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# Unsupervised manufacturing process identification using non-intrusive sensors

**R. DELABEYE<sup>a</sup>, M. GHIENNE<sup>a</sup>, A. KOSECKI<sup>a</sup>, J.-L. DION<sup>a</sup>,**

a. Quartz Laboratory, EA7393, ISAE-Supméca, (romain.delabeye@isae-supmeca.fr,  
martin.ghienne@isae-supmeca.fr, arkadiusz.kosecki@isae-supmeca.fr,  
jean-luc.dion@isae-supmeca.fr)

## Résumé :

*Le suivi de la durabilité énergétique dans l'industrie manufacturière se heurte à un problème d'échelle. La surveillance d'indicateurs de performance est essentielle, en utilisant cependant le moins de capteurs possible et en limitant leur intrusivité vis-à-vis des systèmes existants. Les capteurs non-intrusifs sont particulièrement adaptés à de telles applications, en cela qu'ils captent de nombreuses sources depuis un lieu distant de celles-ci. La reconstitution des indicateurs-cibles nécessite toutefois davantage de traitement du signal. Les méthodes présentées dans cet article visent avant tout à reconstruire, de manière non-supervisée, le processus de production d'une machine à partir de données issues de capteurs. Une série de mesures est ainsi séquencée temporellement en opérations distinctes. Leur contenu en termes d'actionneurs actifs est ensuite estimé par décomposition. Ces méthodes sont toutes particulièrement adaptées aux signaux apparaissant comme stationnaires par morceaux dans la représentation temps-fréquence.*

## Abstract :

*Energy sustainability in the manufacturing industry faces a scalability issue. Monitoring appropriate performance indicators is essential, yet as few sensors as possible should be used, and with limited intrusiveness (software- or hardware-wise). Non-intrusive sensors are well suited to such applications, as multiple sources can be sensed at once. Recovering the desired indicators requires additional signal processing though. This paper focuses on recovering a machine's process from sensor data in an unsupervised fashion, and unveiling which actuators are active within each operation. The proposed method is particularly well suited to mixed signals which appear as stationary in the time-frequency domain within each operation.*

**Keywords : Blind source separation, time series clustering, energy sustainability, bond graph**

## 1 Introduction

The manufacturing industry is energy-intensive by construction. It is therefore essential to improve its energy sustainability, starting with the monitoring of energy key performance indicators (EnPI). These

are tedious to estimate and forecast due to the lack of high-fidelity models for the industrial machines making up manufacturing plants. Moreover, their identification requires much intrusive data which are either lacking or unavailable (e.g., from sensors located inside the machines). For this reason, non-intrusive sensors are more convenient. For instance, accelerometers, temperature and current sensors sense much information, at the expense of a greater difficulty to link these observations to the measurand of interest through physical models.

Instead, models can be entirely built up from data through *model synthesis*, without a priori knowledge. There are two critical aspects to these models. First, the underlying physics semantics must be sufficiently rich to allow for EnPI to be inferred. Second, the constitutive elements of the production process should be inferred as well. A process is defined here as a sequence of operations performed by the same physical components. Associating different models to specific *operations* and *actuators* enables their respective energy sustainability analysis, thus allowing for process enhancement or component replacement.

This paper focuses on the second aspect, namely breaking down a process into distinct operations and finding the actuators used in each of these operations. Non-intrusive sensors are considered here, these have the particularity of yielding mixed signals originated from different actuators. The process identification algorithm shall operate in a completely unsupervised fashion. The control inputs in particular are assumed to be unknown.

This is a special case of under-determined Blind Source Separation (BSS), where restrictions apply on the mixing matrices. Additionally, actuator activation statuses are sought rather than the source signals themselves. The signals are assumed to have short transient responses (with respect to an operation's duration), stationarity being a common assumption in such problems [1].

Despite similarities with a soft clustering problem [2], where the measurement at a certain time step can belong to multiple clusters, the related techniques tend to soften the transitions from a cluster to another. Fuzzy Clustering is used in [3] for time-varying mixing matrices in speech signal reconstruction, and in [4] for switching regression models. In BSS problems, source signals are reconstructed from mixed measurement signals. The number of sources is often assumed to be known a priori [5]. This assumption can be lifted through subspace methods [6, 7], typically by thresholding the eigenvalue spectrum for the high Signal-to-Noise-Ratio (SNR) scenario, or using alternative problem-specific criteria [8].

Along with problem formulation, a dynamical systems representation is described in Section 2.1. The proposed method consists in a two-step process : clustering into operations and decomposing into actuator activation times, detailed in Section 2.2 and Section 2.3 respectively. Simulation and experimental results for this algorithm are detailed in Section 3.

## 2 Method

### 2.1 Problem formulation

As the machine evolves in time and in its process, from an operation to another, sudden changes in sensor signals are encountered (assuming the transient responses are short-enough). Several operations can use the same actuators though. Splitting the signal in terms of operations is helpful for prioritizing process enhancements, whereas decomposing the operations into a minimal set of atoms, representing machine actuators if encountered alone at least once, is essential to isolate an actuator's performance and deterioration.

Bond graph theory [9] is well-suited to energy sustainability modeling. Indeed, such a graph represents the power distribution, towards elements classified either as energy dissipation ( $R$ ) or storage ( $I$  or  $C$ ). Energy efficiency and consumption can thus be inferred from a minimal set of variables. 0- and 1-junctions, as well as multi-port components ( $TF$  and  $GY$ ) represent power transfers without loss (this is essentially a generalization of Kirchhoff's laws). The discrete-event aspect is modeled as *switched power junctions* [10], represented as  $1_{\delta_i}$  in Figure 1, where the power is forced to zero when the actuator is inactive.

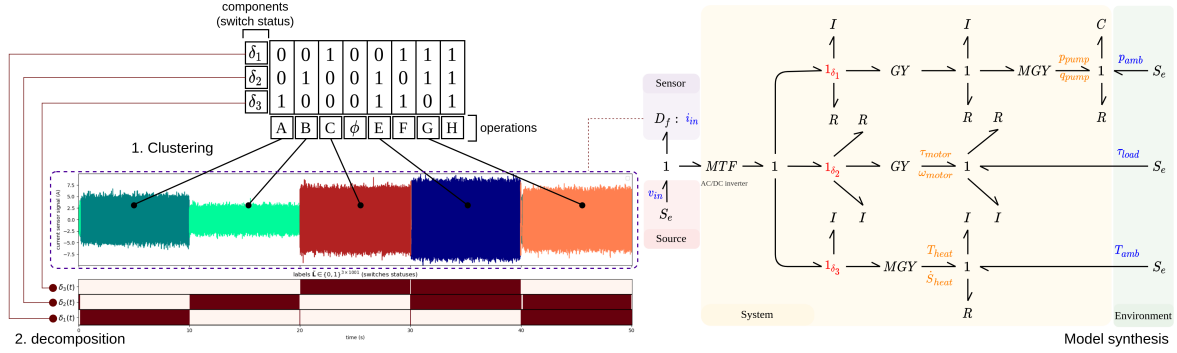


FIGURE 1 – Overview of the proposed method, illustrated upon a machine composed of a pump, a motor and a heating coil (synthetic signal).

As illustrated in Figure 1, we propose the following method : a sensor signal, mixing actuator-originated signals, is clustered into distinct operations to begin with ; each operation is then decomposed into atoms (actuators) when possible. These *actuators* essentially relate to distinct sets of causal paths, which is helpful information for the subsequent bond graph model synthesis.

Formally, a univariate time series  $\mathbf{X} \in \mathbb{R}^{1 \times T'}$  is considered, representing  $T'$  sensor measurements evenly sampled over time. The Short-Time Fourier Transform (STFT) operator  $STFT\{\mathbf{X}\}$  is applied to the data, the extracted features make up the matrix  $\mathbf{Z} \in \mathbb{C}^{f \times T}$  where  $f$  denotes the number of features (frequency bins in this case), and  $T$  is the new number of samples (time window indices). The underlying system performs  $n_{ops}$  distinct operations using  $n_{act}$  different actuators, with  $n_{ops} \geq n_{act}$ .

The matrix  $\mathbf{L} \in \{0, 1\}^{n_{ops} \times T}$  represents the operation the system is in at each time step  $t \in \llbracket 1, T \rrbracket$ , with  $\|\mathbf{L}_t\|_0 = 1$ . Whereas the activation statuses of a system's actuators over time are gathered in a matrix  $\tilde{\mathbf{L}} \in \{0, 1\}^{n_{act} \times T}$ , with  $\|\tilde{\mathbf{L}}_t\|_0 \geq 1$ . Thus the time series  $\mathbf{L}^c$  and  $\tilde{\mathbf{L}}^a$  indicate whether the system is in operation  $c$  (cluster) and uses actuator  $a$  at each time step. Matrix superscripts and subscripts represent vectors lying in the row and column spaces respectively.

## 2.2 Clustering into operations

Data is clustered to begin with. Clustering is a division of data into groups of similar objects [11]. Time series (hard) clustering is an unsupervised technique grouping timestamps according to a similarity measure between vectors describing data at each time step : a data point belongs to one cluster only. This topic has been extensively tackled in the literature, the *k-means* algorithm is considered here, applied to the magnitude of the data's STFT,  $|\mathbf{Z}|$ . Any relevant descriptor applied to sliding windows could be used though, the first four statistical moments for example. The number of clusters (operations)  $n_{ops}$  is chosen manually using a dendrogram. In most cases, this number cannot be known a priori and other clustering techniques such as *DBSCAN* or its variant *OPTICS* [12] are better suited.

The one-hot encoded labels  $L$  are thus obtained, indicating in which operation the system is at each timestamp.

## 2.3 Decomposition into actuators

In this section, *decomposition* refers to expressing an operation as the composition of other operations. Assuming the system's actuators have all been encountered alone at least once, i.e. activated while all others were deactivated, the decomposition yields the actuators' activation sequence. If this assumption is not met, then a minimal set of independent operations is found.

Should the data be aperiodic (still under the stationarity assumption), and should the application converting the data into features be linear, a composition would thus correspond to a linear combination in the least-squares sense.

Alternatively, if the data is periodic, these signal superimpositions are slightly more difficult to unveil. Indeed, each time an actuator is activated, its signal's phase changes and so does the mixed signal's.

In order to tackle the latter case, a *shifted* STFT is applied to the raw data. The STFT is in essence a sliding discrete Fourier transform (DFT) and is hence linear by definition. Due to window sliding, a progressive phase shift occurs. Although the time delay can easily be retrieved, the phase shift is signal-dependent. Exact phase retrieval [13] is computationally expensive and unnecessary in this context. Instead, at each time step, the phase of  $Z_t$  is measured at the maximum of magnitude and shifted accordingly. This takes out both the phase shift of the windowing process as well as the inherent phase of the signal. To this end, the phase-shift operator is used, defined as :

$$S_{\Delta} = \text{diag}\left(\left(e^{-j\frac{2\pi k}{N}\Delta}\right)_{1 \leq k \leq N}\right) \quad (1)$$

where  $N$  is the number of frequency bins and  $\Delta$  is the time delay. This *shifted* STFT makes the phase consistent within a cluster and reduces the intra-cluster variance. The *centroid matrix*  $C \in \mathbb{C}^{f \times n_{ops}}$  can thus be computed, each vector in the column space corresponding to the average of all samples belonging to each cluster.

Because the phase-shift operator is nonlinear with respect to the time delay, the phase of a composite centroid will be different than the sum of its constituents. The sought combination between a centroid  $C_c$  and all others,  $\{C_i\}_{i \neq c}$ , can be expressed as :

$$\arg \min_{\substack{\{\Delta_i\}_{1 \leq i \leq n_{ops}} \\ \{\alpha_i\}_{1 \leq i \leq n_{ops}}}} \|C_c - \sum_{i \neq c} \alpha_i S_{\Delta_i} C_i\|_2^2 \quad (2)$$

where the coefficients  $\alpha = \{\alpha_i\}_{1 \leq i \leq n_{ops}}$  and  $\Delta = \{\Delta_i\}_{1 \leq i \leq n_{ops}}$  are (ordered) sets of scalars, representing combination coefficients and time-delays respectively. The functional is linear in  $\alpha$  and nonlinear with respect to  $\Delta$ , albeit periodic.

In some cases, this projection can lead to misinterpretations. On one hand, if an actuator operates at different regimes, the centroids of the two operations will be collinear, with a combination coefficient corresponding to the ratio between both regimes. On the other hand, in real case scenarios, multiple actuators can also produce very close signatures. For instance, several electrical devices can induce current consumptions at  $50Hz$ . The decomposition would not apply in such a case. This is also why subspace methods in general would not be well suited.

In order to tackle this aspect, we compute a residual matrix  $\mathbf{R} \in \mathbb{R}^{n_{ops} \times 2^{n_{ops}}}$ , with  $\forall r_g^c \in \mathbf{R}$ :

$$r_g^c = \min_{\{\Delta_i\}_{i \in g(2)}} \frac{\|\mathbf{C}_c - \sum_{i \in g(2)} \mathcal{S}_{\Delta_i} \mathbf{C}_i\|_2^2}{\|\mathbf{C}_c\|_2^2} \quad (3)$$

where  $\forall g \in \llbracket 1, n_{ops} \rrbracket$ ,  $g(2)$  corresponds to a possible *group* (i.e., a combination) of centroids, with  $\cdot(2)$  denoting a number expressed in base 2.

By doing so, we constrain the values of  $\alpha_i$  to  $\{0, 1\}$  and evaluate all possible combinations. In the case of a composite operation, this residual (or an alternative distance) would fall below a problem-dependent threshold  $\tau$ . The Broyden–Fletcher–Goldfarb–Shanno (BFGS) [14] algorithm is used to compute these residuals. This approach does not scale due to an obvious combinatorial explosion. For actual systems running only a few distinct operations, this is not limiting.

For clarity, the method is wrapped up as a pseudo-code in Algorithm 1.

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**Algorithm 1:** proposed algorithm

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**Input:** Discretized time series data  $\mathbf{X} \in \mathbb{R}^{1 \times T'}$ ; expected number of operations  $n_{ops}$ ;

**Result:** Clustering labels  $\mathbf{L} \in \{0, 1\}^{n_{ops} \times T}$  and decomposition labels  $\tilde{\mathbf{L}} \in \{0, 1\}^{n_{act} \times T}$ ;

**Step 1 :** extract features and apply clustering

Extract features accurately describing the operations

Apply *K-means* algorithm;

Yield the (one-hot encoded) clustering labels  $\mathbf{L}$ ;

**Step 2 :** extract features for decomposition

$\mathbf{Z} \in \mathbb{C}^{f \times T}$ ,  $\mathbf{Z} = \text{STFT}\{\mathbf{X}\}$

**for**  $1 \leq t \leq T$  **do**

    measure the phase at the maximum of magnitude  $\Delta_m = \angle \arg \max_{z \in \mathbf{Z}_t} |z|$ ;

    shift the phase accordingly  $\mathbf{Z}_t \leftarrow \mathcal{S}_{\Delta_m} \mathbf{Z}_t$ ;

**end**

Compute  $\mathbf{C} \in \mathbb{C}^{f \times n_{ops}}$  :  $\forall c$ , given  $N_c$  samples in cluster  $c$ ,  $\mathbf{C}_c \leftarrow \frac{1}{N_c} \sum_{t \in \{\text{cluster } c\}} \mathbf{Z}_t$

**Step 3 :** decomposition

$\tilde{\mathbf{L}} \leftarrow \mathbf{L}$ ;

**for**  $1 \leq c \leq n_{ops}$  **do**

**for**  $1 \leq g \leq 2^{n_{ops}}$  **do**

$r_g^c \leftarrow \min_{\{\Delta_i\}_{i \in g(2)}} \frac{\|\mathbf{C}_c - \sum_{i \in g(2)} \mathcal{S}_{\Delta_i} \mathbf{C}_i\|_2^2}{\|\mathbf{C}_c\|_2^2}$

**end**

**if**  $\min_{1 \leq g \leq 2^{n_{ops}}} r_g^c \leq \tau$  **then**

        Cluster  $c$  is composed of the clusters present in  $g(2)$ ,  $\forall t \in \{\text{cluster } c\}$ ,  $\tilde{\mathbf{L}}_t \leftarrow g(2)$ ;

**else**

        Cluster  $c$  cannot be decomposed,  $\forall t \in \{\text{cluster } c\}$ ,  $\tilde{\mathbf{L}}_t \leftarrow \mathbf{L}_t$ ;

**end**

**end**

Remove empty rows in  $\tilde{\mathbf{L}}$  (composite operations), yield  $\tilde{\mathbf{L}}$

---

### 3 Results and discussion

The proposed methods have been applied to synthetic and real use cases.

The synthetic use cases follow a pattern : three different waves (no transient) successively activated for 10 seconds each, then all three active simultaneously for 10 seconds. For brevity, only one of such experiment has been shown :

$$x(t) = \delta_2(t) \sin(2\pi 50t) + \delta_3(t) 2 \sin(2\pi 50t + \frac{2\pi}{3}) + \delta_1(t) 2 \operatorname{sgn}(\sin(2\pi 70t)) + w(t) \quad (4)$$

where  $\delta_1(t)$ ,  $\delta_2(t)$ ,  $\delta_3(t)$  denote the switches statuses at time  $t$ . The output signal has been supplemented with a zero-mean Gaussian noise  $w(t)$  with standard deviation  $\sigma = .8$ .

The physical use case consists in an automated coffee machine. It is composed of a pump, a heating coil as well as two motors. The process shown in Figure 2b starts with a series of short heating and pumping sequences, followed by a longer pumping operation, and four heating operations superimposed with the pumping; finally one of the motors displaces the infuser.

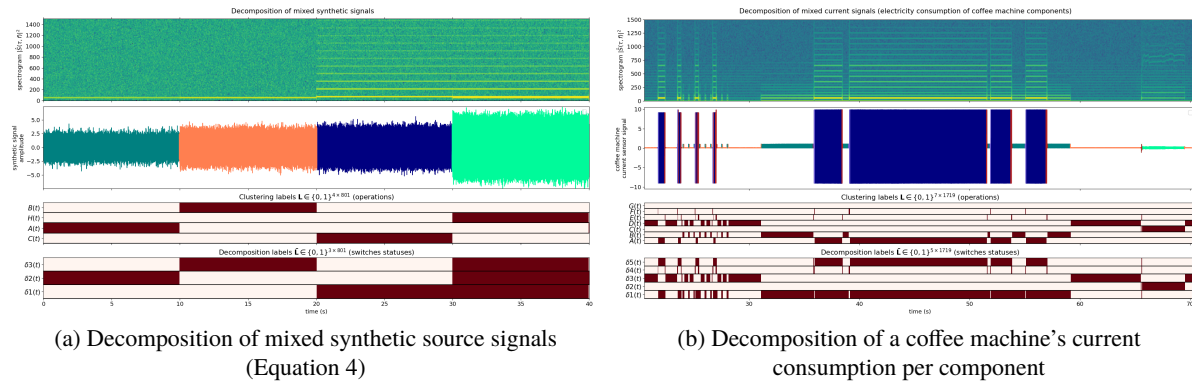


FIGURE 2 – Decomposition results

The results for the synthetic signal and the coffee machine's current consumption are presented in Figure 2a and Figure 2b respectively. The spectrogram highlights the spectral density of the signal. The colored plot represents raw data clustered into distinct groups. The clustering labels (matrix  $L$ ) and decomposition labels (matrix  $\tilde{L}$ ) are displayed.

The experiments run on the synthetic use cases highlight the method's resilience to noise as well as its ability to perform as expected when the signal frequencies are equal or differ, given equal or different signal amplitudes.

As for the coffee making process, all devices produce current signals with a fundamental frequency at  $50Hz$  and different amplitudes. The superimposition of the pumping (switch  $\delta_1$ ) and the heating (switch  $\delta_5$ ) operations is accurately detected.

### 4 Conclusions

In this paper, a decomposition method was proposed in order to detect superimposed operations from non-intrusive sensor data. This approach has been validated upon several synthetic scenarios as well as a laboratory experiment.

Future work will focus on better handling controlled systems capable of operating at different regimes over a production cycle. The approach will be further developed so as to include the transient responses which contain much information regarding the subsystems and could help their differentiation with one another. At last, a bond graph model synthesis algorithm will be designed.

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