Automata-based Explainable Representation for a Complex System of Multivariate Times Series

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Abstract: Complex systems represented by multivariate time series are ubiquitous in many applications, especially in industry. Understanding a complex system, its states and their evolution over time is a challenging task. This is due to the permanent change of contextual events internal and external to the system. We are interested in representing the evolution of a complex system in an intelligible and explainable way based on knowledge extraction. We propose XR-CSB (eXplainable Representation of Complex System Behavior) based on three steps: (i) a time series vertical clustering to detect system states, (ii) an explainable visual representation using unfolded finite-state automata and (iii) an explainable pre-modeling based on an enrichment via exploratory metrics. Four representations adapted to the expertise level of domain experts for acceptability issues are proposed. Experiments show that XR-CSB is scalable. Qualitative evaluation by experts of different expertise levels shows that XR-CSB meets their expectations in terms of explainability, intelligibility and acceptability.

1 INTRODUCTION

A complex system is described by a set of a large number of entities, *i.e.*, variables, interacting over time, which integration achieves a common goal (Harel, 1987). It is thus used in many sectors such as energy, medicine, urban traffic, etc. (Carlos-Sandberg and Clack, 2021). A complex system is characterized by its structure, *i.e.*, the nature of its variables, their interactions, or by their non-trivial collective behaviors (multistationarity, chaos, bifurcations, self-organization, emergence, feedback loops, etc.) (Guespin-Michel, 2016). Although there is no consensus on its definition, a complex system can be represented by multivariate time series, where each series represents a variable of the system (Hassanibesheli et al., 2020). Very often, in complex systems we can describe the values of time series by referring to states, which correspond to intervals of values. Thus, to understand the system is to understand the semantics and the interaction of these states.

Explaining the behavior of a complex system is a challenging task. Actually, domain experts can understand a complex system thought the acquisition of "implicit knowledge," *i.e.*, working habits, expertise, their interaction with the system and their growing experience, that is still difficult to verbalize. The expert's implicit knowledge is important for the cognitive process of inference of non-conscious operating rules. However, extracting and formalizing such knowledge is a complex task, requiring a deep analysis of the system and thorough interaction with it (Chraibi Kaadoud et al., 2022).

Data visualization techniques have been proposed in order to monitor the behavior of a complex system (Harel, 1987; Theissler, 2013; Pham et al., 2019), such as parallel coordinates techniques, scatter plot matrices, etc. However, for an even more complex system, in which the states, the internal (*i.e.*, technicians' interventions) and external context (*i.e.*, regulation), are themselves changing, it is difficult to determine the relevant characteristics that contribute to a change of state. Existing techniques do not allow to visualize these changes in an intelligible way to a human expert. We thus address the following **challenge**: how to understand the states of the complex system's multivariate time series? How to detect and understand the evolution of the system's states over time? How to represent this evolution in an intelligible and explainable way?

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Explainability and intelligibility in AI are an important aspect in crafting acceptable AI systems (Weld and Bansal, 2019), and have been acknowledged as much more important than sheer performance in AI systems (Gunning, 2019; Barredo Arrieta et al., 2020). Several reasons can be given: facilitating user control and acceptance, improving human insight, as well as legal issues[1]. One of the challenges of designing intelligible and eXplainable AI (XAI) is communicating a complex computational process to a human which requires interdisciplinary skills (Lenca, 2002; Le Saux et al., 2002).

Complex systems in form of multivariate time series can be represented as a finite-state automaton (FSA), which is considered as a low-dimensional representation *i.e.*, that results from a dimensional data reduction process that contains as much information as possible as the original data. Recently, automata-based approaches have been proposed that involve discretization of the time series (Zhang et al., 2017; Soto et al., 2021). These techniques reduce the algorithmic complexity and offer a high level of explainability. We thus draw inspiration from these approaches to propose a representation that explains the system's behavior, commonly called an explainable representation. Such a representation captures the states of all or part of a complex system (from now on, by "system" we will mean "complex system").

Our **main hypotheses** are the following: (i) The values of the time series at a timestamp t represent the state of the system at t. Their analysis allows to detect states, and in particular "rare" states. (ii) The states of the system can be characterized by different exploratory metrics related to the evolution of the time series. (iii) The states of the system, as well as their exploratory metrics can be considered as being parts of a FSA, for which there are efficient visual representations. (iv) The FSA is a synthetic, intelligible and comprehensible representation of the behavior of a system over time and therefore a decision making aid. (v) The level of expertise in an application domain has an impact on the acceptability and the perception of explainable representations.

Basing on these hypotheses, we propose an EXplainable Representation of Complex System Behavior (XR-CSB) method using FSA for multivariate times series, with three main **originalities**:

• **Knowledge Extraction:** XR-CSB uses a clustering based approach that we call *vertical clustering* of time series in order to detect states of the system. This approach is original as it is independent of the size of time series and can be applied to uni- or to multivariate series, contrary to traditional clustering. This leads to complexity control.

• **Explainable Knowledge Representation:** XR-CSB uses FSA to represent system's behavior. Automata provide a visual explanation likely to be intelligible for human experts. The acceptability of this representation is evaluated via qualitative experiments.

• **Pre-modeling Explainability:** XR-CSB uses exploratory metrics to enrich automata like in *pre-modeling explainability domain-specific explainable feature-engineering* (Moshkovitz et al., 2020).

The paper is organized as follows. Section 2 presents related works about XAI and representation of complex systems. Related definitions are presented in Section 3 and the proposed method in Section 4. Experimental results are presented in Section 5, and a conclusion is given in Section 6.

2 RELATED WORKS

We here present some state-of-the-art works related to the understanding and representation of a complex system. Having labeled data is often very costly and is simply not possible for several domains. This is the case of our application. Thus, non-supervised methods must be applied (Braud et al., 2021).

• **Clustering for Multivariate Time Series:** Clustering for multivariate time series have already been proposed in order to analyze the behavior of time series (Desmarais and Lemieux, 2013; Aghabozorgi et al., 2015; Zhang et al., 2017). In such approaches, time series are clustered, *i.e.*, entire series are grouped in clusters, according to the similarity of their same-position values. These approaches require that the whole series are available and have the same size for proper functioning of the clustering and reliability of results. They allow the detection of common behavior between time series in order to automatically label the series thereafter, to detect frequent patterns, etc. However, they do not allow representation of the behavior across time series, *i.e.*, the behavior characterized by values from different time series at a given time. Such approaches are thus not suitable for our objective as they do not allow a discretization or a simplification of the entire system.

• **Explainable Artificial Intelligence (XAI):** XAI has become a very challenging domain[2] facing the high

[1] The European Union's General Data Protection Regulation (GDPR) legislation acknowledges the citizens' right to explanation—other nations may follow this initiative.

[2] Recall that models with explanation and transparency goals have been proposed a long time ago (Shortliffe, 1974). However, the term XAI has been introduced only recently.

development of “black-box models” that are very efficient in modeling systems (Guidotti et al., 2019). XAI makes models more intelligible, transparent, and accessible or directly designs explainable ones (Guidotti et al., 2019; Barredo Arrieta et al., 2020). XAI can provide an *explanation* of the internal mechanisms and the reasons behind the behavior of a system. An explanation can be considered as an information that is self-sufficient and addressed to the target audience considering its knowledge and its expectations of the system’s behavior, and the context (van Fraassen, 1988). An explanation is thus an interface between the complex system to explain and the target audience, which are the domain experts in our case (Gunning, 2019; Chraibi Kaadoud et al., 2021). Note that a clear distinction has been made between models that are transparent by design and those that can be explained by means of external methods, *i.e.*, post-hoc methods (Bennetot et al., 2021).

Recently, it has been proved that visual representations highly impact human trust. Moreover, visual representations combined with human knowledge yield much better comprehension of a system and thus lead to much better decisions (Yang et al., 2020). Such studies confirm our choice of visual representation of a system. However, most of recent visualization techniques deal with black box visualization through sensitivity analysis (Cortez and Embrechts, 2013; Weitz et al., 2021), and ignores aspects related to the multidimensionality of data. It is important to note that our objective is to exploit visualization techniques as a way to represent the results of a transparent model (clustering) on a system.

Our work is motivated by state-of-the-art works (Higgs and Abbas, 2014; Zhang et al., 2017) in which time series are segmented by means of change point detection: simple clustering is applied on explanatory variables and time windows. The main disadvantage of such an approach is that it loses sight of dynamic and time information and misses the interaction and dependency between time series.

• **Representation of Multivariate Time Series using Automata:** Using FSA for representing, monitoring, estimating or even predicting the states of systems is of great importance for interaction with the system and for decision taking. Research works on FSA generation based on clustering have been proposed (Desmarais and Lemieux, 2013; Higgs and Abbas, 2014; Zhang et al., 2017). In such works, exploratory variables are extracted from each time series—they constitute the states of the system and the succession of these variables represents a sequence of states, a kind of discretization of each time series. A clustering is then performed to detect similar patterns (successions of states) between the time series. This allows to extract a common behavior shared between the time series, but is not applicable in case of a very small number of series and, in any case, does not allow extraction of the global behavior of the system because it ignores the interaction and the dependence (or not) between the time series. It is important to note that such works are not adapted to complex systems as they do not provide an intelligible simplification of the global behavior of the system.

• **Clustering and Automata Extraction during Dynamic Knowledge Construction of Neural Networks:** We use the automata generation algorithm proposed by (Chraibi Kaadoud et al., 2022) and adapted from (Omlin and Giles, 1996). Note that these algorithms have been used in the interpretability field for the study of recurrent neural network latent representations that are built in the multidimensional space of the hidden layer. See (Chraibi Kaadoud et al., 2021) for a set of definitions about the concepts of latent representations and latent layers.

3 DEFINITIONS

This section is dedicated to the definition of several concepts related to complex systems, multivariate time series and automata. Several are inspired from (Pham et al., 2019; Soto et al., 2021).

Definition 3.1. We denote a **complex system** as a set of variables represented by **multivariate time series**. A **state**, at timestamp t, is represented by the values at t of the system’s variables (*i.e.*, time series). A state can last in time (making a cycle) and thus can be observed within a time period, *i.e.*, a **window**. We represent the evolution of states over time via **finite-state automata** (FSA), the transitions of which represent the evolution of the system. All states are final, since we consider a continuous flow of states rather than given finite-length words of a formal language. These concepts are defined below illustrated in Figure 1.

Definition 3.2. A multivariate time series is an ordered sequence of m vectors: $X = [X_1 \ldots, X_m] \in \mathbb{R}^{d \times m}$. For a timestamp t, $X_t = [x_{t,1}, \ldots x_{t,d}]$ is a d-dimensional vector containing the values recorded at t: $t = 1, \ldots, .m$, *i.e.*, the values of all time series at t. The dimension d of the multivariate time series represents the number of series. A vector of d dimensions recorded at t_0 is noted as $X_{t_0,d}$.

Definition 3.3. Given a multivariate time series $X = [X_1, \ldots, X_m]$, a contiguous segment of X is called a

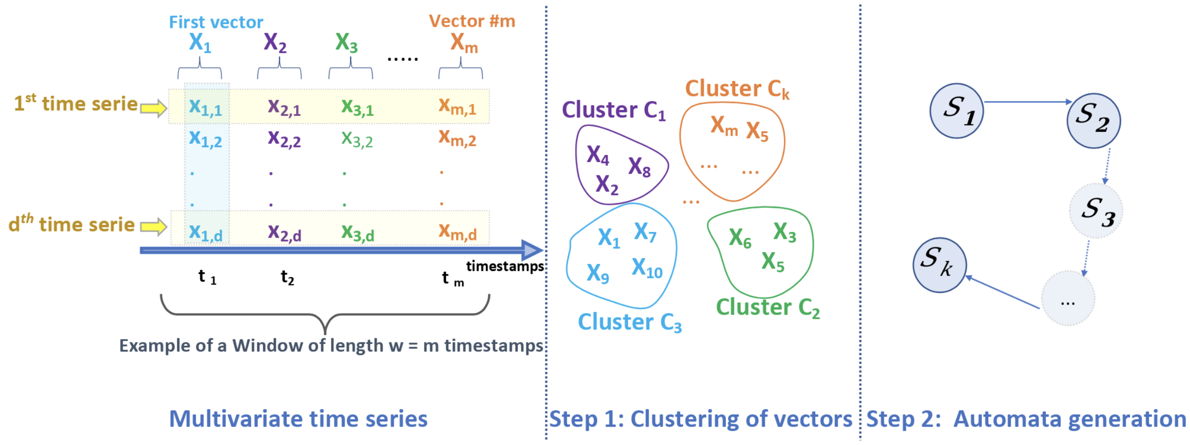


Figure 1: A general scheme of our model XR-CSB: Multivariate time series, clustering and automata.

(sliding[3]) **window** and denoted by W. The length w of W is less than or equal to the length of X: $w \leq |m|$.

Definition 3.4. A finite-state automaton (FSA) A is a tuple $A = (S,T)$ where S is a finite set of states and T is a transition relation (a metric or a reason of this transition). An automaton is represented as a directed graph with states as nodes and transitions as edges.

Definition 3.5. We denote by $S_{(t_{\text{start}},t_{\text{end}})}$ the **state** of the automaton A of the system represented by the multivariate time series X. A state starts at timestamp t_{start} and ends at t_{end} (t_{start} and t_{end} included).

Definition 3.6. In an automaton A, a path p of length k is a sequence of states $S_1,...,S_k$ such that $(S_i,S_{i+1}) \in T$ (the transition relation) for each $1 \leq i < k$. Note that a path p is extracted from a window W. Note also that no relation can be observed between k and w, *e.g.* for a window of length $w = 50$, an automaton path of length $k = 2$ can be obtained.

Definition 3.7. Explainable and Intelligible Representation: Given a representation as the model output. We say that this representation is intelligible according to the degree that a human expert can predict how a change to a feature, (*e.g.*, an increase of the value of a time series) will change the model's output (*i.e.*, the system state). Note that if one can simulate the model, *i.e.*, predicting its output such as the next system's state according to the general tendency of time series, then one can predict the effect of a change, but not vice versa. In our work, the degree of explainability and intelligibility will be measured via a qualitative questionnaire for human experts and also via explicitly reported events.

[3]A sliding window is the most common type of windows.

4 XR-CSB METHOD

We present now the details of XR-CSB. Recall that our work focuses on (i) studying the behavioral changes of a system represented by multivariate time series, (ii) detecting and understanding the evolution of its states to other states, and (iii) representing its evolution in an intelligible and explainable way.

To achieve these objectives, we propose XR-CSB, a 3-step model that (i) performs a vertical clustering of multivariate time series related to the system, (ii) generates an automaton representing the behavior of this system over time, (iii) enriches the automaton with explanatory metrics and semantic information for explainability purposes. A general scheme is presented in Figure 1. Next, we detail XR-CSB steps.

4.1 Step 1: Vertical Clustering

In order to perform what we call a vertical clustering for time series, we use the k-means algorithm (Zeng et al., 1993) but not in a traditional way. Our entry point is the multivariate time series X represented by a set of vectors $X = [X_1,\dots,X_m]$ and a fixed temporal window W of length w (measured in minutes in our application). We apply k-means in a way that it partitions the first w vectors into k clusters. For example, in Figure 1, when $w = 3$, we cluster the first three vectors. Here, k-means minimizes the distance between samples within each partition using the euclidean distance. We thus obtain k clusters that group vectors according to their values and independently of the associated timestamp. The application of such a vertical clustering allows to extract clusters that represent system's states (see definition 3.5). These clusters emerge from the values of the different time series grouped together. Also, by conception, this vertical clustering groups correlated time series in the same cluster, regardless of the distance measure.

By this step, each vector X_t of the window W belongs to a cluster C_i which represents a state S_i of the system. Our method can automatically fix the optimal number of cluster k using the silhouette score (Rousseeuw, 1987). However, for explainability and acceptability issues, k is finally determined in close coordination with domain experts.

Let us go back to the clustering and chosen distance. Clustering multivariate time series is a challenging task and is intrinsically associated to the notion of distance. However, in order to define a distance between arbitrary multivariate time series, no obvious or standard way exists in the state-of-the-art (Ghassempour et al., 2014). For multivariate time series containing only continuous variables, some well-defined distances are usually employed, such as Euclidean distance (Yang and Shahabi, 2004). Euclidean distance has shown a high performance for a high number of variables with complex correlation structure (Giorgino, 2009). For these reasons, after normalizing data (to have the same scale), we use Euclidean distance for vertical clustering using k-means.

4.2 Step 2: Explainable Representation via Automata

Automata Generation Process (figure 2.(a)): Given the clusters extracted in step 1, we generate an automaton that represents the states of the system.

As each vector X_t belongs now to a cluster C_i, we start generating the automaton by verifying, for each vector X_t, whether its associated cluster is already represented as a state in the automaton. If it is not the case, a new node is added to the automaton. Each state is numbered with the corresponding cluster's number. A direct edge is created with a weight of 1 between the previous state and this new state. In case the state already exists in the automaton, the weight of the edge is incremented by 1, otherwise a new edge with a weight of 1 is created. In the case where two consecutive vectors X_t and X_{t+1} belong to the same cluster, a loop (a cycle) is added to the state representing the cluster. This process results in the generation of an automaton with weighted transitions explaining the configuration of the clusters (states). Figure 2.(a) represents an example of the resulting automaton. The weight of the transitions is indicated by a color, it represents how long the system stays in a state: the darker it is, the more important is the weight of the transition. This automaton generation process is inspired from (Chraibi Kaadoud et al., 2022).

Path Generation Process: Unfolded Automaton (figures 2.(b, d)): As represented in figures 2.(a), such an automaton is not always intelligible nor explainable for domain experts. In order to make this representation more explainable, we generate an *unfolded automaton*, which is a temporal path that moves along states of the system (*i.e.* a word in the formal language of the system's behavior). We propose two visual representations of such a path and of the evolution of the states over time (Figures 2.(b) and (d)): Figure 2.(b) represents the duration of each state via numerical information (time in minutes and date UTC and UTC+2 explained). To keep track of similar states at different timestamps, the state number is explicitly displayed inside each state symbol. Figure 2.(d) represents each state by a rectangle, and the state's duration is proportional to the rectangle's size. The longer the system remains in a state, the larger is the associated rectangle. Same states have the same color code.

4.3 Step 3: Pre-modeling Explainability Process: Explanatory Metrics

In order to enrich the unfolded automaton with more intelligible and useful information, a pre-modeling explainability process is applied. To do so, each state $S_{(t_{\text{start}},t_{\text{end}})i}$ is characterized by extracting the values of three metrics out of the set of vectors associated to window $W \in [t_{\text{start}}, t_{\text{end}}]$:

- **Average Speed** Sp that represents the mean of the speeds of change of values between time t and $t-1$.
- **Average Velocity** Vl that represents the mean of the velocities calculated for each speed. This metric also shows the dynamics of the evolution of the values for the considered state S_i.
- **Average Acceleration** Ac that represents the rapidity of change of speed Sp of the states' values in evolution on a given window W.

Note that if a state S_i occurs twice in a window W, then the explanatory metrics will be computed twice. Figure 2.(c) represents an unfolded automaton with the various metrics.

5 EXPERIMENTS

We now present experiments performed in order to evaluate our XR-CSB. We first describe the dataset and then evaluate the scalability of XR-CSB and the explainability power of the representations. The results are discussed at the end of the section [4].

[4] Experiments have been run on a Max OSX BigSur v 12.2.1, Processor Apple M1 8 cores, 16 GB memory. Python scientific stack is used, namely Numpy, Scipy, Matplotlib, Networkx, Scikit-learn and Pandas.

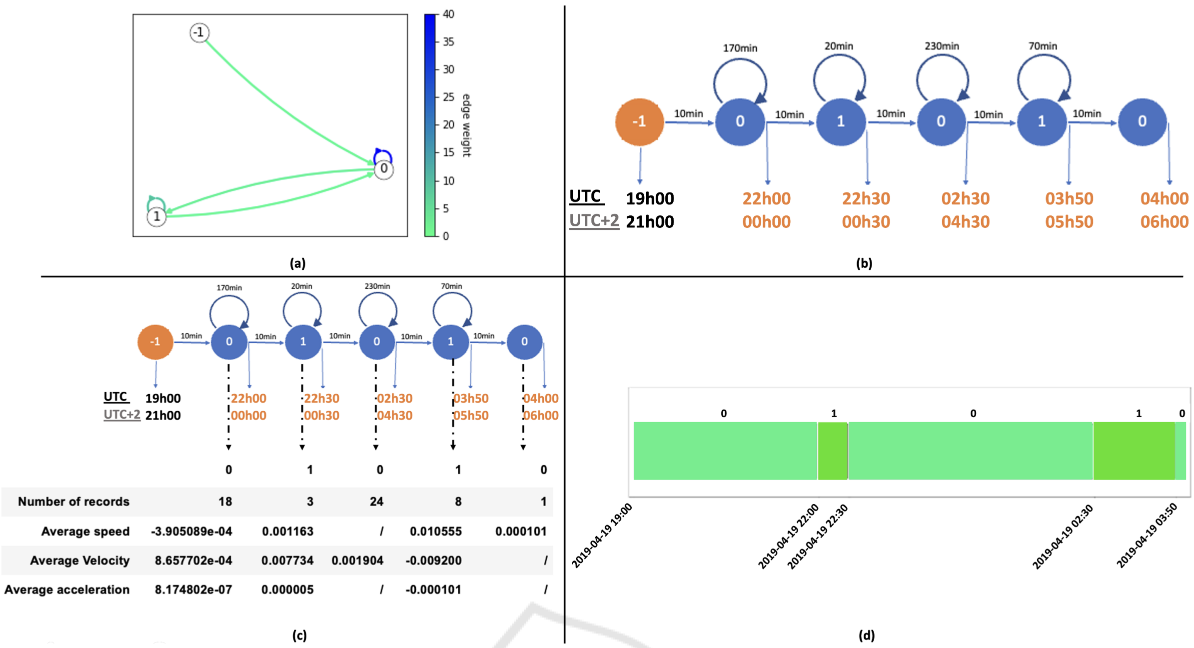


Figure 2: XR-CSB Step 3: The four representations evaluated for the qualitative study obtained from the analysis of a single sensor with monotonic behavior (*i.e.*, no significant variation in values) that has been clustered with $k = 2$. (a) an automaton: the -1 node designates the beginning of the analysis and is not part of the data group. Transitions are given a color that indicates their weight: the darker the color, the higher the weight of the transition; (b) an unfolded automaton with a visual representation of time for each state through numerical values; (c) an unfolded automaton with explanatory metrics; (d) an unfolded automaton with a visual representation of time for each state.

5.1 Description of the Industrial Dataset

Our dataset is related to energy generation: a thermal power station that burns coal and gas to produce steam in order to generate electricity. This power station has five boilers and other equipment. Each equipment is monitored through a multitude of sensors. Our dataset contains 377 times series representing the recordings of 377 sensors every 10 minutes during three years. In the current work we present the results on 92 time series of a specific boiler B. For each window W, we consider the related PDF reports (written every 8 hours by technicians that maintain the power station) for post-hoc validation. For confidentiality issues, the dataset cannot be published online. Practically, at the pre-processing level, given a time window W and a number of times series to analyze, the considered data can be represented as a matrix of dimension $(m \times d)$ where $m \in \{1, \ldots, w\}$ and dimension d is the number of time series (see Figure 1). Data processing can be incremental and dynamic: in real-time processing, for each new timestamp, a new column is added to the matrix with the values of the corresponding variables, which is a real advantage. As time series represent sensors with different units, all values are normalized (through mean and standard deviation). When $d > 1$, an average is calculated from the normalized values.

5.2 Scalability Evaluation

Figure 3 represents the execution time w.r.t. **the number of clusters** k, for a fixed window. We study 92 time series over $w = 144$ timestamps (i.e. 24 hours). k varies between 3 and 100. Figure 4 represents the execution time w.r.t. **the window length** w, for $k = 7$ clusters. w is varied in such a way that we can evaluate the necessary computation time over days, months and years. For both analyses, the execution time increases nearly linearly and the algorithm presents a good scalability. For $k < 40$, the execution time is reasonable: 1.25 seconds. For $k = 100$, the execution time is of 1.997 seconds. To analyze more than 2 years of data, our method requires about 20 minutes. This time remains relatively reasonable given the industrial context and the fact that the technicians themselves generate reports every 8 hours.

5.3 Qualitative Evaluation of Explainability

The results of XR-CSB are intended to domain experts of our industrial partners. Thus, a *subjective* analysis was done via a questionnaire on the representations quality and the explainability of the thermal

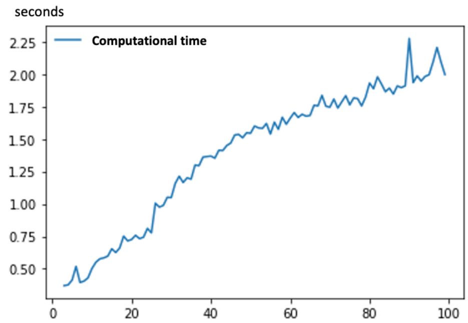


Figure 3: Execution time w.r.t. the number of clusters k: Analysis of 92 sensors over 24 hours, *i.e.*, 144 records, for k in $\{3,\ldots,100\}$.

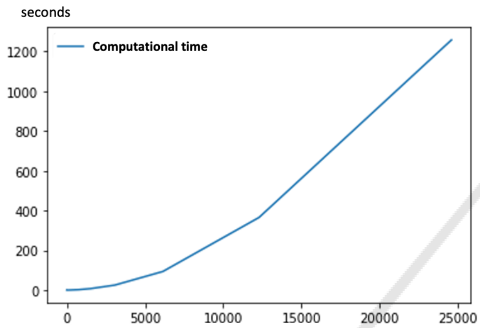


Figure 4: Execution time w.r.t the window length w: Analysis of 92 sensors, for $k = 7$ and hours h in $\{8, 16, 24, 48, 96, 192, 384, 768, 1.536, 3.072, 6.144, 12.288, 24.576\}$.

power station's behavior. The questionnaire contains four parts. The first three ones deal with case studies and the last one deals with the domain expert's profile.

5.3.1 Use Cases

We evaluate several representations aiming at explaining the system's behavior over time according to different use cases: **(i) Use case (A.1):** analysis of a sensor C_1 whose physical unit is "tons per hour" (t/h) when it presents a monotonous behavior i.e. flat curve, **(ii) Use case (A.2):** when C_1 presents a dynamic behavior as the curve varies; **(iii) Use case (B)**: analysis of 92 sensors of boiler B. For each use case, 4 representations, presented in Figure 2, are proposed.

5.3.2 Profile of Sampled Respondents

The employees of two IT companies answered the questionnaire: Company 1 works with data from the thermal power station and therefore has a precise knowledge about the industrial context. Company 2 works on the development of websites and interfaces of tools dedicated to data management.
Concerning Company 1, among the 6 respondents: 4 data scientists, 1 machine learning engineer and 1 operations manager. All of them have been working on complex systems: 3 for less than a year, 1 for 1 to 2 years and 2 for more than 5 years. They all use visual representations in their daily work to explain or transmit information. Regarding Company 2, among the 7 respondents: 4 developers/engineers, 1 project manager, 1 product manager, 1 R&D engineer. None of them have experience in complex systems, few have experience in AI tools, but 6 of them have more than 1 year experience in interface design and user experience issues (human-machine interaction and human factors): 2 have an experience between 1 and 2 years, 2 have an experience between 2 and 5 years and two have an experience of more than 5 years. Finally, concerning the use of visual representations in their daily work: 4 use them only when necessary, 2 use them regularly and only 1 daily.

- **Trust and Explanations in AI System Behavior:** For Company 1: 4 respondents prefer multi-modal explanations (combining several forms), 1 prefers visual representations and 1 answered that only results matter (especially in supervised machine learning). Regarding Company 2: 6 prefer multi-modal explanations and only 1 prefers visual explanations. Let us underline two important points: (i) on both companies no respondent prefers uni-modal explanations (textual or tabular), and (ii) all have trust in AI systems results only according issues at stake.
- **Professional Experience Related to the Behavior of Complex Systems:** Regarding the problem of representing the behavior of complex systems over time, at the level of Company 1, 2 encounter it "occasionally" (50% of their projects), 3 encounter it "sometimes" (60% of their projects) and 1 encounters this problem "regularly" (70% of his/her projects). In Company 2, 1 encountered this problem "occasionally", 1 "rarely", and 5 never worked on this type of problem.

5.3.3 Evaluation of Acceptability and Explainability Power of Representations

In this section, we evaluate the acceptability of the representations for each of the 3 use cases for both companies. Figure 5 and 6 present respectively the results of the evaluation by the industrial experts of Company 1 and those of Company 2.

Globally, for Company 1, representations (b), (c) and (d) are considered as "Little representative" or "Totally representative". Representation (a) did not convince the experts. Of the 3 use cases, representation (d) proved to be the most interesting for the experts. Finally, the free comments of the experts show a recommendation to merge the representations (b) and (d) described as intuitive and interesting as the states are identifiable as well as the temporal distribu-

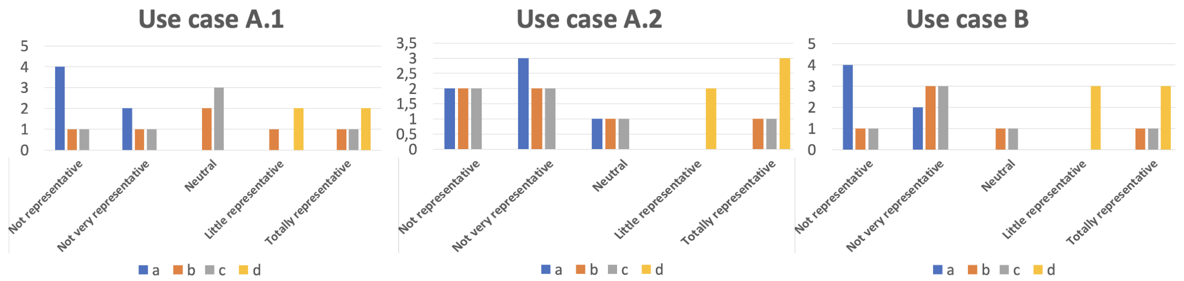


Figure 5: Company 1: Explainability evaluation of representations a, b, c, d for each use case. Values designate number of respondents.

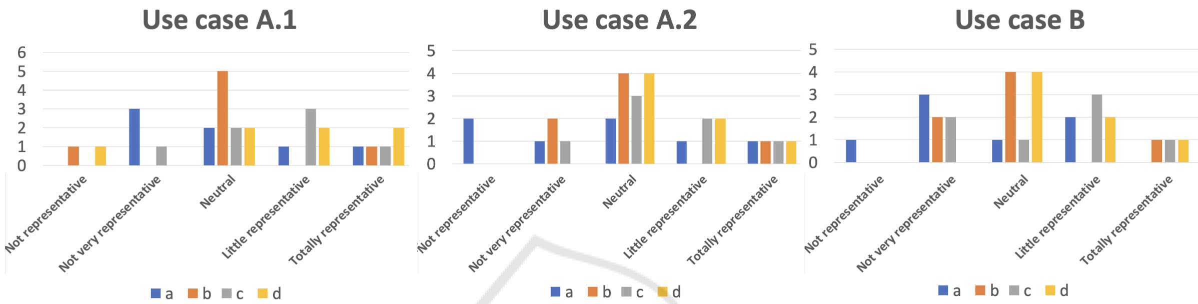


Figure 6: Company 2: Explainability evaluation of representation a, b, c, d for each use case. Values designate number of respondents.

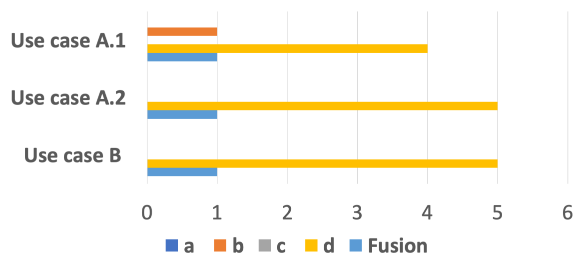
tions.
For Company 2, representations (c) and (d) were positively perceived regardless of the use case considered. Representation (a) evolved from a globally positive perception ("clear representation" according to one respondent) to a more negative perception as the complexity of the use cases and the number of nodes in the automaton increased. The perception of the representation (b) is mostly neutral in the 3 use cases. Finally, the comments added by the experts show that the representation (c) is to be preferred as it is more informative due to the added explainable metrics. It was designated as the most useful on the three case studies to understand the behavior of a system during a time range. Finally, representation (d) is described as the most explicit in terms of time representation.

5.3.4 Acceptability of Representations: The Role of Exploratory Metrics

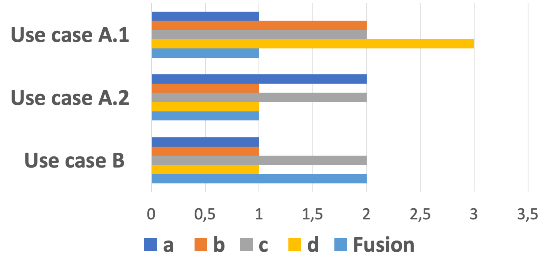
According to Figure 7, regardless of the case studies and the respondents' Company, the unfolded representations (b) and (c) received a good evaluation on its ability to represent the behavior of a system over time. Representation (d) was particularly convincing due to the color systems, simplicity of the color schemes and simplicity of visualization.

Representations (a) and (c) were perceived differently by respondents from Company 1 and Company 2: Respondents from Company 1 considered representation (c) interesting but limited in terms of explainability of behavior. There was no rejection of it but no major adoption either. Several factors can explain this result: the choice of metrics and the creation of the representations were done (i) by a data-oriented approach (data science approach), (ii) without a strong involvement of the experts (our target audience), (iii) without an explicit need for explainability on their part, and (iv) without a context on the objective of the present work. Finally, representation (a) did not find support at Company 1.
Respondents from Company 2, on the other hand, perceived representations (a) and (c) as informative, with a better evaluation of representation (c). The combination of visual and numerical information, *i.e.* multi-modal explanations, made it possible to evaluate the representation as informative and to be favored for the understanding of the behavior of complex systems. Thus, our multi-modal representation (c) has proven to be aligned with the preferences of the respondents who mostly prefer multi-modal explanations.

Finally, the experts' feedback on the intelligibility thresholds of the automata is sensibly the same between the two companies: between 5 and 10 nodes maximum for a graph. The number of sensors beyond which the analysis of the system becomes complex varies between the respondents of both companies: For Company 1, the threshold is between 10 and 15



(a) Company 1



(b) Company 2

Figure 7: Experts answers to the question "To understand the system which of these representations is most useful to you?".

(confirmed by a senior expert of Company 1[5]) and for Company 2, between 5 and 50 (the respondent who marked 50 sensors underlined his lack of knowledge of the domain). Finally, a respondent from Company 2 considered that the proposed graphs allowed to free oneself from the thresholds of intelligibility in terms of sensors number.

To conclude, the results of the questionnaire show a difference in perception of the acceptability of a representation according to the profile of the company's experts, the apriori knowledge of the domain, and the technical experience with the subject: the neophyte profiles of a domain prefer more information on the considered complex system (Company 2), whereas those familiar with the subject seem not to need this information there (Company 1). The average comments of the experts leads to the following conclusion: the visual representation seems essential for the information transmission aspect, but it must, of course, be relevant and easily understandable. This highlights an important trade-off between the performance of AI approaches, the relevance of the visual explanations and its intelligibility for the target audience. Note that in our study, the representations and the clustering have been validated by the domain experts. Finally, all the results confirm that the XR-CSB method allows generating an explainable and intelligible visual representation of the behavior of a complex system that interfaces with experts as well as neophytes.

6 CONCLUSION

We proposed XR-CSB: an original method to represent and explain complex system's behavior based on vertical clustering and (unfolded) automata through four original representations (Figure 2). Our experimental study shows that representations are interesting for experts with different profiles and levels of expertise because they give multi-modal explanations *i.e.* information about the behavior of the system whether it is simple (one time series) or complex (in our case, almost a hundred time series). Experts with different expertise levels have evaluated and validated specific proposed representations showing a difference the acceptability of a representation according to their profile.

In future works, we aim to include the technical PDF reports (that have comments with explicit temporal information about actions undertaken) to make an automatic post-hoc validation process of the extracted unfolded automata. It is thus possible to link states of the unfolded automaton to specific comments and hence to label those states, which can be done easily as our method is flexible. In addition, we would like to integrate additional time series represented by categorical variables (*e.g.* PDF reports). However, this makes it impossible to extend traditional clustering techniques because of the traditional distance measure. Therefore, it is important to propose an adapted distance measure, that can be inspired from (Ghassempour et al., 2014) in order to handle the data heterogeneity. Finally, we aim to focus on the detection and explainability of relevant sensors that play a discriminatory role in the state of the system. This can help managers to identify boilers that are most important for the power station management, and globally contributes to explainability issues related to time series clustering.

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[5]The respondent with a technical profile who has the most experience (more than 5 years) in the given industrial domain recommends 6 nodes for an unfolded graph and an analysis between 10 and 15 sensors.

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