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An Implementation of Abrupt Changes Detection and Principal Component Analysis for Monitoring the Thermal Processes in a Cement Rotary Kiln

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Abstract
Rotary kilns for the manufacture of cement, lime and other inorganic binders are widely used in the industry due to their technological advantages: high efficiency, increased reliability, and superior quality of the final product. Modern rotary kilns are equipped with infrared cameras for monitoring the processes inside the kiln, surface infrared scanners for monitoring the temperature at the outer shell of the kiln as well as control systems of all components of the kiln - burner, electric drive, materials supply. The complex chemical, physical, transport and thermal processes that occur inside the cement rotary kilns are stationary processes but space-distributed by sectors along the kiln's length. The main idea in this article is estimating the length of the sectors where these processes occur. We propose estimating the sectors length by means of the Abrupt Change Detection Algorithm implemented onto the temperature spectra provided by the surface infrared scanner. The results provided by the implementation of this algorithm are the estimated position of the abrupt changes onto the space series of the temperature at the outer shell of the kiln which is correlated with the processes inside the kiln. The analysis of the statistical correlations between the estimations of the locus and length of the processes' sectors on one side, and the average and the variance of the temperature observations on the other side, allow increasing the accuracy and demonstrating the repeatability of the proposed method. For this purpose, in this article we propose implementing the Principal Component Analysis on the observations of the kiln's outer shell temperature.

Keywords
signal processing algorithms, principal component analysis, cement industry, rotary kiln

1. Introduction

Rotary kilns for cement manufacturing are widely used in the industry due their technological advantages - high efficiency, increased reliability, etc. - and the superior quality of the final product. On the other hand, rotary kilns are high consumers of thermal energy and have a negative impact on the environment being generators of greenhouse gases. Due to these aspects, the decision-makers in the cement industry are constantly concerned with optimizing the processes that occur in rotary kilns for cement manufacturing and with reducing their negative impact on the environment.

Modern rotary kilns are equipped with infrared cameras to monitor the flame length inside the kiln (in the flame zone), infrared scanners to monitor the temperature of the outer shell of the kiln for fault detection purposes and with control systems at the level of the component installations of the kiln - burner, the electric drive of the kiln, the installation of supply with raw materials. Overall, all the systems are integrated into a Supervisory Control and Data Acquisition System (SCADA) that largely eliminates the need for manual intervention. However, the operation of the rotary kiln must be monitored manually because the control system fails the control by about 20%, [1].

In the literature, many articles are dedicated to the processes monitoring and control of the rotary kilns in the cement industry. These contributions are mainly based on the images provided by the infrared cameras that monitor the burning sector of the kiln and use the image processing techniques, [2 - 5].

In this work we propose using the information provided by the surface infrared scanner that provides the temperature distribution on the outer shell of the kiln. The scans provided are averaged and the matrix of the corresponding space series is obtained. The space series is then analyzed by means of an Abrupt Changes Detection algorithm and the change points of the temperature are detected. These change points estimate the sectors' length of the processes inside the kiln.

Weekly, the kilnman manually adjusts the flame's length. This procedure features a large dead-time. During this procedure, the parameters of the kiln's processes change significantly. This feature is used to compare the results supplied by the Abrupt Change Detection algorithm with the results provided by Principal Component Analysis method.

2. Methods

2.1. Overview of processes of the clinker's manufacturing

The rotary kilns for the cement manufacture are technological installations of cylindrical shape positioned slightly inclined to the horizontal. The kiln's body is rotated around its longitudinal axis to ensure uniform flow of the powder consisting of a mixture of limestone, dolomite and coke. The heating of the kiln is made by means of a burner that produces a counter current flame. The combustible material is fine coke powder injected with pressured air in the burner, [1].

The transformation of the raw material into clinker is performed in three stages:

(a) the decomposition stage – this is a chemical decomposition of the mineral limestone into silica and aluminium oxide, as well as the decomposition of dolomite into calcium carbonate and magnesium oxide

(b) the transition stage – the calcium carbonate reacts with silica and forms the belite, and

(c) the sintering stage – the belite reacts with the calcium oxide to form the alite. At this stage, about 20% - 30% of the material aggregates into lumps of 1 - 10 mm. This aggregate is called clinker and represents the final product of the kiln.

In the rotary kiln, the three stages take place simultaneously in different sectors which can be identified by their specific temperature correlated with the physical/chemical reactions that take place. The temperature in the decomposition sector is between 400 - 600 degrees Celsius. The temperature in the transition sector is between 650 - 900 °C; in order to ensure the decomposition of calcium carbonate into calcium oxide and carbon dioxide, in the final part of this sector, the temperature must reach the value of 900 - 1050 °C. The temperature in the sintering sector is 1300 - 1400 °C, [1].

The typical aspect of the spatial temperature distribution at the outer shell of the cement rotary kiln is represented in Figure 1.

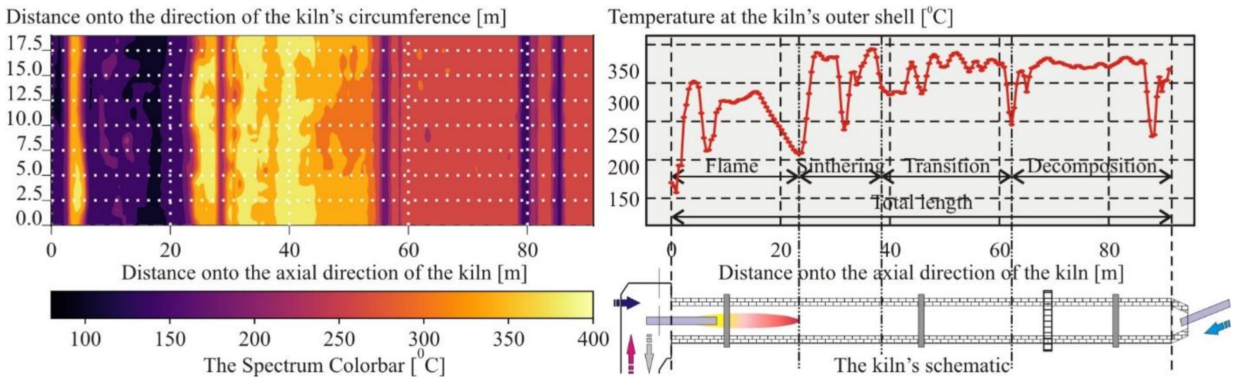

Fig. 1. The spectra of the temperature distribution over the outer shell of the rotary (to the left) and the average of the temperature and the processes' sectors (to the right)

2.2. The detection of changes in univariate sequences

The problem of detecting abrupt changes in time series has arisen due to the increasing complexity of observations on technological processes made by means of the smart sensors. The abrupt changes detection in time series is mainly used for early detection and correction of changes of the technological parameters. The major difficulty of this problem is the detection of changes in the installation parameters when the observations are disturbed by noise.

The problem of detecting the abrupt changes in time series was first formulated by E.S. Page in 1954. Page introduced the Cumulative Sum algorithm (CUMSUM). The algorithm was improved over the years by numerous other researchers, [7]. The CUMSUM algorithm involves the evaluation of the cumulative sum computed by iterations. The samples from a given process x_n are assigned the weights ω_n

representing the likelihood function and the recursive sums are calculated:

$$S_{n+1} = max(0, S_n + x_n - \omega_n). \quad (1)$$

If at a certain step of the iteration, the value of the sum S_{n+1} exceeds a predetermined threshold then, an abrupt change in the time series values is detected. The algorithm detects abrupt changes only in the positive direction. In order to detect the changes in the negative direction, in the expression (1), instead of the *max* operator, the *min* operator must be implemented.

In the case of the moving sum processes, the algorithm for detecting abrupt changes consists in evaluating the Welch's t-statistic, *D*. For two size samples:

$$D_{t,h} = \sqrt{h} \cdot \frac{\hat{\mu}_r - \hat{\mu}_l}{\sqrt{\hat{\sigma}_r^2 + \hat{\sigma}_l^2}} \quad (2)$$

Where T is the length of the sequence, $h \in \{1, \ldots, T/2\}$ is the size of the window, $t \in \{h, \ldots, T - h\}$ is the local variable, $l \in \{T - h + 1, \ldots, t\}$ and $r \in \{t + 1, \ldots, t + h\}$ are the value ranges of the indexes l and r, respectively. $\hat{\mu}_j, \hat{\mu}_l, j \in \{l, r\}$ are the mean and the empirical variance of the random variables.

To solve the problem of choosing the optimal window size, *h*, in [6, 7] the multi-scale change point detection algorithm (MSCP) has been proposed. In this approach, both parameters *t* and *h* are time functions defined in the isosceles triangle $\Delta_h \in \mathscr{R}$ where the hypotenuse is related to the fixed size *h*, Figure 2. The detection algorithm subsequently acts on subsets of Δ_h by locally exploiting the Welch's *t*-statistic, [6].

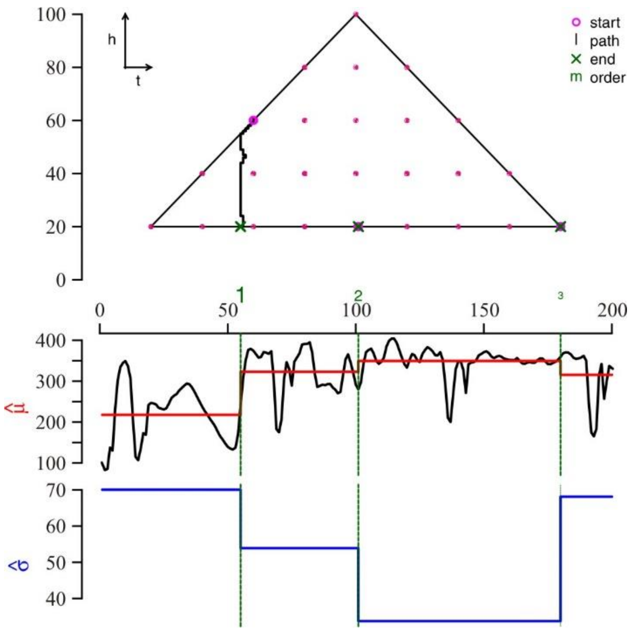

Fig. 2. The implementation of the Multi-Scale Change Point Detection (MCSP) algorithm for the detection of the temperature distribution onto the surface of the outer shell kiln from experimental data; window size = 200

The detection algorithm starts from an initial given value and constructs a zigzag-path towards the lower edge of Δ_h. When a first change point is detected, the estimation restarts and iteratively the change points are detected until a breaking criterion applies. The algorithm is software implemented in the R software package, [7].

2.3. The principal component analysis of the random data sets

The Principal Component Analysis (PCA) is a method that allows reducing the size of a data set represented by an array $\mathbf{X}_{n \times m}$; *m* is the number of components and *n* is the number of samples. The method highlights the array's simplified structure. Given the matrix of observations **X**, a linear transformation **P** is determined **Y** = **P** × **X** such as the matrices are ortho-normal and verify the relationship:

$$\mathbf{C}_Y = \mathbf{P} \times \mathbf{C}_X \times \mathbf{P}^T \tag{3}$$

$\mathbf{C}_X = (1/n)\cdot\mathbf{X} \times \mathbf{X}^T$ and $\mathbf{C}_Y = (1/n)\cdot\mathbf{Y} \times \mathbf{Y}^T$ are the associated covariance matrices. The elements of the matrix **P** are the main components of the matrix of observations. It is proven that, by choosing the elements of the matrix **P** such as each line $\mathbf{p}_i$ is an eigenvector of the matrix $\mathbf{C}_X$ then the following properties apply, [8]:

- $\mathbf{C}_Y$ is a diagonal matrix where the i^{th} diagonal element is the variance of the matrix **X** onto the direction $\mathbf{p}_i$;
- The principal components of the matrix **X** are the eigenvectors of the matrix $\mathbf{C}_X$.

The eigenvector with the highest eigenvalue is called the first principal component and contains the most relevant information about the observed data set.

The PCA method is software implemented, for example in the FactoMineR module that is implemented in the R software environment. The FactoMineR module, [9], was used in this work.

3. The Experiment

3.1. The organization of the experiment

The technical data of the rotary kiln are: 97.6 m – the length of the kiln, 6.04 m – the outer diameter of the kiln, 2.1 rpm – the angular speed of the kiln. The thermal spectrum at the kiln's surface was determined using an infrared scanner of type Infrared Kilscan. The scanned length is 91 m; the distance between two successive scan points is 0.4 m. The time interval between two successive scans is approx. 9 minutes.

The data for the experiment came from 1716 images of the thermal spectrum acquired from the scanner over 2 weeks of observations. The data set acquired during the first week was used for computation purposes and the data set acquired during the second week was used for validation. The experimental data were provided by a local partner, "CRH Ciment Romania" - Hoghiz Cement Factory.

The analysis of the observations was made by means of a dedicated software application implemented in the R software environment. The Multiscale Change Point Detection (MCSP) module, [7] and FactoMinerR module, [9], were embedded within the main routine of the dedicated application. The main steps of the procedure were as follows.

- The scans acquired from the kiln's surface temperature were structured into a matrix of daily and weekly point-to-point scans.
- This matrix provided the input data for the MCSP module. By means of this module, the abrupt change points - corresponding to the sectors within the kiln - were detected.
- For each sector detected, the average value and variance of the temperature were computed. The Principal Component Analysis of data was performed by means of the FactoMineR module. Two qualitative variables: the day and week of the observations where also introduced in the input frame of the FactoMineR module.
- The results of the PCA analysis were evaluated - in statistical sense - and compared with the results provided by the Abrupt Change Detection algorithm to emphasise the statistical correlations between the space distribution of sectors and the first two components of the PCA.

3.2. The change points detection and the PCA analysis of the temperature distribution onto the surface of the outer shell's kiln

Figure 2 depicts an example of the Abrupt Change Detection algorithm's implementation onto a day of observations. One may observe that the Abrupt Change Detection algorithm detects the position of the flame sector and the sinthering sector. The change point between the transition and the decomposition sectors is not detected.

In Table 1 the results of the PCA analysis over the same data set are presented. The analysis was performed for the first 11 components of the observations. The first and the second components represent almost 74% in the cumulative percentage and thus, these components contain most of the information in the data structure.

Table 1. The eigenvalues and the variance of the PCA components

Component	Eigenvalue	Percentage of variance	Cumulative percentage
comp 1	5.0422	45.8382	45.84
comp 2	3.0564	27.7850	73.62
comp 3	1.5266	13.8782	87.50
comp 4	0.6441	5.8554	93.36
comp 5	0.5277	4.7973	98.15
comp 6	0.0807	0.7340	98.89
comp 7	0.0674	0.6128	99.50
comp 8	0.0299	0.2720	99.77
comp 9	0.0219	0.1995	99.97
comp 10	0.0023	0.0206	99.99
comp 11	0.0008	0.0069	100.00

4. Results and Discussion

For the statistical interpretation of the results, the analysis focused on (a) the space distribution of loci of the processes sectors - represented in Figure 3 and (b) the graphical representation of the PCA results in the form of biplots for all categories, Figure 4 – the left side.

In the first week of observations, during the third day (Thursday) the distance from the origin of the coordinate system to all three change points increased due to the increase of the flame's length. This change is reflected in the change of the corresponding point onto the biplot – week1, day 3. In day 5 (Friday) the position of the change point from the sintering to decomposition and transition sectors also changed due to the reduced level of coke; this change is also reflected onto the biplot – week 1 day 5. Both points are outside the ellipsis of confidence in Figure 4 the left side. All the other observations are inside the ellipsis of confidence onto the biplot in Figure 4 and the positions of the change points are similar – Figure 3 left side.

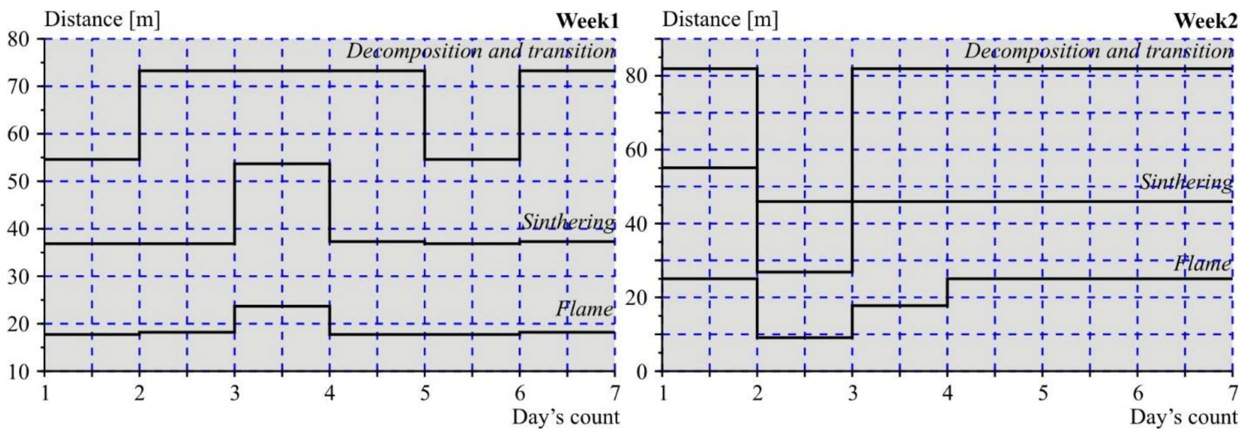

Fig. 3. The dependency of the sector's loci in the rotary kiln with time during the first and the second week of observations

Follows, there are positive correlations between the estimated loci of the change points and the point-to-point daily average and variance of all observations.

The method proposed produce similar results onto the validation data set. For the observations in the week two of observations, the distance between the origin and all change points decreased during the second day (Tuesday). This change reflects onto the biplot – the point Week2, Day2 – which is located outside the ellipsis of confidence. It is to observe that the slight change of the flame's length in day three also reflected onto the position of the corresponding point – Figure 4, left side, Week2, Day3.

The biplot graph of correlations between the categories Mean for all components– Figure 4, right side features a higher value for the first PCA component – 50.57% than its counterpart for the all the categories. The positions of the observation points are aligned – in statistical sense – with the direction of the first component. Follows the first component conserves better the most of information within the data set. This result suggests using the mean point-to-point values for the practical implementation of the method instead of both features, mean and variance.

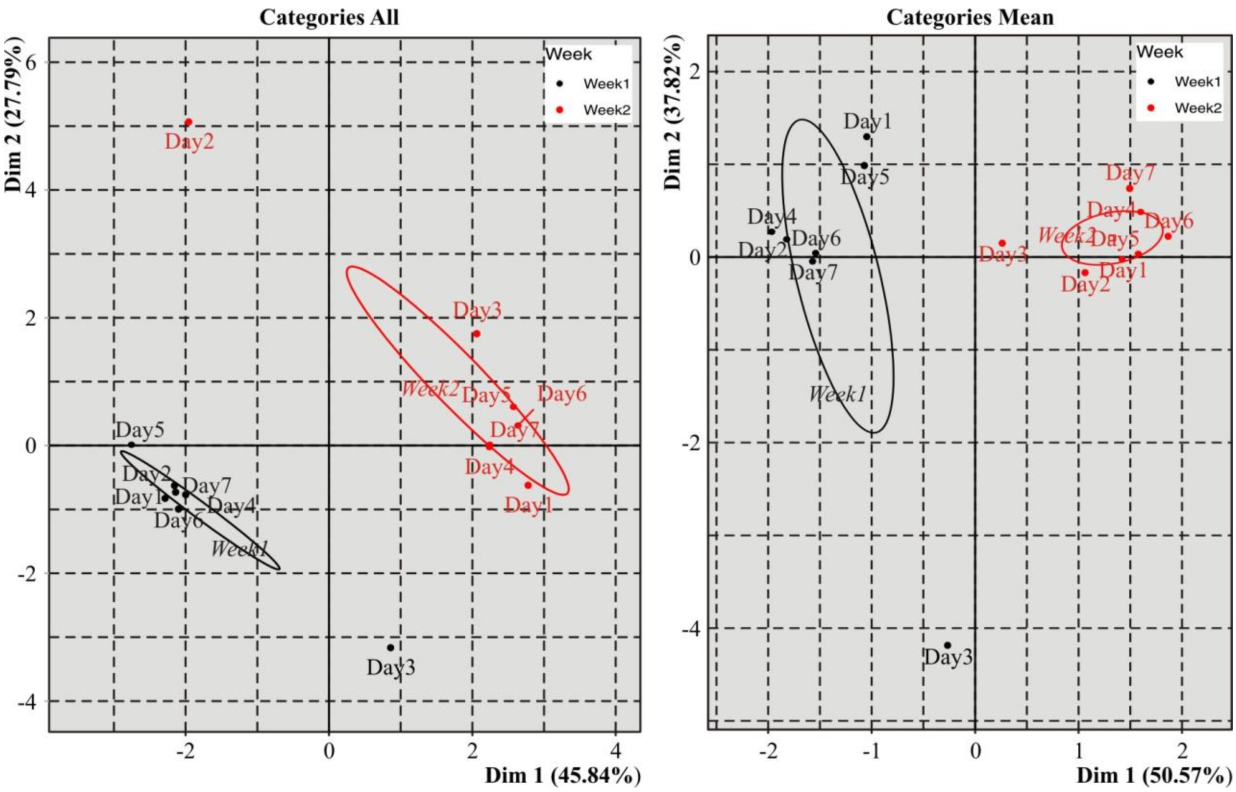

Fig. 4. The biplot of the PCA for all features (to the left), and
the biplot of the PCA for the features Mean (to the right)

5. Conclusions

In this article the Multiscale Change Point Detection module implementing the Abrupt Change Detection Algorithm and the Principal Component Analysis were implemented on observations of the thermal spectrum at the outer surface of a rotary kiln in order to detect the loci and length of the main sectors of processes inside the cement rotary kiln.

The results of the Abrupt Change Detection Algorithm implementation were suitable for the detection of the flame and synthering sectors. The change point between the decomposition and the transition sectors could not be detected in this approach.

The analysis proved the existence of a statistical positive correlation between the distances measured from the origin of the coordinate system to the change points defining the sectors onto the spatial distribution of temperature at the kiln's shell, and the average and variance of the daily observations of the thermal spectra at the outer shell of the kiln.

The experimental results lead to the following conclusions:

- The average value of temperature evaluated by sectors is the variable that statistically defines the evolution of kiln's processes.
- Estimating the loci of sectors based on the MSCP algorithm may be made with a confidence level of over 80%.
- The method proposed in this article allows emphasizing the weekly dependence with the days when the observations are uncorrelated with the overall observed data due to the regular operation of the kiln.

The proposed method allows estimating the length and loci of the processes sectors within the rotary kiln in addition with the temperature observations at its outer shell and improves the functionality of the infrared scanner. The results provided are important in both normal operation of the kiln – for the manual/automated control of the flame's length - but also for the prediction of faults of the kiln's thermal coat.

References

1. Boateng A.A. (2008): *Rotary Kilns. Transport Phenomena and Transport Processes*. Oxford, Butterworth-Heinemann, ISBN 978-0750678773, pp. 16-32, 59-97, 173-238
2. Pham D.-S., Ridley J., Lazarescu M. (2020): *An Efficient Feature Extraction Method for the Detection of Material Rings in Rotary Kilns*. IEEE Transactions On Industrial Informatics, ISSN 1941-0050, vol. 16, no. 9, pp. 5914-5923, https//doi.org: 10.1109/TII.2020.2965996
3. Shankar S.S., Thomas L., Pratheesh H., Suresh K. (2018): *Burning Zone Temperature Estimation of Rotary Kiln Using Flame Image Analysis in Cement Plants*. 2018 International CET Conference on Control, Communication, and Computing (IC4), ISBN 978-1-5386-4966-4, pp. 255-259, https//doi.org: 10.1109/CETIC4.2018.8531041
4. Wang J.-S., Zhang L., Gao X.-W., Sun S.-F. (2010): *Intelligent Control Method of Rotary Kiln Process Based on Image Processing Technology: A Survey*. Proceedings of the 29th Chinese Control Conference, ISBN 978-7-8946-3104-6, pp. 2930-2935
5. Liu J., Zhu Y., Sun P. (2010): *Sintering Status Recognition System for Cement Rotary Kiln*. 2010 International Conference on Computer Application and System Modeling (ICCASM 2010), ISBN 978-1-4244-7237-6, Vol. 13, pp. V13-212-V13-216, https//doi.org: 10.1109/ICCASM.2010.5622727
6. Levajkovic T., Messer M. (2021): *Multiscale change point detection via gradual bandwidth adjustment in moving sum processes*. Cornell University, arXiv:2103.01060v1, https://doi.org/10.48550/arXiv.2103.01060
7. Levajkovic T., Messer M. (2021): *mscp: Multiscale Change Point Detection via Gradual Bandwidth Adjustment in Moving Sum Processes. R package version 1.0.* [online], Available at: https://cran.r-project.org/web/packages/mscp/. Accessed: 2021-05-10
8. Rouaud M. (2016): *Probabilités, statistique et analyses multicritères* (*Probabilities, Statistics and Multi-criteria Analysis*). http://www.incertitudes.fr/proba-stat-acp/livre.pdf, pp. 154-170
9. Husson F., Josse J., Le S., Mazet J. (2021): *Multivariate Exploratory Data Analysis and Data Mining, Package 'FactoMineR*. [online], Available at: http://factominer.free.fr. Accessed: 2020-09-01