Intelligent Automatic Operational Modal Analysis: Application to a Tall Building

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Abstract. The stochastic subspace identification (SSI) technique is widely adopted for operational modal analysis of structural systems. Regardless of the specific implementation, its workflow basically consists of four main steps: definition of the control parameters governing the SSI algorithm; estimation of the system poles and construction of the stabilization diagram (SD); interpretation of the SD; quantification of the confidence level associated to the modal results. The definition of the control parameters ruling the modal identification via SSI algorithms play a crucial role. Manual selection procedures and rules-of-thumb have been largely employed for this task, but they are unsuitable for reliable automatic applications. Therefore, a new paradigm for automatic operational modal analysis is presented in this work. The proposed approach is named intelligent automatic operational modal analysis (i-AOMA) method and relies on the effective integration between the SSI algorithm and a machine learning technique. Initially, quasi-random samples of the control parameters for the SSI algorithm are generated. Once the SSI algorithm is performed for each sample, the corresponding SDs are processed to prepare a database for training the intelligent core of the i-AOMA method. This is a machine learning technique that drives intelligently the selection of the control parameters for the next applications of the SSI algorithm, which is performed until a convergence criterion is fulfilled. At the end, the uncertainty level about the modal estimates due to the variability of the control parameters is assessed. The potential of the proposed approach is demonstrated through the identification of a large structure.

Keywords: Machine Learning · Automatic Operational Modal Analysis · Stabilization Diagram · Stochastic Subspace Identification · Tall Building.

1 Introduction

In recent years, an increasingly urgent demand manifests for monitoring the health state of existing civil infrastructures for mainly preventing safety issues. Not only in civil engineering but also in aerospace and mechanical engineering the role of structural health monitoring (SHM) solutions gained growing importance [1]. Several different approaches were proposed to inspect the health state during time based on measuring some physical quantities, often with indirect and output-only solutions [2]. A common strategy that is based on the in-depth analysis of the vibration response is known as the operational modal analysis (OMA) [3]. The aim is to characterize the dynamic response of structures providing its modal information, viz. the natural frequencies, damping ratios, and mode shapes. One of the most widespread OMA techniques is stochastic subspace identification (SSI), i.e. a parametric time-domain method based on the state space representation with stochastic components related to process and measurement noise components [4]. According to the specific procedure to resolve the stochastic state space representation, two main variants were formulated for the SSI, namely the covariance-based SSI (SSI-cov) [5] and the data-driven SSI (SSI-data) [6].

The installation of a functional long-term SHM system requires mounting an efficient data management and acquisition setup with proper configurations to work automatically and autonomously during time, and additionally equip the entire system with efficient data processing and interpretation tools [7]. These requirements moved the research efforts toward automatic operational modal analysis (AOMA) methods. Several recent AOMA proposals can be formalized as four steps solutions [8,5]: 1. An arbitrary choice of the SSI control parameter is still required; 2. The stabilization diagram (SD) is computed; 3. The SD is post-processed with stability check hard and soft criteria to retain only stable poles; 4. The use of novel tools such as Machine Learning (ML) methods has been extensively adopted lately to identify the clusters of stable poles alignments associated to the natural modes.

Despite [9,10] evidenced some reasonable criteria to select the best set of SSI control parameters, their arbitrary choice is still a limitation to the full automation of a proper AOMA method. Moreover, their poor choice may compromise the quality of the experimental modal estimates. Indeed, in the current study, a recently developed intelligent AOMA method, denoted as i-AOMA, is herein described. This method attempts to improve the automation level of the existing AOMA solutions.

The current manuscript is organized as follows. In the next section, the key principles of i-AOMA method are illustrated. Thereafter, the benefits of i-AOMA are tested on a real-world tall building case study, the Al-Hamra Tower in Kuwait. In section 3 a brief description of the case study is reported, and in the subsequent section 4 its dynamic identification results are discussed.

2 Intelligent Automatic Operational Modal Analysis method

In the current section, only the crucial aspects of the recently developed Intelligent Automatic Operational Modal Analysis method, denoted as i-AOMA, are discussed here for completeness. An exhaustive presentation is instead reported in [11]. The related implementation code has been developed in Python language and it is freely accessible at the following Github repository: https://github.com/marco-rosso-m/i-AOMA.

Since the structures under investigation are usually characterized by an unknown and infinite number of degree of freedoms (DOFs), the mathematical procedures involved in the SSI method are based on the calculation of the state-space solutions for progressively increasing model orders. This conservative overestimation approach provide both physical and spurious poles arranged in the acknowledged graphical representation denoted as stabilization diagram (SD) [3]. The identification of stable poles alignments reveals the natural frequencies of the system under study. Nonetheless, a poor choice of the SSI-cov control parameters may jeopardize the quality of the entire identification process. Therefore, first steps in this direction were moved by [12,13]. They proposed to employ a Monte-Carlo-based approach to construct the stabilization diagram. Their crucial vision was that based on various SSI-cov analyses, spurious modes exhibited only occasionally, whereas physical ones occur recursively. Based on these key aspects, the authors proposed in [11] an enhancement of the starting proposal of [12,13] and overcoming their main limitations. In fact, Zhou et al. [12,13] fixed an arbitrary number of Monte Carlo simulations equal to 100 without any apparent reason. Secondly, the Monte Carlo sampling scheme applies only for the maximum model order and the time window slicing, which extract only a sub-portion of the entire vibration signal. Nevertheless, this approach is still preventing a full automation of the process since the other crucial control parameter, i.e. the number of block rows of the Hankel matrix, was still arbitrarily defined. Eventually, no uncertainty evaluation was committed despite an underlying Monte Carlo scheme.

Therefore, the main novelties introduced by the i-AOMA method with respect to the existing AOMA solutions are the adoption of a Monte Carlo scheme to enhance the automation level, the uncertainty evaluation of the Monte Carlo-based modal estimates, and the adoption of a not-conventional ML clustering method for selecting the stable pole alignments, i.e. the Kernel Density Estimation (KDE) algorithm [14].

The i-AOMA is formalized as a two-step methodology. Phase 1, denoted as the exploration phase, starts with the rough definition of the SSI control parameters which are sampled according to a quasi-Monte Carlo scheme [15]. The user has to define an arbitrary number of Monte Carlo simulations, i.e. defining a set of SSI-cov to be computed. To further save computational time, if the sampling scheme selects an infeasible set of parameters or if the SSI-cov last more than 30 seconds, the analysis is interrupted and the corresponding set of control parameters is labeled as infeasible. After collecting the prescribed number of useful results, the stabilization diagrams are overlapped and post-processed with the stability check criteria to retain only the stable ones. Afterwards, the KDE algorithm is employed to select the stable poles alignments with an automatic statistical-based rule. An information content metric (IC_k) is computed for every simulation k to quantify the quality of the results for every set of governing parameters in providing several stable retained poles $N_{stp,k}$ concerning all the stable and unstable poles computed $N_{totp,k}$.

Phase 2, denoted as intelligently-driven quasi-Monte Carlo scheme, starts with training a ML random forest (RF) algorithm based on the sampled sets of governing parameters and their relative IC_k [16]. In this way, the RF can intelligently drive the subsequent sampling of SSI control parameters, thus saving computational resources by discarding those sets that are predicted to provide almost negligible information contents. The acceptable shifting convergence band rule (ASCBR) [17] acts as a stopping criterion, i.e. when the total sample variance of the considered mode shapes exhibits a variation limited within the ±2% for the last batch of simulations, set e.g. to 50. When the convergence criterion is met, the intelligent-driven RF phase is stopped and post-processing procedures are performed, similarly to phase 1. The stabilization diagrams are overlapped and only stable poles are retained, then the KDE algorithm identifies the mode clusters. Since every cluster of stable poles' alignments contains poles coming from various choices of input parameters, the authors analyzed the confidence bands for epistemic uncertainties of the modal parameters, i.e. for natural frequencies, for damping ratios, and even for mode shapes.

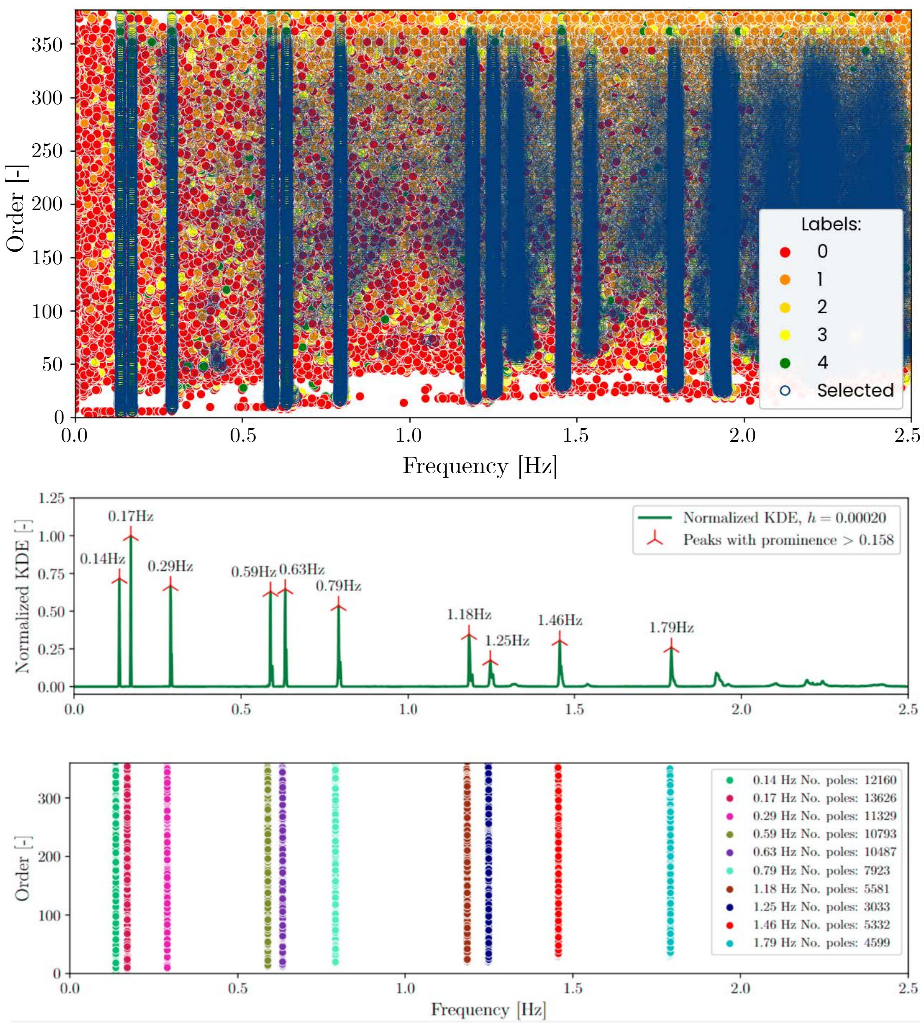
3 A tall building case study: the Al-Hamra Tower in Kuwait

The i-AOMA method has been tested on a real-world tall building case study: the Al-Hamra Tower in Kuwait city, i.e. the tallest building in Kuwait. This is a 413 m high twisting reinforced concrete structure with a square plan, hosting a five-story mall and offices in its beyond 70 floors above the ground. Completed in 2011, the tower has been equipped with a long-term monitoring system composed of a total of 24 biaxial force balance accelerometers, deployed three at a time for every monitored floor. The monitored floors are the 76th, the 65th, the 54th, 42nd, the 29th, the 16th, the 6th, and the basement floor B2.

4 Al-Hamra tower dynamic identification

The data herein considered were sampled in 2022, on May 2nd, with a sampling rate of 200 Hz. The one-hour recording was decimated with a decimation factor of 40. Indeed, as previously detailed in [18], a high-fidelity model was calibrated on the experimental dynamic data, showing that the dynamic of actual interest is below 1 Hz, in other words, demonstrating that the first dozen modes are very closely spaced.

The number of user-defined quasi-Monte Carlo sampling for phase 1 of i-AOMA was set to 200. Afterward, the so far computed stabilization diagrams were overlapped and processed with the KDE algorithm in order to select the stable pole alignments associated with the first modes of interest. The information content was calculated for every simulation in order to



(a)

Fig. 1. i-AOMA Phase 2, overlapped SD and KDE selection of modal clusters.

quantify the quality of the results of every simulation. The RF algorithm was then trained based on the IC values to intelligently drive the quasi-MC sampling in the subsequent phase 2 of the i-AOMA method. Finally, the convergence criterion was met after collecting 500

Table 1. Al-Hamra Tower experimental modal properties. Notes: EW - east-west; NS: north-south; Freq: Frequency; Damp: Damping ratio; Std.Dev: Standard deviation.

	i-AOMA				Reference [18]	
No.	Freq. [Hz]	Freq.Std.Dev. [Hz]	Damp. [%]	Damp.Std.Dev. [%]	Freq. [Hz]	Mode Description
1	0.14	0.0005	1.08	0.32	0.14	1st NS Bending
2	0.17	0.0004	0.54	0.21	0.18	1st EW Bending
3	0.29	0.0004	0.66	0.19	0.31	1st Torsion
4	0.59	0.0004	0.76	0.14	0.61	2nd NS Bending
5	0.63	0.0005	0.58	0.10	0.66	2nd EW Bending
6	0.79	0.0004	0.62	0.17	0.84	2nd Torsion
7	1.18	0.0005	0.82	0.14	1.24	3rd NS Bending
8	1.25	0.0006	1.11	0.31	1.30	3rd EW Bending
9	1.46	0.0006	0.75	0.15	n.a.	3rd Torsion
10	1.79	0.0006	1.05	0.17	n.a.	4th NS Bending

new useful results, intelligently discarding about 1811, thus saving computational resources. The first ten modes have been eventually identified by the KDE post-processing of the final overlap of all the computed stabilization diagrams retaining only stable poles as illustrated in Fig. 1. These modal properties are reported in Tab. 1. The first four modes are depicted in Fig. 2. It is worth noting that the uncertainties associated with the natural frequencies are very limited, whereas greater orders of magnitude are associated with damping ratios and mode shapes. Therefore, from these results, it is evident how the various choice of parameters may provide quite uncertain results which propagate especially in the final mode shape of interest, and thus an automatic approach likewise the present one may avoid an arbitrary poor choice with deleterious effects. Furthermore, the i-AOMA demonstrated its ability to discriminate among very closely spaced modes.

5 Conclusions

A recently developed machine learning-based automatic operational modal analysis (AOMA) framework, the intelligent AOMA, has been presented in this study. This method attempts to overcome the main limitations of the commonly widespread AOMA frameworks. The actual benefits of this procedure have been tested on a real-world tall building, i.e. the Al-Hamra Tower. Located in Kuwait city, it is the highest building in Kuwait, and it has been equipped with a monitoring system of 24 biaxial accelerometers. The case study is challenging since the first dozen modes are very closely spaced and appear below 2 Hz. The obtained results demonstrated how the various choice of parameters may provide quite uncertain results which propagate especially in the final mode shape of interest. Therefore, an automatic approach likewise the present one may avoid an arbitrary poor choice with deleterious effects. Future

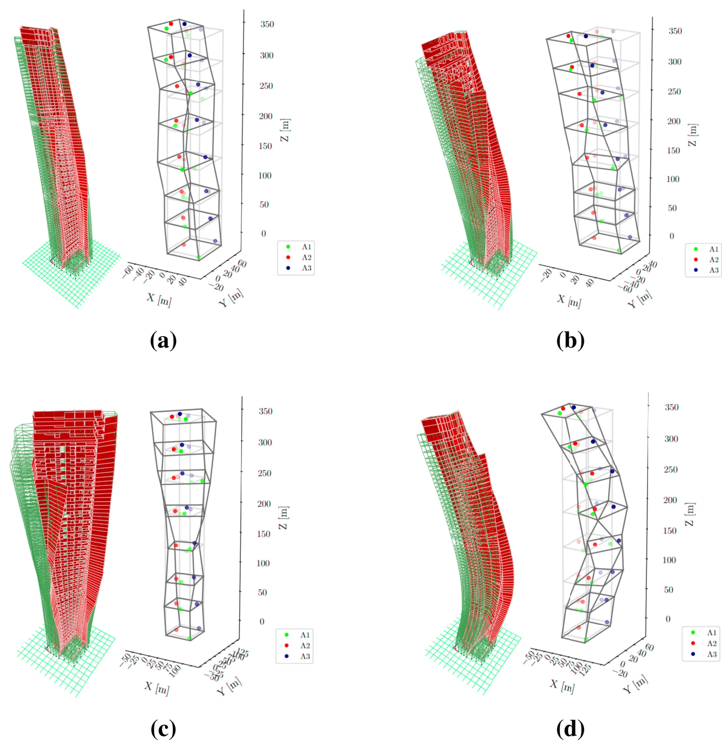


Fig. 2. Illustration of the first four mode shapes retrieved by the i-AOMA and comparison with the reference finite element model [18].

studies aim to further improve the current methodology to provide increasingly smart, reliable, and more automatic methods for structural health monitoring purposes.

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