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IFAC PapersOnLine 55-6 (2022) 649–654

Timing Aspects in Causality Analysis with Multilevel Flow Modelling ⋆

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Abstract: Temporal aspects of multilevel flow modelling (MFM) are important for reasoning about causes and consequences. In particular real time reasoning about sensor data are dependent on proper temporal ordering of events in order to cope with plant dynamics. The purpose of the present paper is to contribute to the further development of the temporal aspects of MFM by explaining how time stamps associated to the measured signals can be used to enhance the causality analysis and infer the possible causes of a sequence of alarms.

Keywords: Fault diagnosis, Causality analysis, Multilevel flow modelling, Timing analysis

1. INTRODUCTION

Multilevel flow modelling (MFM) provides concepts and tools for acquisition and reasoning about causality in complex systems that helps the operators to identify possible root causes in SCADA systems including a large number of alarms. There exists a large literature that presents the main principles of MFM. The reader is invited to refer to Lind (2011a,b) for an introduction to MFM models and to Kirchhubel et al. (2017) for causality inference and alarms processing with MFM models. Current MFM techniques have a limitation, namely the timing aspects of the propagation of deviations are not considered in the MFM-based reasoning. In addition, during consequence reasoning, the occurrence of a specific event that will possibly occur can be inferred, but when the event will happen cannot be inferred. However, in many cases, time-related data such as the order of the event occurrence or the interleaving times between event occurrences would be helpful to enhance cause and consequence reasoning.

To treat the dynamic features of a system by MFM, only a few works have introduced timing aspects in such models. Rosen (1998) made the first proposal of how to introduce temporal information in MFM, and Lind (2016) presented a more recent overview of its temporal aspects. In this paper, time is introduced by adding a constant delay to the relations between functions and goals. Lind (2011b) presented overall principles for cause and consequence reasoning including MFM-patterns. Kim and Seong (2018) proposed extensions to MFM for reasoning about dynamic situations including time-to-detect and time-to-effect concepts. More precisely, a time-to-detect is associated to each function of the MFM model where a variable is measured and monitored and a time-to-effect is associated to each relation between functions. For a given path between a cause and an alarm, the detection delay is obtained from the sum of the successive times-to-effect and the final time-to-detect. The previous approach suffers from two limitations: (i) time values are essentially associated with relations rather than functions, that is in a certain sense counter intuitive and inconsistent with MFM principles because only functions support how variables change during operation; (ii) a single time value is assigned between two given variables and uncertainties are not considered. The authors in Guo et al. (2010) have proposed another formalism based on temporal logic to infer the decision from time information. However, this approach was not directly applied to MFM. Observe that a large literature exists about the use of temporal logic for fault detection and diagnosis applications. In particular, in the framework of discrete event systems, temporal logic has been implemented with stochastic automata Capacho et al. (2017) or other formalisms Reinhardt et al. (2020). In addition, recent works have explored several research directions. In Dorgo et al. (2021), the authors discuss the definition of alarms and propose to make the alarms more informative by enhancing the alarm messages. Another approach relies on data-based methods, in particular, Monte Carlo simulations Nielsen et al. (2020). This approach has been introduced for validation purpose but it can be also used to estimate the distribution of time delays in a given MFM model.

The ultimate goal of our research is to extend the modeling capability of MFM with timing aspects. In such cases, two important issues should be considered: how to insert the timing aspects in MFM and how to use such aspects for cause and consequence inferences. In this contribution we assume that the timing aspects have been already inserted in the model and we focus on the use of these aspects to improve the cause and consequence inferences. The rest of

⋆ This work has been supported by Kairos Technology AS and University Le Havre Normandie

10.1016/j.ifacol.2022.07.201

the paper is organized as follows. Section 2 describes the basis of MFM, causality analysis and other related notions. Section 3 presents the main contribution: the use of time stamps in the causality analysis. Section 4 is an illustrative example and Section 5 concludes the paper.

2. PRELIMINARIES

2.1 Multilevel flow modelling and fault analysis

MFM represents the goals and functions of a system by decomposing the mass, energy and information streams in the operations as a set of means-end relationships. Each stream component along the means-end dimension is described by basic flow functions. By combining the means-end decomposition of the overall operation and part-whole perspective of individual flows the function of the system is analyzed and can be represented as a graphical model. The process of establishing the MFM model starts from available engineering knowledge about the system Wu et al. (2020). The represented causality can be refined to match the dominant physical effects and the model can be completed by representing the imposed control strategies. Heussen and Lind (2012)

Based on the MFM modelling primitives, the propagation of faults through the system can be analyzed. In particular propagation trees can be extracted systematically from MFM. Since faults are considered as root causes that may explain the unexpected behaviours in the system, one can use a causal analysis to identify the functions in the system that are affected by a given fault. From a phenomenological perspective, i.e., by considering the measurement $\hat{x}$ of the variable x, if an observation is made somewhere down in the tree, propagation must have passed through the previous sensors for the possible cause to be valid. It would therefore be premature to include these sensors in the likelihood evaluation of the possible cause. Repeating this for all possible causal trees may help differentiate their likelihood sufficiently to provide useful ranking without formal quantification.

Such a reasoning is no longer fully correct if one consider the alarms $A(\hat{x})$ instead of the variation of the measurements $\hat{x}$. In such a case, the system and sensors are considered as a whole and the conclusions of the timed causality analysis will depend also on the location and tuning of the sensors. As far as the propagation times from causes to alarms are assumed to be known, one can infer a decision but if one changes the sensors, the propagation times and decision should be updated. In other words, if we consider the consequence of an initiating cause as the propagation of an event horizon, it is not only the speed of propagation that will determine the timing of alarms, it will also be the alarm set-points versus the initial state before the cause appeared Kim and Seong (2018).

2.2 Sequences of alarms and related notations

The considered systems are assumed to be monitored with a set of sensors and the proposed analysis studies the system plus its sensors as a whole. Each sensor measures the variation $\hat{x}$ of a given physical variable x and an alarm

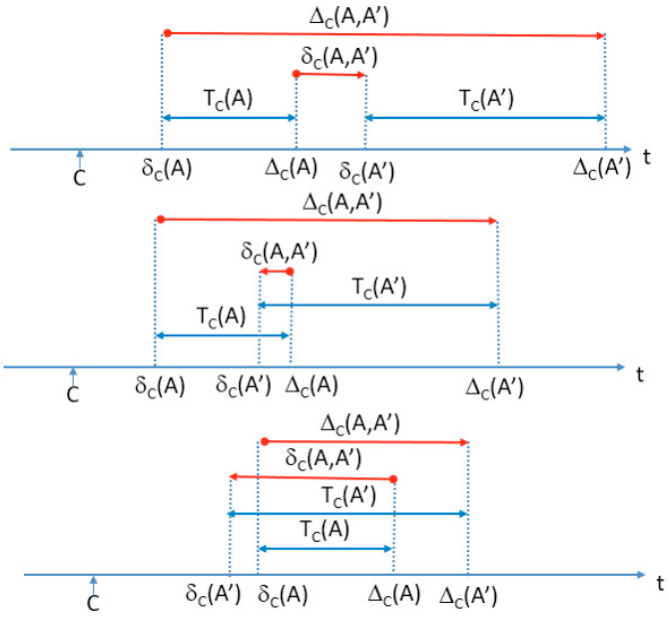

Fig. 1. Computation of the range between alarms: A necessarily occurs before A' (top), the time constraints on A and A' intersect (middle), the time constraints on A are included in the ones of A' (bottom).

$A(\hat{x})$ is triggered when some unexpected variations of x occur, i.e., when the measurement $\hat{x}$ exceeds some limit thresholds The timed/causal analysis proposed in this paper concerns the sequences of alarms that is different from the order in which the characteristic variables are influenced by a given fault. After the occurrence of a given fault (i.e., a root cause) a sequence of n successive alarms with their time stamps is captured. Such a sequence σ is formalized as

$$\sigma = (A_1, \tau_1)...(A_n, \tau_n), \tag{1}$$

where A_i, $i = 1, ..., n$, are the successive alarms associated to the measurements $\hat{x}(A_i)$ of the physical variables $x(A_i)$, and τ_i, $i = 1, ..., n$, are the corresponding time stamps that satisfy $\tau_1 \leq ... \leq \tau_n$. The following notations are also introduced to manage such sequences of alarms.

- $Paths(C, A)$ refers to the set of causal paths between a cause C and a function where a measured variable h may trigger an alarm A,
- $path = Cx(1)...x(k)A$ refers to a particular path in $Paths(C, A)$ that passes trough k successive functions with variables $x(1), ..., x(k)$,
- $[\delta_C(path), \Delta_C(path)]$: refers to the time interval to propagate a given cause C along a given path, $\delta_C(path)$ and $\Delta_C(path)$ denoting respectively the left and right bounds of this interval,
- $T_C(A) = [\delta_C(A), \Delta_C(A)]$ refers to the time interval for a given cause C to trigger a given alarm A, $\delta_C(A)$ and $\Delta_C(A)$ denoting respectively the left and right bounds of this interval,
- $w_C(A) = \Delta_C(A) - \delta_C(A)$ refers to the time uncertainties for a given cause C to trigger A,
- $D_C(A, A') = [\delta_C(A, A'), \Delta_C(A, A')]$ refers to the time range between alarms A and A', conditioned by the cause C ($\delta_C(A, A')$ and $\Delta_C(A, A')$ denoting respectively the left and right bounds of this interval), i.e.,

the time interval when a given cause C propagates between two alarms A and A'.

2.3 Manipulation of intervals

Time intervals are manipulated according to the IEEE 1788 standard for interval arithmetic IEEE (2015). In particular:

$$\begin{array}{ll} -[a,b] & = [-b,-a], \\ ([a,b])^{-1} & = [1/b, 1/a] \text{ if } 0 \notin [a,b], \\ [a,b]+[c,d] & = [a+c, b+d]\,, \\ [a,b]-[c,d] & = [a,b]+[-d,-c] = [a-d, b-c]\,, \\ [a,b]\times[c,d] & = [\min(ac,bc,ad,bd), \max(ac,bc,ad,bd)]\,, \\ [a,b]\div[c,d] & = [a,b]\times([c,d])^{-1}, \\ \sqrt{[a,b]} & = [\sqrt{a}, \sqrt{b}] \text{ if } a \geq 0. \end{array}$$

3. CAUSALITY ANALYSIS WITH TIME

The association of temporal aspects to MFM functions introduces an interesting possibility for consistency checking of an MFM model. In this section, the time delays or advances between occurring events are manipulated as time intervals in order to eliminate some possible root causes when a timed sequence of successive alarms, i.e., a sequence of pairs formed by alarms and their time samples, is measured.

Basically, for a cause C that is a possible cause for alarms A and A', the range $D_C(A,A') = [\delta_C(A,A'), \Delta_C(A,A')]$ of possible interleaving times between A and A', conditioned by the cause C is computed. In such a case, there is a causal relation from C to the variable h associated to A and another causal relation from C to the variable h' associated to A'. When $\delta_C(A,A') \geq 0$, this range is interpreted as the delay required to trigger the alarm A' after having triggered the alarm A. More generally, a time interval can be interpreted as a delay or an advance depending on the signs of $\delta_C(A,A')$ and $\Delta_C(A,A')$:

- an interval with positive values only (i.e., $\delta_C(A,A') \geq 0$) means that the time between A and A' is a delay and that A' should be triggered after A when C is the cause for A and A',
- an interval with negative values only (i.e., $\Delta_C(A,A') \leq 0$) means that the time between A and A' is an advance and that A' should be triggered before A when C is the cause for A and A',
- an interval with $\delta_C(A,A') < 0$ and $\Delta_C(A,A') > 0$ may be a delay or an advance and one cannot infer the order in which A' and A are triggered when C is the cause for A and A'.

Consequently in some cases, the order in which alarms A and A' are triggered is enough to eliminate some possible root causes. Otherwise, the measured interleaving time between A and A' should be compared with $D_C(A,A')$ to infer whether C is a t-possible root cause.

3.1 Computation of the time intervals between alarms

The main principle to compute the time interval on propagation paths in MFM models is to give preference to the shortest path (with respect to the time). This principle is motivated by the fact that the first occurrence of a given alarm is used to infer causality in the time context. Replications of a given alarm are not considered at this point. For the set of paths $Paths(C,A)$ that exist from C to A, $T_C(A) = [\delta_C(A), \Delta_C(A)]$ is defined by:

$$\begin{array}{l} \delta_C(A) = \min\limits_{path \in Paths(C,A)} \{\delta_C(path)\}, \\ \Delta_C(A) = \min\limits_{path \in Paths(C,A)} \{\Delta_C(path)\}. \end{array} \quad (2)$$

where the time interval $[\delta_C(path), \Delta_C(path)]$ of a given path from a cause C to the variable h associated to alarm A is assumed to be estimated according to data collected in the considered systems, simulations, or even digital twins.

The time range $D_C(A,A') = [\delta_C(A,A'), \Delta_C(A,A')]$ between two alarms A and A' is then computed according to equation (3). Such an equation is valid for a large variety of scenarios: (a) when A necessarily occurs before A' (Figure 1-top), (b) when the time constraints on A and A' intersect (Figure 1-middle), (c) when the time constraints on A are included in the ones of A' (Figure 1-bottom).

$$\begin{array}{l} \delta_C(A,A') = \delta_C(A') - \Delta_C(A), \\ \Delta_C(A,A') = \Delta_C(A') - \delta_C(A). \end{array} \quad (3)$$

Observe that, in some particular cases it is possible to improve the approximation of the range between A to A' by studying the intersection of the causality paths from C to A and C to A'. For simplicity this discussion is not pursued in this paper.

Property 1. Let A_1, A_2 and A_3 be 3 alarms, we have:

$$\begin{array}{l} D_C(A_1,A_2) + D_C(A_2,A_3) \\ = D_C(A_1,A_3) + [-w_C(A_2), +w_C(A_2)]\,. \end{array}$$

Proof : The proof results from the property of the the sum of two intervals:

$$\begin{array}{ll} & D_C(A_1,A_2) + D_C(A_2,A_3) \\ = & [\delta_C(A_2) - \Delta_C(A_1) + \delta_C(A_3) - \Delta_C(A_2)\,, \\ & \Delta_C(A_2) - \delta_C(A_1) + \Delta_C(A_3) - \delta_C(A_2)]\,, \\ = & [\delta_C(A_3) - \Delta_C(A_1), \Delta_C(A_3) - \delta_C(A_1)] + \\ & [\delta_C(A_2) - \Delta_C(A_2), \Delta_C(A_2) - \delta_C(A_2)]\,, \\ = & D_C(A_1,A_3) + [-w_C(A_2), +w_C(A_2)]\,. \end{array}$$

3.2 Elimination of possible root causes

In this section we assume that timing aspects have been included in MFM models according to some physical-based or data-based approaches and that the time intervals $D_C(A,A')$, $C \in \mathcal{C}$, $A, A' \in \mathcal{A}$ have been computed in a systematic way. Now consider a set of k possible root causes $\mathcal{C} = \{C_1, ..., C_k\}$ and a sequence σ of n successive alarms with their time stamps collected by the SCADA system within the time interval $[0, \tau]$. σ is of the form of equation (1). There is no difficulty to extend Property 1 to series of $n_2 - n_1$ alarms in the sequence σ:

$$\begin{array}{l} \sum\limits_{i=n_1 \ldots n_2-1} D_C(A_i, A_{i+1}) \\ = D_C(A_{n_1}, A_{n_2}) + \sum\limits_{i=n_1+1 \ldots n_2-1} [-w_C(A_i), +w_C(A_i)]\,. \end{array} \quad (4)$$

Single root cause Let us first study the simple situation where a given cause C can explain all alarms of a given sequence. Assumption H1 is considered for this purpose

(H1): a single fault occurs within $[0,\ \tau]$.

Assumption H1 means that a single root cause explains the n alarms of σ.

Property 2. Let $\sigma = (A_1, \tau_1)...(A_n, \tau_n)$, be a sequence of alarms collected under assumption H1, and $C \in \mathcal{C}$. If there exist n_1, n_2 with $n \geq n_2 > n_1$ such that $\tau_{n_2} - \tau_{n_1} \notin, D_C(A_{n_1}, A_{n_2})$, then, C is not a possible cause for both (A_{n_1}, τ_{n_1}) and (A_{n_2}, τ_{n_2}). Consequently, C cannot explain σ.

Proof : By contradiction, if C can explain σ then the interleaving time $\tau_{n_2} - \tau_{n_1}$ between A_{n_1} and A_{n_2} necessarily belongs to $D_C(A_{n_1}, A_{n_2})$.

Observe that the previous property can be simplified in some particular situations. C is not a possible cause for both (A_{n_1}, τ_{n_1}) and (A_{n_2}, τ_{n_2}), if $n_2 > n_1$ and either (1) or (2) is satisfied.

(1) $\Delta_C(A_{n_1}, A_{n_2}) < 0$,

(2) $\delta_C(A_{n_2}, A_{n_1}) > 0$.

Property 3. Let $\sigma = (A_1, \tau_1)...(A_n, \tau_n)$, be a timed sequence of alarms collected under assumption H1. The set $\mathcal{C}' \subseteq \mathcal{C}$ of possible causes that can explain σ is obtained by:

$$\mathcal{C}' = \{C \in \mathcal{C} : \forall n_1, n_2, \text{ with } n \geq n_2 > n_1 \geq 1, \\ \tau_{n_2} - \tau_{n_1} \in D_C(A_{n_1}, A_{n_2}). \tag{5}$$

Proof : The set of possible causes that can explain σ is obtained by elimitating from $\mathcal{C}$ each cause C that satisfies Property 2. Equation (5) holds as a consequence.

Observe that, in general, several root causes may equally explain a given sequence of alarms. In such a case one could be interested in deciding which cause is the most *probable* or *likely*. Discussing about probability of the causes need to introduce probabilistic distributions in the model whereas discussing about likelihood required only to quantify a certain belief in the decision e.g., by counting the number of occurrences of each root cause. Both aspects have been studied in the framework of temporal logic. The authors in Chen et al. (2021) consider switches systems and find a temporal logic formula to detect the faulty behaviours with a probability guarantee. In Kim and Seong (2018), the authors also develop a probabilistic reasoning consistent with the timing aspects added into the model. In Nielsen et al. (2020), the authors study the causal influence of an actuator on a process variable as the probability of a qualitative and discrete causal state. By testing an MFM model, and interpreting the propagation paths produced by MFM, the results from MFM are compared to the stochastic causality analysis to determine the model accuracy. The authors in Chen and Kumar (2015) use input-output stochastic hybrid automaton and estimate the probability distribution over the discrete locations of system. This results is then used to compute the likelihood of faults, a sistic that they employ for the purpose of fault detection.

Our perspective is to discuss belief rather than probability and to define such a belief with respect to the history about fault occurrence. In detail, each root cause C is assumed to be characterized by a frequency of occurrence $f(C)$, i.e., the number of occurrences of C by time period. Then if the subset of root causes $\mathcal{C}' \subseteq \mathcal{C}$ can explain the sequence of alarms σ, the belief of each cause $C \in \mathcal{C}'$ is computed as:

$$Belief(C) = \frac{f(C)}{\sum_{C' \in \mathcal{C}'} f(C')}.$$

In simple words, the most frequent faults obtain a highest score and will be preferred.

Multiple root causes In this section assumption H1 is relaxed and we consider the more general case where one or more causes are necessary to explain a given sequence of alarms. Let us first extend the notion of time range to a set of causes. For a set of k possible root causes $\mathcal{C} = \{C_1, ..., C_k\}$, and for any subset $\mathcal{G} \subseteq \mathcal{C}$, the time range $D_{\mathcal{G}}(A, A') = [\delta_{\mathcal{G}}(A, A'), \Delta_{\mathcal{G}}(A, A')]$ between two alarms A and A' with respect to $\mathcal{G}$ is computed according to equation (6):

$$\begin{aligned} \delta_{\mathcal{G}}(A, A') &= \min_{C \in \mathcal{G}} \delta_C(A, A'), \\ \Delta_{\mathcal{G}}(A, A') &= \max_{C \in \mathcal{G}} \Delta_C(A, A') \end{aligned} \tag{6}$$

The problems are (i) to check if a given subset $\mathcal{G} \subseteq \mathcal{C}$ of possible root causes can explain the sequence of alarms $\sigma = (A_1, \tau_1)...(A_n, \tau_n)$; (ii) to search about minimal subsets $\mathcal{G} \subseteq \mathcal{C}$ of possible root causes that may explain σ. The notion of "minimality" should be understood in the perspective of set manipulation: substracting any root cause from a minimal subset $\mathcal{G}$ will lead to a subset $\mathcal{G}'$ that cannot explain σ any longer.

The belief of the minimal subset of causes $\mathcal{G}$ within a list E of several possible minimal subsets is computed as

$$Belief(\mathcal{G}) = \frac{\sum_{C \in \mathcal{G}} f(C)}{\sum_{\mathcal{G} \in E} \sum_{C' \in \mathcal{G}} f(C')}$$

where $f(C)$ is the frequency of occurrence of C.

4. EXAMPLE

In this section we consider the example of an injection system in Fig. 1. This system is based on an industrial study prepared by Kairos Technology and details and parameters values are omitted for privacy purpose. The system is composed of a deareator and a set of fine filters to clean the water before injection. The sea water is lifted by pumps, enters the system and passes first through four fine filters, which filter the water. Each filter works during 3 periods of time, then it is cleaned during 1 period of time and so on. The cleaning operations are planed in order to stop only 1 filter at each time. For simplicity, the fine filters are abstracted by a fictive valve $V1$ controlled by a pressure difference between the inlet and outlet of the filter. The filtered water then passes to the $V2$ valve which regulates the flow rate into the deaerator DA, represented by a tank which water level h can be indirectly regulated.

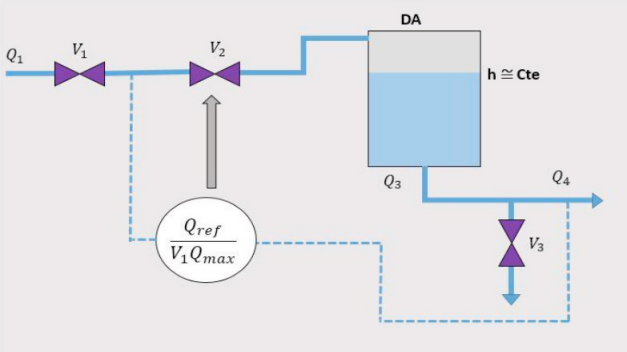

Fig. 2. Water injection system

Then the water exits the deaerator (Q_3) towards the outlet of the system. When the outlet flow Q_4 exceeds a certain reference, the $V3$ valve rejects the excess water into the sea.

According to the MFM model of this system LMansouri (2021), two possible faults may occur: a smooth decrease of inlet flow $C(Q1)$ (here, the inlet flow is an imput arriving from the external environment and is assimilated to an actuator fault) or a fault in the cleaning of the fine filters $C(FF)$. Multiple faults are not considered. Three sensors are used to trigger alarms: one on the position $\hat{V}2$ of valve $V2$, the second on the position $\hat{V}3$ of valve $V3$ and the last one on the measurement of the deareator level $\hat{h}$. Alarms are triggered when $\hat{V}2$ exceeds 0.75 (in percentage), $\hat{V}3$ exceeds 0.25, and $\hat{h}$ decreases below 2m. The thresholds are tuned such that the normal conditions do not trigger any alarm. Validation is made by simulations with the following setting

- an inlet flow of 1 $m^3 s^{-1}$ is considered and the outlet flow reference is depicted in Fig. 5 (dashed line);
- 100 scenarios with fault $C(Q1)$ and 100 scenarios with fault $C(FF)$ are executed;
- each scenario has a period of 24 hours;
- faults occur at random time from time 6 to time 18;
- a Gaussian noise is added to the measured variables.

With the proposed scenarios, only alarms associated to the measurements $\hat{V}2$ and $\hat{h}$ may be triggered and for all scenarios, $A(\hat{V}2)$ occurs before $A(\hat{h})$. Some scenarios, where only $\hat{V}2$ occurs (before the end time of simulation), have been removed from analysis.

Fig. 3 to 5 illustrate the case where a fault $C(FF)$ affects the cleaning of the filters after 12 hours. As the filters are no longer cleaned, the average differential pressure increases and the enthalpy (represented by the position of the fictive valve $V1$) decreases from time 12 leading to a decrease of the flow entering in the deareator. The control loop reacts by opening the valve $V2$ in order to compensate the decrease of flow. $V2$ reaches an abnormal value after 3.2h (Fig. 3). Unfortunately, as the differential pressure continues to increase, this flow becomes finally too weak in order to maintain the expected level in deareator (Fig. 4) that starts to decrease and reaches the limit threshold of 2m after 6.8h from the occurrence of the fault. The interleaving time between the two alarms is 3.6h in this scenario.

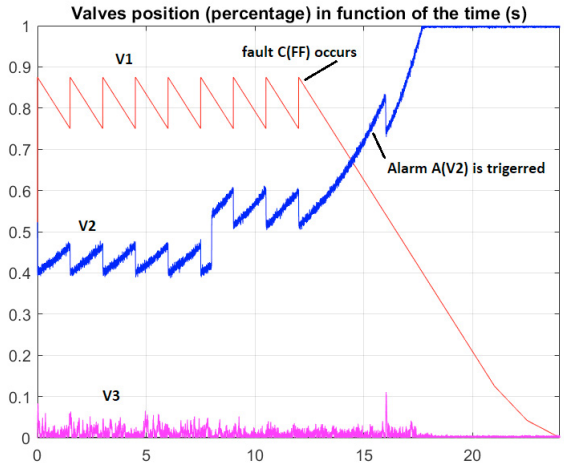

Fig. 3. Variation of valves position due to an increase of the filter differential pressure

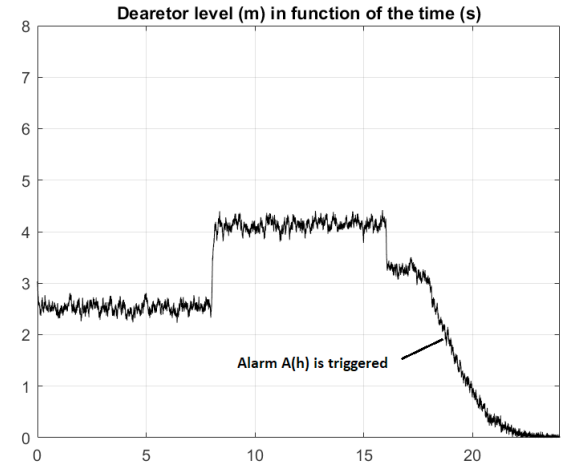

Fig. 4. Variation of the deareator level due to an increase of the filter differential pressure

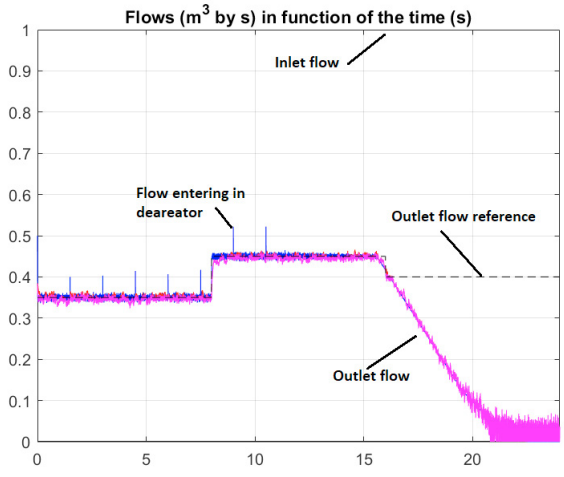

Fig. 5. Variation of the flows due to an increase of the filter differential pressure

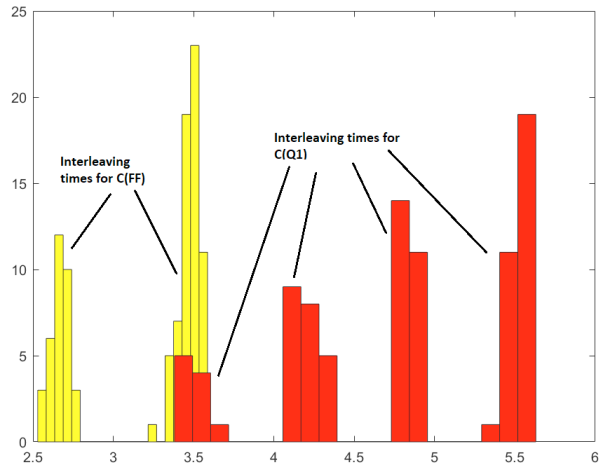

Fig. 6. Histograms of the alarm interleaving times

For each scenario, an alarm sequence of the form of Equation (1) is collected. Considering the series of simulations, the histograms of the interleaving times from $A(\hat{V}2)$ to $A(\hat{h})$ are reported in Fig. 6. One can conclude that for a interleaving time less than 3 hours, the cause is $C(FF)$ whereas for a interleaving time larger than 4 hours the cause is $C(Q1)$. When the alarm interleaving time belongs to the interval [3h, 4h] one cannot conclude and an additional alarm or other information should be considered to consolidate the inference. This is the case of the scenario reported in Figs. 5 to 7.

5. CONCLUSION

This paper has proposed a method that uses the timing information in order to filter the sequences of alarms collected by SCADA systems. Assuming that the timing aspects have been already inserted in a MFM model, the main contribution was to show how this method can be combined with the causality analysis obtained from the multilevel flow modelling approach and how it can refine such analysis.

The paper is the beginning of introducing quantification of temporal information in MFM. The aim is as stated to enhance the ability to distinguish between possible causal reasoning paths. At present the cost will be, however, a large overhead in learning and maintaining relevant model parameters for accurate time representation. The ultimate goal of our research is to develop a timed/causal analysis and include it in standard tools that help operators to assess sequences of alarms in case of critical event.

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