

## Modal Identification of Bridges based on Continuous Dynamic Monitoring

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**Key words:** Modal identification, Ambient vibration, Dynamic monitoring, SSI-COV, Cable-stayed bridge.

### Abstract

The identification of modal parameters of bridges based on ambient vibration measurements has motivated an increased interest as a tool for detection and diagnosis of small changes in vibratory characteristics and, thus, provides important information to support an efficient maintenance policy. However, the large volume of data continuously produced by a dynamic monitoring system requires an automatic data processing to extract the modal parameters. This paper presents an integrated system developed for this purpose and its application to the data collected from a large cable-stayed bridge.

## 1 INTRODUCTION

Vibration-based structural identification has become an important part of structural health monitoring and a very convenient tool for safety evaluation. This tool is particularly useful in structures built in areas of high seismic hazard, allowing the continuous identification of its dynamic behaviour and giving very important information about the structural behaviour after an earthquake.

For this purpose, vibration-based continuous monitoring systems are installed, usually including a large number of sensors with high rates of sampling. These systems continuously generate huge volumes of data, which need to be processed in order to extract the relevant information concerning the structural dynamic characteristics. The processing of such large data volume requires an automatization of procedures to perform automatic identification of structural modal parameters from vibration measurements.

In order to allow an effective and real-time structural identification, based on ambient vibration measurements, an integrated method was developed, using the Stochastic Subspace Identification technique (SSI) and cluster analysis.

To demonstrate its applicability this new methodology was validated with a case study: the data generated during one year by the monitoring system of a large cable-stayed bridge, recently built in Constantine, Algeria, was processed by the developed method. The evolution of the modal parameters is presented and analysed.



## 2 OPERATION MODAL ANALYSIS

### 2.1 General

The process for identifying the modal properties of a structure based on structural responses (outputs) when the structure is under its operating conditions is usually called Operational Modal Analysis (OMA) or Output-only Modal Analysis. The identification of modal parameters is usually performed with the purpose of achieve an accurate estimation of natural frequencies, mode shapes and modal damping ratios.

Models of dynamic systems can be established either in time or frequency domain with continuous time equations (analytical models) or discrete-time equations. The methods in the time domain are also called parametric methods. The models parameters are evaluated by the different techniques, fitting to the correlation functions of the structural response or even directly to their response time series. The modal identification of the systems is then performed through evaluation of dynamic characteristics of adjusted models.

Classified as a time domain, parametric model identification method, the COVariance driven Stochastic Subspace Identification (SSI-COV) method identifies a stochastic state-space model from the output covariance matrix (or correlation, as the mean of the signals is assumed to be zero) [1]. As two-stage modal identification method, the correlation function is being estimated as first stage, and then modal parameters are identified.

### 2.2 Data pre-processing

Prior to the modal identification process, the acceleration time series were taken out from the record file and were pre-processed with the following operations: trend removal; low-pass filtering with a 8 poles Butterworth filter; and decimation of the records. The advantage of decimating the records was to reduce the data sets size, speeding up all the following computing processes without losing information in the frequency range of interest.

The data is also cleaned from spikes in the time domain which occur occasionally, presumably due to connection problems or electrical interference. Although they are short in duration, these spikes may reach much higher values than ambient vibration amplitudes and contaminate an otherwise useful vibration record.

### 2.3 The random decrement technique

In this approach the random decrement (RD) technique is used to estimate the correlation functions of the structural responses. Under the assumption that the structural responses are a realization of a zero mean stationary Gaussian stochastic process, the RD functions are proportional to the correlation functions of the responses and/or to their first derivatives in relation to time [2], [3].

The RD functions are obtained by averaging time segments of the measured structural responses, with a common initial or triggering condition. Beside the auto RD functions, where the triggering condition and the time segments are defined in the same response signal, the cross RD functions can be also estimated, if the triggering condition for one response signal is used and the time segments to be averaged are taken from the other simultaneous response signals. The process is far more efficient than computing the systems' correlation functions from the response [4].

For that purpose, a level crossing triggering condition was considered, with the optimal value of the triggering level  $a = \sqrt{2} \sigma_x$ , where  $\sigma_x$  is the variance of the measured structural response  $x(t)$  [5].

## 2.4 SSI-COV Method

The stochastic identification methods are based on fitting the model to the correlation functions of the observed system response, which allows obtaining better accuracy of the identified dynamic characteristics than other methods that are based on the analysis of the functions of the response characterization [2].

The state-space representation matrices of a discrete-time dynamic system can be derived from the following factorization of the correlation functions  $R$ :

$$R_k = CA^{k-1}G \quad (1)$$

where  $C$  is the discrete output matrix,  $A$  is the discrete state matrix and  $G$  is the next-state output correlation matrix.

For this purpose the correlation functions are arranged in the two Hankel matrices,  $H_0$  and  $H_1$ , where the matrix  $H_1$  is shifted in time by one time interval in relation to matrix  $H_0$ :

$$H_0 = \begin{vmatrix} R_1 & R_2 & R_3 & \dots & R_q \\ R_2 & R_3 & R_4 & \dots & R_{q+1} \\ R_3 & R_4 & R_5 & \dots & R_{q+2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ R_p & R_{p+1} & R_{p+2} & \dots & R_{p+q-1} \end{vmatrix} \quad H_1 = \begin{vmatrix} R_2 & R_3 & R_4 & \dots & R_{q+1} \\ R_3 & R_4 & R_5 & \dots & R_{q+2} \\ R_4 & R_5 & R_6 & \dots & R_{q+3} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{p+1} & R_{p+2} & R_{p+3} & \dots & R_{p+q} \end{vmatrix} \quad (2)$$

The SSI-COV method is based on the factorization of the Hankel matrix ( $H_0, H_1$ ) in the product of the observability matrix ( $O_p$ ) by the stochastic controllability matrix ( $\Gamma_q$ ):

$$H_0 = O_p \Gamma_q; \quad H_1 = O_p A \Gamma_q \quad (3)$$

Applying the Singular Value Decomposition (SVD) algorithm to matrix  $H_0$ , the matrices  $O_p$  and  $\Gamma_q$  can be obtained, from which the dynamic characteristics ( $\Phi, \omega, \xi$ ) of the system can be identified [2].

## 2.5 Automated modal identification

For parametric model identification methods, the stabilization diagram is a useful tool for selecting a model order and eliminating the identified non-physical modes. The modal analysis is carried out at sequentially increasing model orders. A mode is considered to be “stable” between different model orders if its estimated characteristics agree within set limits. Modes which correspond to the physical mode generally have similar modal parameters at different orders. The model order can be chosen to maximize the number of stable modes. Alternatively, stable modes can be selected from different model orders. In either case, modes which have not stabilized are eliminated.

As an example, Figure 1 presents a stabilization diagram of the Salah Bey Viaduct deck vertical accelerations and pylons longitudinal accelerations. The average spectrum is also included in this figure. The modal parameters of the several stabilized modes could be obtained by selecting the model order.

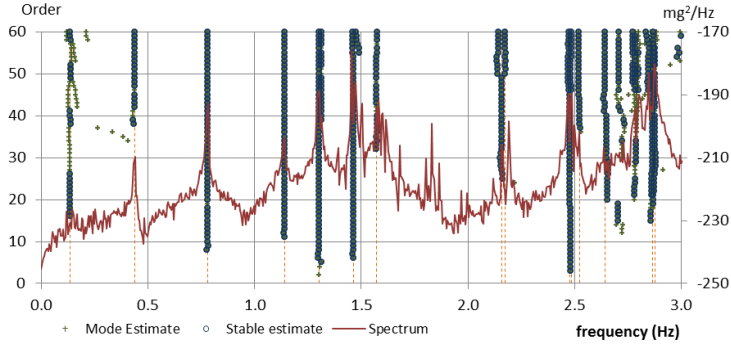


Figure 1: Stabilization diagram

However, for automating the process of identifying the structural vibration modes, Magalhães [6] proposed the cluster analysis procedure in place of the stabilization diagram, to group the mode estimates associated with the same physical mode and rule out the numerical or noisy estimates. For this propose, the mode estimates of the different model orders are evaluated using the Euclidian distance criteria:

$$d_{i-j} = \left| \frac{f_i - f_j}{f_i} \right| + (1 - MAC_{ij}) \quad (4)$$

where  $f_i$  and  $f_j$  are the natural frequencies of the mode estimates  $i$  and  $j$ ,  $MAC_{ij}$  is the Modal Assurance Criterion between the mode shapes of the estimates  $i$  and  $j$  [7]:

$$MAC_{ij} = \frac{|\mu_i^T \mu_j|^2}{(\mu_i^T \mu_i)(\mu_j^T \mu_j)} \quad (5)$$

However, to evaluate a similarity between the complex mode shapes the extension of Modal Assurance Criterion is used [8]:

$$MAC_{ij} = \frac{(|\mu_i^* \mu_j| + |\mu_i^T \mu_j|)^2}{(|\mu_i^* \mu_i| + |\mu_i^T \mu_i|)(|\mu_j^* \mu_j| + |\mu_j^T \mu_j|)} \quad (6)$$

where  $\mu_i$  and  $\mu_j$  are vectors associated to the mode estimates  $i$  and  $j$ ,  $*$  is the conjugate transpose of a complex vector and  $T$  is the transpose operation.

If the distance between two mode estimates is short, that means both estimates present similar natural frequencies and mode shapes. Therefore, they are probably representing the same physical mode, and so they should be included in the same cluster. For this purpose, the Euclidian distance limit should be lower to avoid the inclusion of estimates for different physical modes in the same cluster. However, if the distance is too small, the estimates associated with the same physical mode might be separated in several clusters.

For this approach, the modal analysis is performed sequentially for model orders from 2 to 60 (numbers of modes from 1 to 30) and the Euclidian distance limit is set to 0,01, that means the mode estimates are similar if the frequency matches within 1% and the mode shapes match within 99% (MAC or MACX). The cluster analysis is completed in two stages.

At first, the estimates are clustered based on the Euclidian distance criteria. If the distance between the estimate to be clustered and its cluster closest point is within the set limit, the estimate will be included in this cluster. At this phase, the modal damping ratios are not taken

into account because their estimates present a high scatter. However, the mode estimates with the damping ratio more than the 10% are eliminated.

Once the physical modes have similar modal parameters at different orders, in many cases from low-order model, it is expected that the clusters corresponding the physical modes contain the larger numbers of the mode estimates. Therefore, the groups with more elements should be selected. The number of groups to be selected could be the same number of physical modes expected in the frequency range of analysis. However, it is observed that some selected clusters may be not associated with any physical modes. Furthermore, it also happened that slight excited modes (with little weight on experimental data) are stabilized on higher orders. Therefore, the number of the clusters to be selected would be larger than the number of physical modes expected (Figure 2).

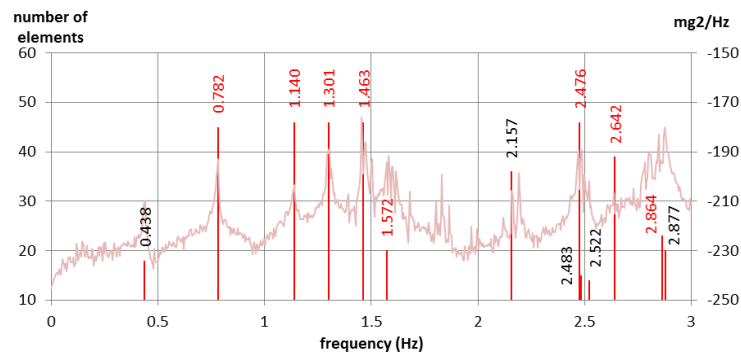


Figure 2: Selected clusters and the median frequencies

At the second stage, the convergence between the estimates of the same cluster is evaluated. The damping ratio factor is also appreciated.

Two mode estimates of the same cluster are judged convergent since the Euclidian distance is within the set limit and the difference of their modal damping ratios is less than 5%. The mode estimate is removed if no convergence is matched with more than one half elements of the cluster. Finally, the clusters whose mode estimates are not convergent are eliminated (Figure 2: clusters with black label). The maximum distance between the deduced estimates of the same cluster is within the set limit. The final outputs are the median values of the modal parameters (natural frequency, modal damping ratio and mode shape) corresponding to the estimates that belong to the same cluster.

Finally, the identified modes were paired with the known vibration modes, initially obtained from the experimental tests or numeric model.

### 3 SALAH BEY VIADUCT

#### 3.1 Description of the structure

The Salah Bey Viaduct in Constantine, Algeria, is a cable-stayed bridge with two pylons and a single suspended deck in its median plane, with a total length of 756 m [9]. The viaduct comprises 9 spans, including three suspended spans (Figure 3).

The main bridge has a 259 m central span and lateral spans of 119 m (South) and 105 m (North). The deck is a concrete prestressed box-girder, 3.75 m high, with large lateral cantilevers, reinforced each 7 m by diaphragms, including all cable anchoring sections.

Both pylons are in reinforced concrete: the South (P3) supports 17 pairs of cable-stays while the North (P4) has only 15 pairs anchored on it, making it an asymmetric structure.

**3.2 The structural health monitoring system**

The viaduct’s structural health monitoring system was set up during the construction, in order to detect the structural damage. This system includes the monitoring of weather conditions, static, dynamic and seismic structural behaviour, as well as a component related to durability.



Figure 3: General view of Salah Bey Viaduct

The dynamic component of the monitoring system includes 38 uniaxial accelerometers, 2 triaxial accelerometers, 6 horizontal displacement sensors and 4 bidirectional inclinometers, placed as presented in Figure 4. This system provides, by one hand, daily extraction of fundamental modal parameters and, by the other hand, monitoring of the bridge seismic behaviour.

The wide dispersion of sensors, along with the high sampling frequency required, led to the choice of a modular system Q series of Gantner Instruments [10]. The data is acquired continuously, with a sampling frequency of 250 Hz. The binary record file size is around 220 MB per hour.

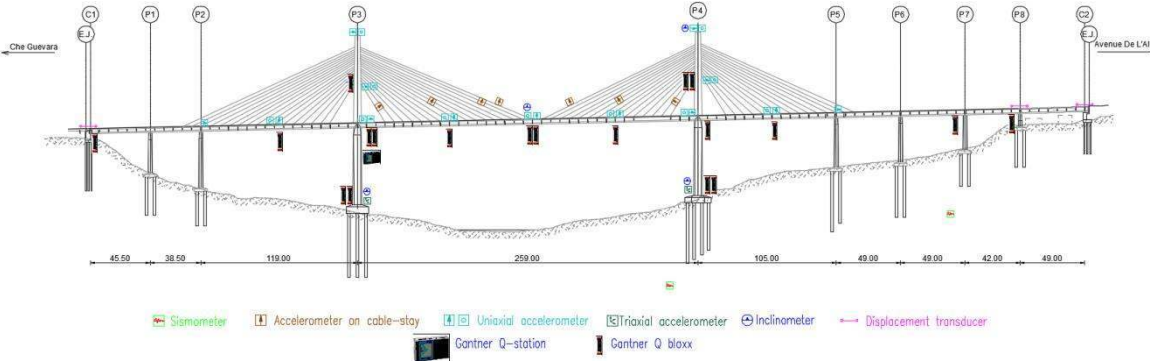


Figure 4: Dynamic monitoring system of the Salah Bey Viaduct

## 4 DATA FROM THE SALAH BEY VIADUCT SHM SYSTEM

### 4.1 Dynamic tests

In July 2014, after the construction completion, reception static and dynamic tests were carried out.

The ambient vibration tests provided the experimental identification of the bridge main modal parameters, which were compared with the corresponding parameters predicted by the numerical model. During these tests the 17 uniaxial accelerometers placed in the deck and pylons were used with a sampling rate of 250 Hz.

The viaduct's modal parameter identification was performed with the software ARTeMIS [11], using the technique of Enhanced Frequency Domain Decomposition (EFDD). The natural frequencies, mode shapes and damping ratio of a total of 17 vibration modes were thus identified based on measured response only (Table 1).

N°	Calc.	EFDD		SSI		MAC
	f (Hz)	f (Hz)	$\xi$ (%)	f (Hz)	$\xi$ (%)	
Vertical mode						
1	0,425	0,429	0,74	0,429	0,08	1,000
2	0,775	0,762	0,41	0,761	0,18	1,000
3	1,112	1,106	0,71	1,107	0,36	1,000
4	1,282	1,269	0,32	1,269	0,64	0,975
5	1,471	1,418	0,43	1,423	0,52	0,991
Torsion mode						
1	--	1,261	0,46	-	-	-
2	--	2,422	0,45	2,418	0,41	0,982
3	--	2,538	0,30	2,538	0,23	1,000
Longitudinal mode						
1	1,568	1,560	1,76	1,565	1,17	0,997
Transversal mode						
1	0,375	0,357	0,93	0,358	0,12	1,000
2	0,475	0,442	0,74	0,441	0,08	0,999
3	0,686	0,639	0,77	0,639	0,18	0,998
4	0,885	0,837	0,48	0,837	0,25	0,996
5	0,986	0,915	0,86	0,916	0,26	0,996
6	1,404	1,311	0,53	1,309	0,24	1,000
7	1,876	1,756	0,79	1,753	0,84	0,995
8	2,542	2,292	0,31	2,288	0,57	0,984

Table 1: Experimental identified modal parameters from ambient tests

The ambient vibration tests data was also used as benchmarking for the proposed automated modal identification SSI method. The identified modal parameters (frequencies and damping ratios) are also presented in Table 1.

There is a good agreement between the results obtained by EFDD and SSI techniques for both frequencies and for mode shapes, as reflected in the high Modal Assurance Criterion (MAC) values. However, the damping ratios obtained by SSI are, in general, lower than those obtained by EFDD.

The modal parameters identified from the ambient vibration tests are compared with the parameters computed by the 2D finite element model. In general, a very good accordance was achieved.

**4.2 Continuous dynamic monitoring**

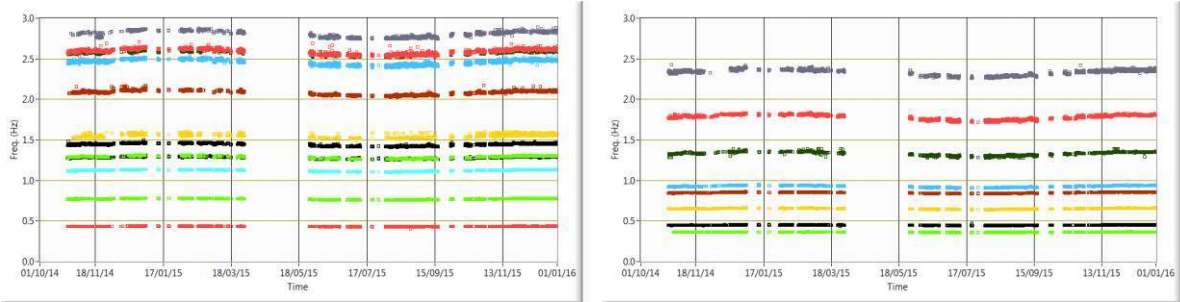
The dynamic monitoring system has been operating since October 2014. The proposed methodology was implemented in the continuous monitoring system.

The modal parameters of the vertical, torsion and longitudinal modes were identified from the measurements of 18 accelerometers (10 vertical and 8 longitudinal accelerations). The transverse modes were obtained from the transverse accelerations acquired by 11 transducers. The records were processed with low-pass digital filtering at 4 Hz with Butterworth filter of order 8 and were decimated to a sampling frequency of 10 Hz.

The variation of the frequencies associated with the identified modes in the period from October 2014 to December 2015 is presented in Figure 5. The Figure 6 shows some modal shapes, corresponding average values of the identified modal shapes in same period.

Temperature and humidity affect material properties and boundary conditions. Large volumes of traffic can change a structure’s mass. All these factors can influence the bridge modal parameters but temperature is the more important variable.

The variation of the 2<sup>nd</sup> vertical mode frequency with temperature is presented in Figure 7. The frequency increases during the winter and decreases during the summer, with a difference of about 0,03 Hz. The relationship between the temperature and the frequency is almost linear. This behaviour can be found in all the identified vibration modes and the thermal sensitivity varies between 0,06% and 0,18%, increasing for higher order vibration modes.



a) Vertical, torsion and longitudinal modes

b) Transverse modes

Figure 5: Frequencies of the identified modes



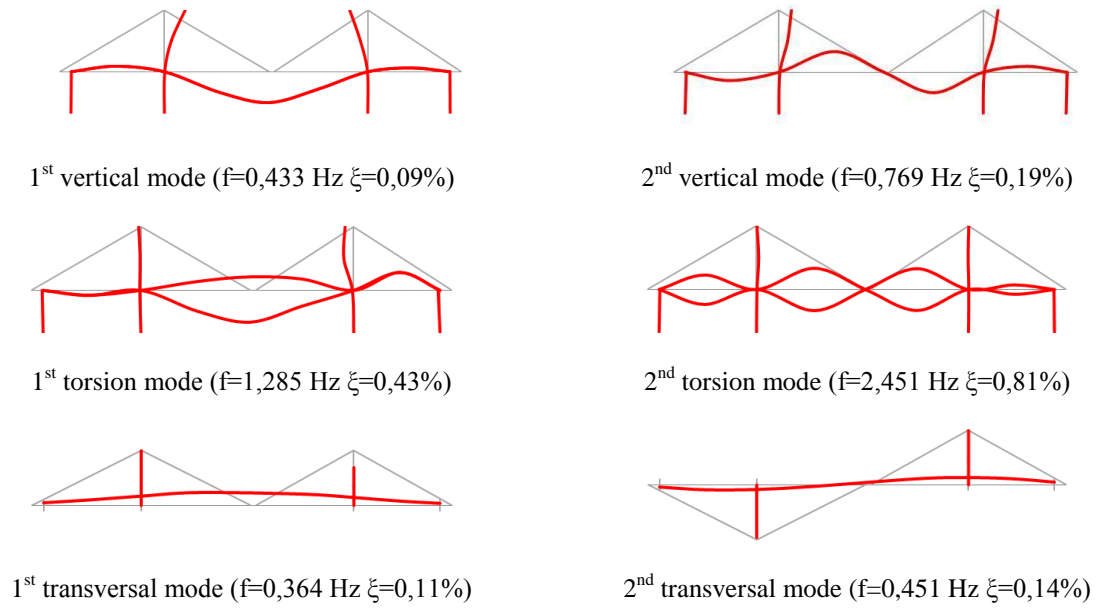
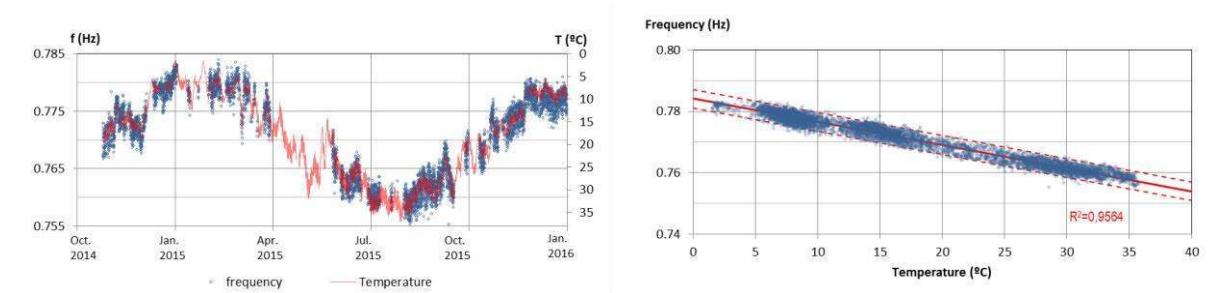


Figure 6: Some identified modal shapes



## 5 CONCLUSIONS

An integrated modal identification method was developed. This method uses the covariance-driven stochastic subspace identification method (SSI-COV) and the random decrement technique to obtain correlation functions of the structural responses. The modal parameters automatic selection is carried out by a cluster analysis procedure based on the Euclidian distance criteria.

In order to validate and illustrate the proposed method, it was applied to the data provided by the dynamic monitoring system of a large cable-stayed bridge, continuously operating since October 2014. The values obtained by the proposed method have a good correlation with those provided by the technique of Enhanced Frequency Domain Decomposition (EFDD) implemented in ARTeMIS.

The modal parameters evolution during one year of measurements shows the temperature influence in the modal parameters (the variation of the natural frequency was 2% to 5%). This influence has to be taken into account in a damage identification procedure.

## 6 ACKNOWLEDGEMENTS

The authors would like to acknowledge the cooperation of the Direction des Travaux Publics de la Wilaya de Constantine, Andrade Gutierrez, bridge contractor, and Betoteste, partner in the bridge instrumentation.

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