.

As previously presented, the required coefficients for the calculation of $F_{r/p}$ are: δ indicating the relative distance between a variable and its threshold; $W(\Delta t)$, the weight resulted from a continued behaviour over time; $A(p)$ defining the maximum reinforcement or penalty contribution.

2.4. **Definition of the rule's certainty factor.** After calculation of the reinforcement/penalty function ($F_{r/p}$), the following step – defining a certainty factor of the rule (CF) – becomes a trivial task. Given the relative distance of the current value y with respect to its threshold θ (denoted by P in Equation (2)), it is sufficient to add up the value of $F_{r/p}$, as shown in Equation (6).

$$CF = P + F_{r/p} \tag{6}$$

The proposed approach also allows the use of logical operators to aid the modeling of rules, making it possible to design more complex rules. In this case, calculation of the global certainty factor (CF_{global}) of a given rule is performed for each variable individually (CF_i), and they are combined according to the logic operation, as indicated in Table 1 (exemplified by the presence of multiple conditions C_i).

In short, the logical conjunction of conditions results in the arithmetic mean between the degrees of accuracy (C_i) of each of the conditions. For logical disjunction of conditions, the result is the highest degree of accuracy (CF_i) between all conditions.

Table 1. Calculation of the global certainty factor

Expression	**Calculation of CF_{global}**
C_1 *and* C_2 *and* ... *and* C_n	$avg(CF_1, CF_2, \ldots, CF_n)$
C_1 *or* C_2 *or* ... *or* C_n	$\max(CF_1, CF_2, \ldots, CF_n)$

3. Applications and Results.

3.1. **Process description.** The Tennessee Eastman process was first introduced by Eastman Chemical Company as a realistic simulation of a plant-wide chemical process for assessment of control algorithms and fault monitoring and diagnosis. Based on an actual system, slight modifications were made to protect the identity of the reactants and products. Introduced and adapted by Downs and Vogel in 1993 [23], the TE process is a response to the need for real problems for the application and discussion of different methods and techniques in the academic and scientific community.

The plant consists of five major operation units: a two phase reactor, a product condenser, a vapor/liquid separator, a recycle compressor, and a product stripper. Figure 7 shows the flowsheet of TE process. The TE process model is an open loop unstable process without control and it reaches shutdown limits within an hour, even for very small disturbances [24]. A large number of interacting process and manipulated variables (41 measured variables and 12 manipulated variables) are incorporated into the model, making it a truly significant plantwide control problem. The process description also defines 20 types of process disturbances in addition to 6 operating modes corresponding to different production rates [25].

TE process description also lists specific operational constraints that the control system should respect. In the case that the process conditions deviate beyond high or low shut down limits, the interlock strategy is activated to immediately shut down the process. Tennessee Eastman process normal operating constraints are listed in Table 2. Modern industrial processes like the one described in this paper are often accompanied with high temperature, high pressure, flammable and explosive environment, and monitoring those measured variables according to its thresholds is an important step to improve safety and reliability.

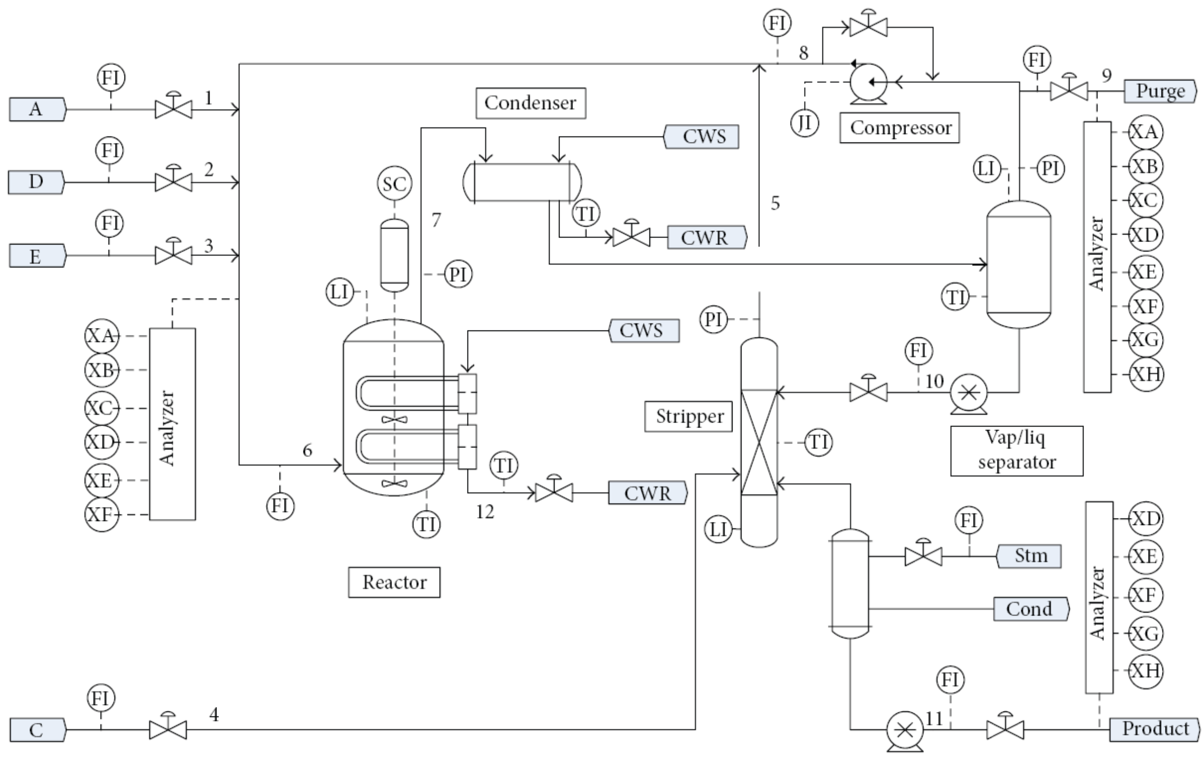

FIGURE 7. The flowsheet of Tennessee Eastman process

Table 2. Process operating constraints

Process Variable	**Normal operating limits**	
	Low	*High*
Reactor pressure	n/a	2895 kPa
Reactor level	11.8 m^3	21.3 m^3
Reactor temperature	n/a	150 °C
Separator level	3.3 m^3	9.0 m^3
Stripper level	3.5 m^3	6.6 m^3

Several research groups have used the Tennessee Eastman process for wide range of applications. For instance, fault detection and diagnosis systems are often validated using the TE process, such as described by [26, 27, 28]. [29, 30] have designed different control systems for the process. Also, [31, 32] presented process monitoring strategies with application to Tennessee Eastman process. These studies promote and validate the use of the TE process as a successful benchmark.

3.2. **Results.** In order to obtain numeric results, it was chosen to supervise two process variables: the reactor pressure and the liquid/vapor separator level. Those process variables were chosen due to its characteristic of having quick dynamics, being more susceptible to variations in accordance to abnormalities in the process. Those aspects result in an interesting analysis of its behaviour and certainty factor according to its thresholds.

3.2.1. *Monitoring the reactor pressure high threshold.* As listed in Table 2, the process operating constraints for the reactor pressure are defined in 2895 kPa for the high threshold. Based on that information, it is clear that a continuous monitoring of that variable is required to maintain the process in a normal operating profile. In the case of abnormalities significantly affecting this variable, it could be necessary a human intervention. Thus, we can model this situation with the following rule: If the reactor pressure is greater than 2895 kPa, then take necessary measures to keep process in a normal operating mode. This could be simplified by:

IF

reactor pressure > 2895 kPa

THEN

"Take necessary measures."

Control loop set-point for this measured variable is defined at 2770 kPa, turning that value the normal operation value (μ) for the reactor pressure. By monitoring this variable, taking account of also its behaviour over time, it is possible to estimate how close a rule is to be completely true, thus allowing the operator to perform the required actions in order to prevent the undesirable situation. It is noteworthy that, the human operator reasoning is much more qualitative (based on trends and behaviours) than quantitative (strictly numeric). Therefore, by incorporating trend weighted variable, monitoring the operation becomes more efficient and effective.

Behaviour of the monitored process variable over a given time interval (1600 samples, in a total of 16 hours of simulation) is shown in Figure 8. During the simulation, random disturbances as described on the Tennessee Eastman process were simulated in order to deviate the process of its normal operation profile. After the polynomial approximation phase, the obtained time series is shown in Figure 9. As an on-line method, the algorithm only keeps track of the last current polynomial, discarding previous time windows. For

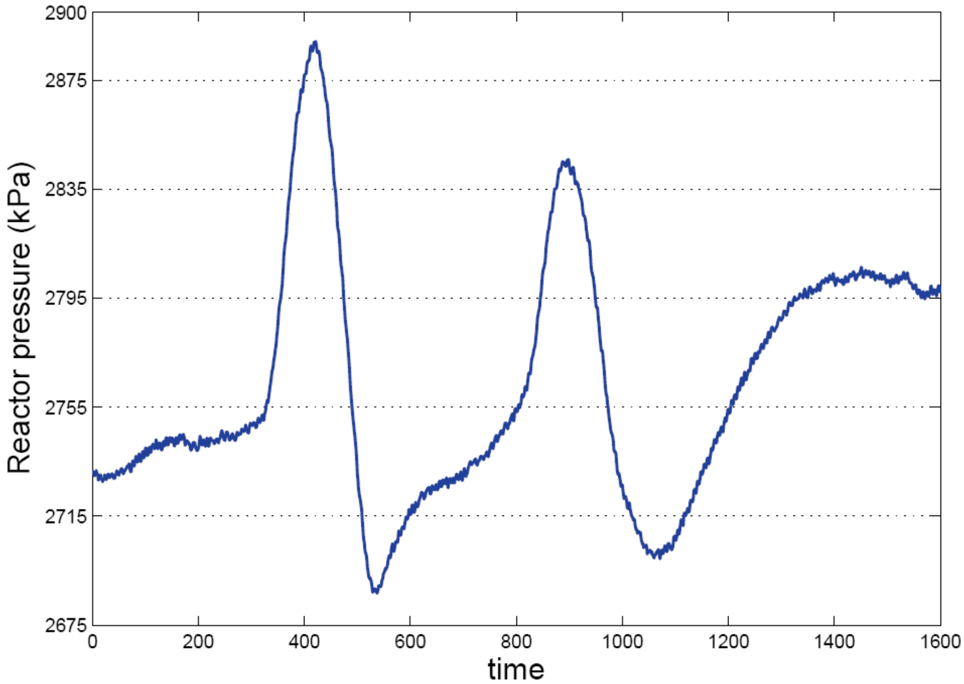

Figure 8. Reactor pressure

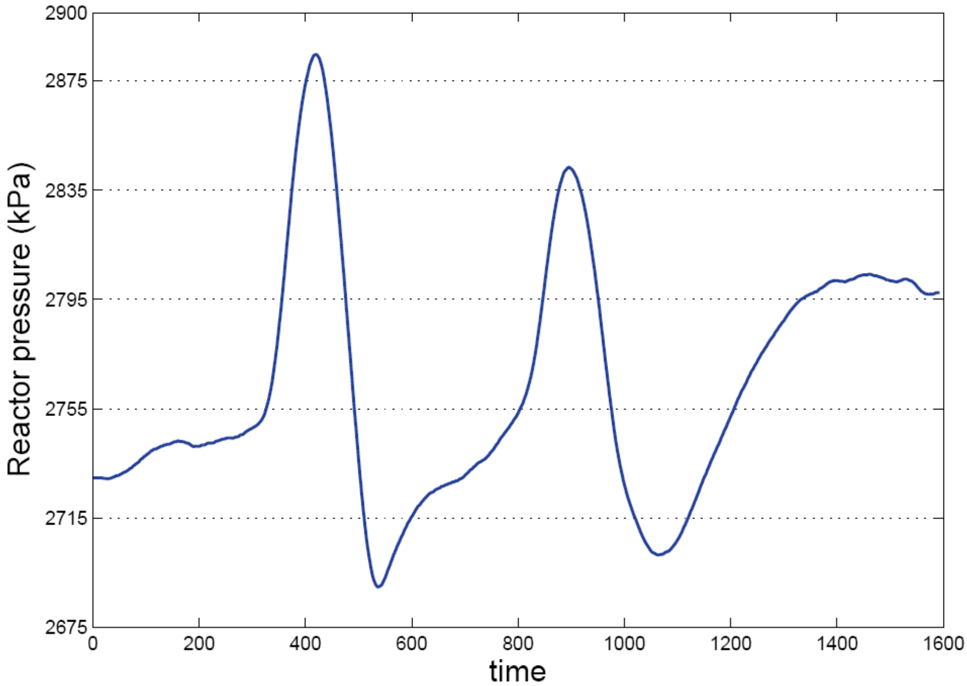

Figure 9. Reactor pressure after polynomial approximation

didactic purposes, the whole observed time series (1600 samples) are being shown in the charts.

Figure 10 illustrates the certainty factor behaviour over time. An interesting study is made by analyzing the monitored signal and the TWRBES conclusions in different time intervals, as described in Table 3. At time stamps 387, 472, 890 and 931, the numeric value of the process variable reactor pressure is exactly the same (2835 kPa), and in the case of a purely quantitative analysis, represent the same level of proximity in relation to

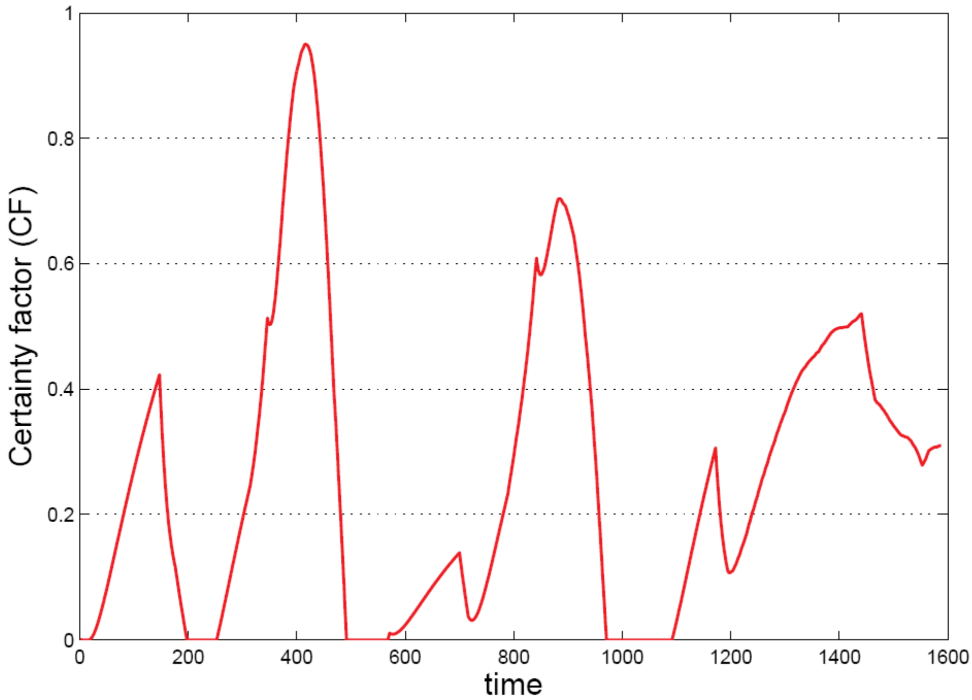

FIGURE 10. Reactor pressure certainty factor

TABLE 3. Analysis of the reactor pressure

t	y	Δt	p	$F_{r/p}$	CF
387	2835 kPa	07	$(+,-)$	$+0.0729$	**0.6530**
472	2835 kPa	19	$(-,0)$	-0.0215	**0.5623**
890	2835 kPa	23	$(+,-)$	$+0.0270$	**0.6158**
931	2835 kPa	14	$(-,-)$	-0.0263	**0.5567**

its monitored upper threshold θ. Taking consideration of qualitative aspects, those four different periods represent different certainty factors.

3.2.2. *Monitoring the separator level low threshold.* Another operation unit of the Tennessee Eastman process is a vapor/liquid separator. Listed in the process constraints are a low level limit for normal operation set in 3.3 m^3 (equivalently to 30%) and set-point is set to 50%, a lower threshold example for the proposed model. The monitoring rule to this variable would be:

IF
separator level $<$ 30%
THEN
"Take necessary measures."

Similar to the previous experiment, during the simulation random disturbances were generated in order to deviate the process of its normal operation profile. The monitored signal is shown in Figure 11, and the polynomial approximation is shown in Figure 12.

Different from the previous experiment, the observed variable actually exceeds its lower threshold, resulting in a certainty factor of 1 until the process returns to its normal state. This is clearly seen in Figure 13. At time stamps 287, 413, 963 and 1138, the numeric value of the separator level is exactly the same (40%), and in the case of a purely quantitative analysis, represent the same level of proximity in relation to its monitored

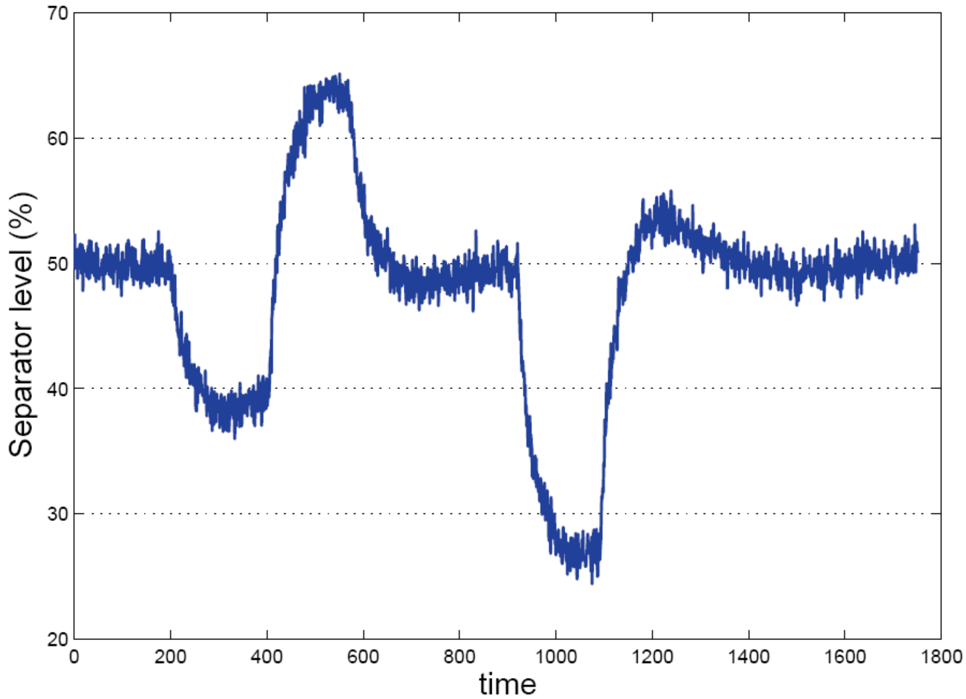

FIGURE 11. Separator level

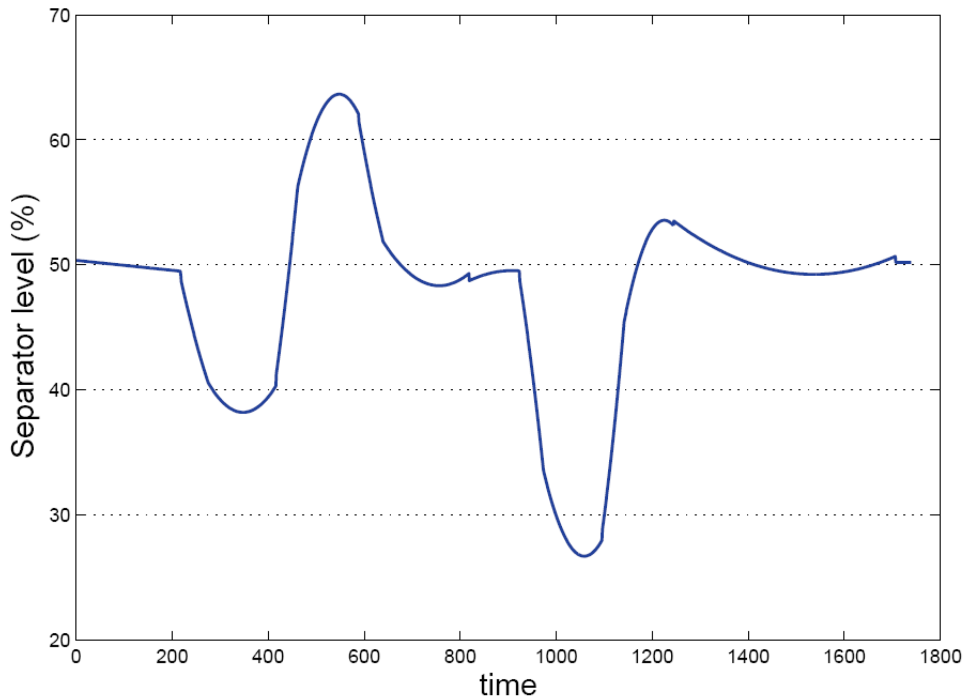

FIGURE 12. Separator level after polynomial approximation

upper threshold θ. Taking consideration of qualitative aspects, those four different periods represent different certainty factors, as described in Table 4.

4. **Conclusions.** In this paper, a technique referred as trend-weighted rule-based expert system is presented to the scientific community, as one of its many possible applications.

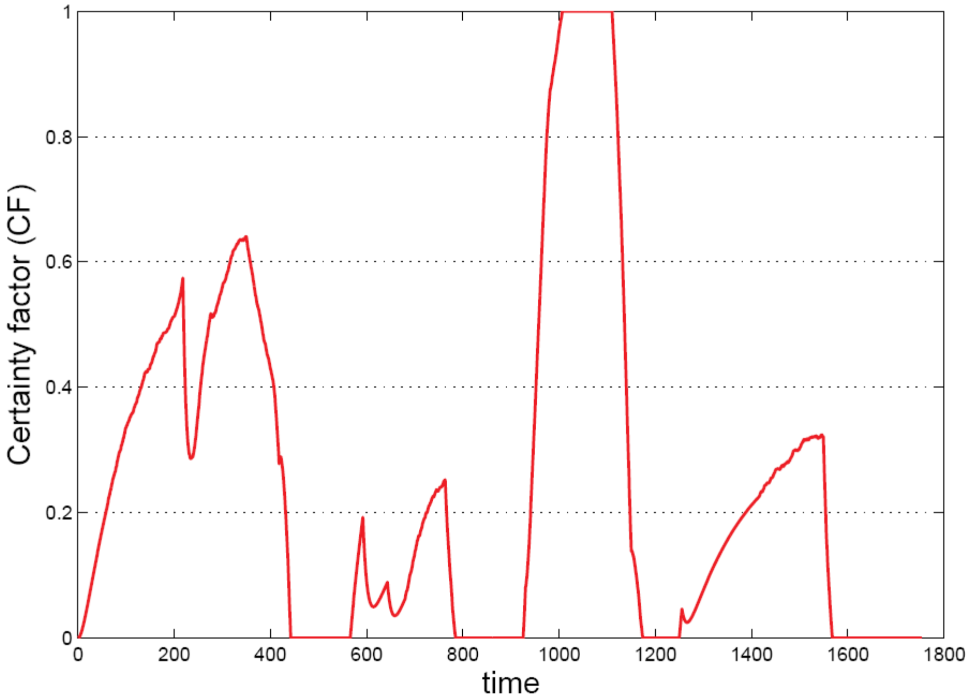

FIGURE 13. Separator level certainty factor

TABLE 4. Analysis of the separator level

t	y	Δt	p	$F_{r/p}$	**CF**
287	40%	10	$(-,+)$	$+0.0236$	**0.5234**
413	40%	62	$(+,+)$	-0.1539	**0.3443**
963	40%	32	$(-,-)$	$+0.0934$	**0.6011**
1138	40%	33	$(+,+)$	-0.0624	**0.4375**

In the intelligent automation field, the proposed method allows a wide range of possible applications, such as on-line process diagnosis and fault detection.

The key feature of this methodology is to allow a continuous and efficient monitoring of the behaviour of the process, since it is widely known that the human operator's reasoning is more qualitative than based on precise values. Thus, by taking account of the description of the variables evolution in a time interval using a set of qualitative symbols, the tool became capable of emulating the reasoning ability of a human operator. The main objective of this enhanced monitoring method is to minimize chances of human error, and improve the safety and reliability of industrial processes.

Further work is aimed in enhancing the method and applying it to different applications in order to validate its usability and efficiency.

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