Evaluation of a MEMS–based sensing unit for structural health monitoring: results on a medieval tower

Roberto Guidorzi[a], Roberto Diversi[a], Loris Vincenzi[b] and Vittorio Simioli[c]

[a] DEIS, University of Bologna, Bologna, Italy.
[b] DIMEC, University of Modena and Reggio Emilia, Modena, Italy.
[c] TELECO SpA, Lugo, Italy.

December 13, 2011

Abstract

Structural health monitoring is a field that relies on different methodologies to develop procedures that characterize the dynamic properties of physical structures to identify possible deteriorations of their behaviors. SHM systems include usually a data acquisition subsystem suitable for recording the structure response to ambient or external excitations. The recorded data are then analyzed in order to characterize the dynamic properties of the considered structure. This paper describes some tests performed by means of a new advanced SHM system, the Teleco SHM602, on a truncated middle-age tower presently included in an ancient palace of the XVI century located in the central part of Bologna. These tests rely on models obtained by means of standard and advanced identification techniques.

Keywords: Structural health monitoring, Identification, AR models, AR+noise models.

1 Introduction

Civil infrastructures like highways, bridges, airports, seaports, railroads, water management systems, oil and gas pipelines, are of paramount importance for economic and industrial development. These systems are characterized by high costs, strong impact on the safety and quality of life for large communities and long operative lives. Their proper management requires, consequently, the adoption of carefully selected policies developed taking into account the delicate balance between potentially conflicting requirements like, for instance, achieving high safety standards and limiting maintenance costs. Moreover, some specific events like earthquakes, floods or tornadoes can lead to very critical decisions in ascertaining the integrity of surviving structures and their suitability to fulfill their intended role. Similar problems afflict the evaluation of the state of structures built during the last century (e.g. many bridges in the United States) and of ancient buildings inside large cities, exposed to the stress caused by the increase of surface and underground urban transport systems. The relevance of these problems is not limited, however, to the evaluation of the state of structures potentially damaged by traumatic events; the advanced technologies implemented in the realization of new projects like, for instance, buildings with active seismic response control systems are even more demanding since they require a proper monitoring concerning the whole operating life of the structures.

All dynamic Structural Health Monitoring (SHM) implementations rely on data, measured with a suitable sampling rate by a certain number of sensors mounted on the structure to be monitored [1, 2]. Traditional

SHM systems are essentially composed by a certain number of analog sensors (strain gauges, accelerometers, temperature sensors) connected, through signal conditioning units, to multichannel data loggers. The measures obtained with these sensors describe the structure response to external or internal mechanical excitations due to wind and other meteorological phenomena, vehicle traffic, seismic events, mass movements [3] or to the use of specific excitation hardware like mechanical shakers [4]. The evaluation of the information contained in the data is then performed off-line by experts relying on suitable models of the structure to be analyzed and on the compliance of these models with the measured data [5]. The state of the structure can be finally evaluated by comparing the responses obtained in reference (integrity) conditions with the current ones; these comparisons could be (and, sometimes, are) performed by directly extracting from the collected time series information depending only on the structure, for instance their power spectra. In general it is preferable to avoid the storage and manipulation of the enormous amounts of data usually generated by SHM systems and to work only on some form of concentrated information extracted from the data, like dynamic models extracted from the data by means of identification techniques [2]. These techniques allow not only a large condensation of information but can also be effectively used to separate the information contained in the acquired data sets from the observation errors due to the intrinsic noise of the sensors and to other errors due to the inevitable misfits between the considered class of models and the real process to be described. Thus the power spectrum associated with an identified model will look as (and will be) a smoothed version of that directly obtained by applying a FFT to the measured sequences that contains spurious lines due to additive noise.

In this complex and demanding context, SHM (Structural Health Monitoring) methodologies are moving, taking advantage of the unprecedented development of sensor, microelectronics and microprocessor technologies, towards their life-long integration in new projects while still playing the role of advanced analysis tools for evaluating the state of structures not endowed with permanent monitoring systems. In particular, the introduction of MEMS sensors allows the realization of systems that conjugate a reduced cost with performances suitable for SHM applications. A new generation of SHM systems that integrates advanced sensor technologies with distributed computational power as well as efficient implementations of identification methodologies is now appearing on the market. These advanced systems rely on intelligent sensors that elaborate local models and exchange data, information and models on a local network under the supervision of a control/storage unit accessible also on the Internet. The purpose of this paper is to describe some tests performed with the new Teleco SHM602 system that has been developed on the basis of researches performed at Bologna University and realized by Teleco SpA. In order to verify the capabilities of this system, some tests on a truncated middle-age tower presently included in an ancient palace of the XVI century, Palazzo Saraceni, have been performed and compared by using identified autoregressive (AR) and "autoregressive plus noise" (AR + noise) models.

The paper is structured as follows. Section 2 describes the purpose of the tests, the structure of the considered tower and the collected data sets. Section 3 recalls some basic identification results concerning traditional AR models and the more sophisticated class of AR + noise models that have been used in this analysis; it reports also a computational procedure for the identification of these models. Section 4 reports the results of the modal analysis performed on AR and AR + noise models identified from data concerning an artificial stimulation of the structure and from data where the excitation was due to urban traffic. Some concluding remarks are finally reported in Section 5.

2 Purpose of the tests and data collection

The purpose of the tests described in the following is to evaluate the suitability of the new SHM system Teleco SHM602 developed in the context of a cooperation between the University of Bologna and Teleco SpA, in monitoring old buildings inserted in urban environments. The tests, therefore, do not concern the construction of a complete description of the dynamical behavior of the considered structure. The architecture of the SHM602 is compliant with the recommendations reported in [6, 7] and differs from that of traditional SHM systems in that it is based on a network of sensing units (TSM02) based on MEMS accelerometers (Figure 1a) and on local computing resources that manage data acquisition, filtering, transmission and also the local construction of dynamical models. These units are connected to a remote data acquisition and storage controller (TSD10 - Figure 1b) by means of a bus in order to avoid the invasiveness of analog radial connections as well as their sensitivity to electromagnetic disturbances. MEMS sensors exhibit, in general, a noise floor higher than traditional piezoelectric seismic accelerometers and this requires a suitable smoothing of the data. They are endowed, however, with a better behavior at low frequencies and with a faster recovery from overload conditions. Moreover, the identification techniques used for the extraction of dynamical models from the raw measures perform, intrinsically, an operation that, asymptotically, cancels the effects of the noise. The tests described in the paper have been performed during the development stage of the TSM02, with the purpose of evaluating the overall behavior of this unit and of comparing the possible identification techniques to be implemented in the local firmware.

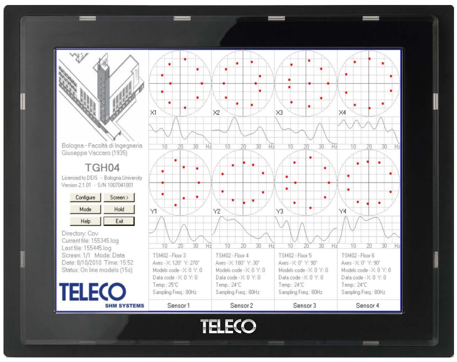

Figure 1: SHM602 system: (a) sensing units TSM02 and (b) data acquisition and storage controller TSD10

The building where the tests have been performed, Palazzo Saraceni, is one of the most interesting architectural examples of Renaissance palaces in Bologna (Figure 2). It was constructed at the beginning of the XVI century by the Saraceni family and includes in its structure the much older Bertolotti tower built between the end of the XII and the beginning of the XIII century and subsequently truncated in the second half of the XV century. Its present height is 16 m, every side of its square basis has a length of 8.64 m and its walls have a width of 1.47 m (at ground level). The walls are constructed with the typical technology adopted in Bologna towers, consisting in two separate walls (an internal ticker wall and an external thinner one); the space between the walls was filled with stones and mortar. The purpose of the data collection concerned the identification of models of the dynamic behavior of the tower under artificial and natural excitation conditions for evaluating the performance of the TSM02 sensors and for comparing different identification procedures. The main components of this system consist in a controller/storage unit and in intelligent sensing units connected to the controller by means of a serial bus. Every unit can send the measures of the accelerations measured on two orthogonal axes and that of the temperature, with a sampling rate that can be selected by the user between 20 Hz and 80 Hz. The sensing units, that rely on proprietary signal processing techniques, perform the identification of dynamic models whose order can be selected between 2 and 10. Due to its good signal-to-noise ratio even in the low and medium-low frequency ranges, the SHM602 system is a suitable tool for monitoring flexible structures like suspended bridges and tall towers; moreover, thanks to its flexibility, it can be efficiently used also for more stiff structures like historical buildings and short-span bridges. The data concerning the tests described in this paper have been collected at a sampling rate of 80 Hz.

Figure 2: Palazzo Saraceni in Bologna

3 Identification of AR and AR+noise models

The dynamic behavior of the tower has been identified by using two types of models: standard AR models and AR + noise models.

A classic AR model of order n is described, in the scalar case, by the equation

$$y(t) + \alpha_1\, y(t-1) + \cdots + \alpha_n\, y(t-n) = e(t) \tag{1}$$

where the driving process $e(t)$ is white noise and $y(t)$ denotes the measure of the process to be modeled at time t [8, 9]. Note that $e(t)$ plays the double role of excitation of the system modes and equation error. Starting from N observations $y(1), y(2), \ldots, y(N)$, the AR parameters can be consistently estimated by means of the well-known least squares formula

$$\hat{\theta} = \left(\sum_{t=n+1}^{N} \varphi_y(t)\varphi_y^T(t) \right)^{-1} \sum_{t=n+1}^{N} \varphi_y(t)\, y(t) \tag{2}$$

where

$$\varphi_y(t) = [\, y(t-1)\ \ldots\ y(t-n)\,]^T \tag{3}$$

$$\hat{\theta} = \left[\hat{\alpha}_1\ \cdots\ \hat{\alpha}_n\right]^T. \tag{4}$$

To take into account also the presence of measurement errors, it is possible to consider "AR + noise" models of the type

$$x(t) + \alpha_1\, x(t-1) + \cdots + \alpha_n\, x(t-n) = e(t) \tag{5}$$

$$y(t) = x(t) + w(t), \tag{6}$$

where $x(t)$ denotes an AR process driven by the input $e(t)$ and $y(t)$ is the available observation, affected by the additive noise process $w(t)$. It will be assumed that $e(t)$ and $w(t)$ are zero–mean white processes, mutually uncorrelated and with unknown variances σ_e^{2*} and σ_w^{2*}. It is easy to show that the model (5)–(6) is not an all–pole model and the use of the least squares estimator (2) leads to biased estimates [10, 11]. In particular, it can be proved that the estimated AR poles are biased toward the center of the unit circle, leading thus to a smoothed spectrum [11]. In this paper, the AR + noise models will be identified by means of the approach introduced in [12], that is characterized by a reduced computational complexity and by a good estimation accuracy. This method, that maps the AR + noise identification problem into an errors–in–variables one, is summarized in the next subsection (see [12] for further details).

3.1 Identification of AR + noise models

Let us define the vectors

$$\bar{\varphi}_x(t) = [\, x(t)\, x(t-1)\ \ldots\ x(t-n)\,]^T \tag{7}$$

$$\bar{\varphi}_y(t) = [\, y(t)\, y(t-1)\ \ldots\ y(t-n)\,]^T = [\, y(t)\, \varphi_y^T(t)\,] \tag{8}$$

$$\bar{\varphi}_w(t) = [\, w(t)\, w(t-1)\ \ldots\ w(t-n)\,]^T \tag{9}$$

$$\bar{\varphi}_e(t) = [\, e(t)\ \underbrace{0\ \ldots\ 0}_{n}\,]^T, \tag{10}$$

and the extended parameter vector

$$\bar{\theta}^* = \left[\, 1\ \alpha_1 \ldots\ \alpha_n \,\right]^T = \left[\, 1\ \theta^{*T} \right]^T. \tag{11}$$

It is possible to represent model (5)–(6) in the form

$$\left(\bar{\varphi}_x^T(t) - \bar{\varphi}_e^T(t)\right)\ \bar{\theta}^* = 0 \tag{12}$$

$$\bar{\varphi}_y(t) = \bar{\varphi}_x(t) + \bar{\varphi}_w(t). \tag{13}$$

Define also the covariance matrices

$$R_{xe} = E\left[\, \left(\bar{\varphi}_x(t) - \bar{\varphi}_e(t)\right)\left(\bar{\varphi}_x(t) - \bar{\varphi}_e(t)\right)^T \,\right] \tag{14}$$

$$R_y = E\,[\, \bar{\varphi}_y(t)\, \bar{\varphi}_y^T(t)\,], \tag{15}$$

where $E[\,\cdot\,]$ denotes the mathematical expectation. By taking into account (12), (13) and the assumptions on $e(t), w(t)$, it is possible to obtain the relations

$$R_{xe}\, \bar{\theta}^* = 0 \tag{16}$$

$$R_y = R_{xe} + \tilde{R}^*, \tag{17}$$

where

$$\tilde{R}^* = \text{diag}\,[\sigma_e^{2*} + \sigma_w^{2*},\, \sigma_w^{2*}\, I_n]. \tag{18}$$

Note that the AR coefficients cannot be directly estimated by means of (16)–(17) because the variances $\sigma_e^{2*}, \sigma_w^{2*}$ are unknown and only the matrix R_y can be estimated from the data sequence $y(1), y(2), \ldots, y(N)$. Consider now the problem of finding the family of all nonnegative definite diagonal matrices $\tilde{R}$ of the type

$$\tilde{R} = \text{diag}\,[\sigma_e^2 + \sigma_w^2,\, \sigma_w^2\, I_n] \tag{19}$$

such that

$$R_y - \tilde{R} \geq 0, \qquad \min \text{eig}\,(R_y - \tilde{R}) = 0. \tag{20}$$

It is possible to prove [12] that this family is defined by the pairs (σ_w^2, σ_e^2) defined by

$$\sigma_w^2 \in [\,0, \sigma_{w\,\max}^2\,] \tag{21}$$

$$\sigma_e^2 = \sigma_y^2 - \sigma_w^2 + r^T\,\theta(\sigma_w^2). \tag{22}$$

where

$$\sigma_{w\,\max}^2 = \min \text{eig}(R_y) \tag{23}$$

$$\theta(\sigma_w^2) = -(R - \sigma_w^2\, I_n)^{-1}\, r, \tag{24}$$

while the scalar σ_y^2, the vector r and the matrix R can be obtained from the following partition of R_y

$$R_y = \begin{bmatrix} \sigma_y^2 & r^T \\ r & R \end{bmatrix}. \tag{25}$$

Every value of $\sigma_w^2 \in [\,0, \sigma_{w\,\max}^2\,]$ leads to a coefficient vector (24). Moreover, also the variance σ_w^{2*} of $w(t)$ belongs to $[\,0, \sigma_{w\,\max}^2\,]$ and the associated coefficient vector coincides with θ^*, i.e. $\theta(\sigma_w^{2*}) = \theta^*$. To estimate σ_w^{2*} (and thus θ^*) within the admissible interval, the following cost function can be proposed [12]

$$J(\sigma_w^2) = \|R_y^h\, \bar{\theta}(\sigma_w^2)\|_2^2 = \bar{\theta}(\sigma_w^2)^T (R_y^h)^T R_y^h\, \bar{\theta}(\sigma_w^2), \quad \sigma_w^2 \in [0, \sigma_{w\,\max}^2], \tag{26}$$

where

$$\bar{\theta}(\sigma_w^2) = \left[\,1\ \theta^T(\sigma_w^2)\right]^T \tag{27}$$

$$R_y^h = E\,[\,\varphi_y^h(t)\,\varphi_y^T(t)\,] \tag{28}$$

$$\varphi_y^h(t) = [\,y(t-n-1)\, y(t-n-2)\, \ldots\, y(t-n-q)\,]^T, \tag{29}$$

and $q \geq n$ is a user–chosen parameter. In fact, it is easy to show that

$$R_y^h\, \bar{\theta}^* = 0. \tag{30}$$

Relation (30) consists in a set of q high–order Yule–Walker equations that are not directly used to identify the parameters θ^* but only to construct the cost function (26).

In the practical implementation of the algorithm, the covariance matrices R_y and R_y^h must be replaced by the sample estimates

$$\hat{R}_y = \frac{1}{N-n} \sum_{t=n+1}^{t=N} \varphi_y(t)\, \varphi_y^T(t) \tag{31}$$

$$\hat{R}_y^h = \frac{1}{N-n-q} \sum_{t=n+q+1}^{t=N} \varphi_y^h(t)\, \varphi_y^T(t), \tag{32}$$

so that the variance σ_w^{2*} is estimated by minimizing $J(\sigma_w^2)$ on $[\,0, \hat{\sigma}^2_{w\,\max}\,]$, where

$$\hat{\sigma}^2_{w\,\max} = \min \mathrm{eig}(\hat{R}_y). \tag{33}$$

4 Experimental results

All measures have been performed by positioning a TSM02 sensor at the highest floor of the tower. A first set of measures describes the response to a pulse applied to the structure by means of a falling mass; the considered sampling frequency was 80 Hz. Two typical responses, concerning time intervals of 6 and 7 s are reported in Figure 3; it can be observed that the measured acceleration is relatively high, of the order of 100 mg. The identification of these data has been performed by means of order 14 AR and AR + noise models. The power spectral density of the AR models is reported (dashed line) in Figure 4 where the power spectral density of the AR + noise models is plotted with a solid line. It can be observed that in both plots the difference between the spectra of AR and AR + noise models is barely visible and that the results concerning the two data sets are strongly congruent. Both plots show peaks at the frequencies of, approximately, 10 Hz, 23 Hz and 35 Hz.

Other data have been collected by recording the response to the excitation provided by urban traffic. Two

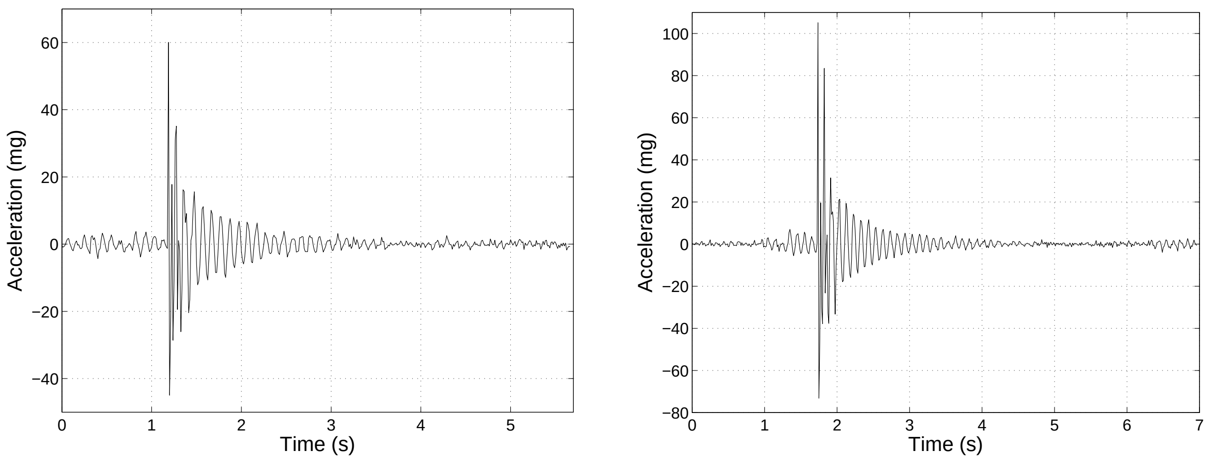

Figure 3: Measured response to falling mass impulses

typical sequences are reported in Figure 5; they refer to time intervals of slightly more than 60 s and 350 s. In these cases the maximal acceleration that has been observed (4 mg and 8 mg) is remarkably lower than in the previous tests and the signal to noise ratio is worse; the background noise clearly visible in Figure 5 is due both to the sensor and to the traffic. Also in this case order 14 AR and AR + noise models have been identified from the data. The power spectra concerning AR models are reported (dashed line) in Figure 6 versus the power

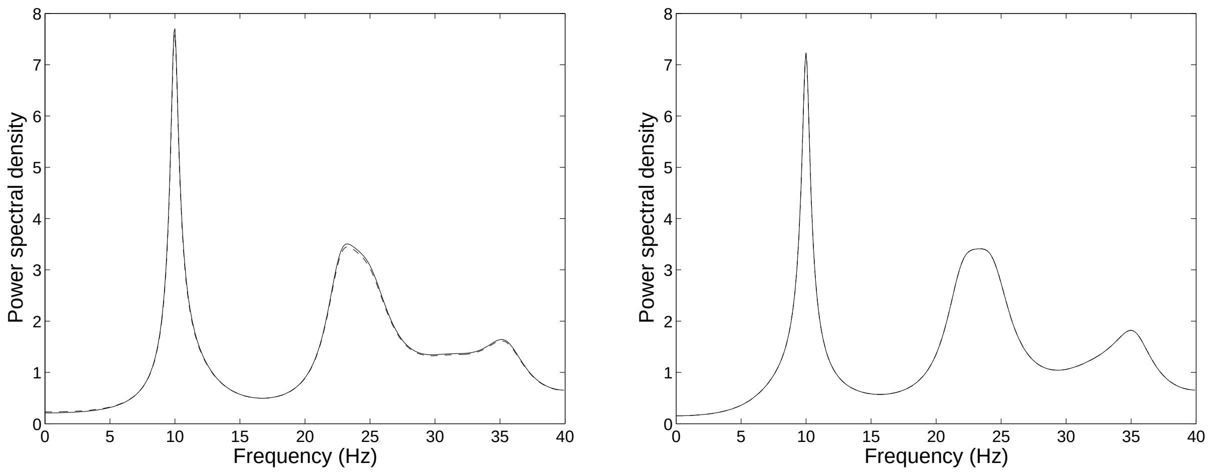

Figure 4: Power spectra of AR (dashed) and AR + noise (solid) models (impulse excitation)

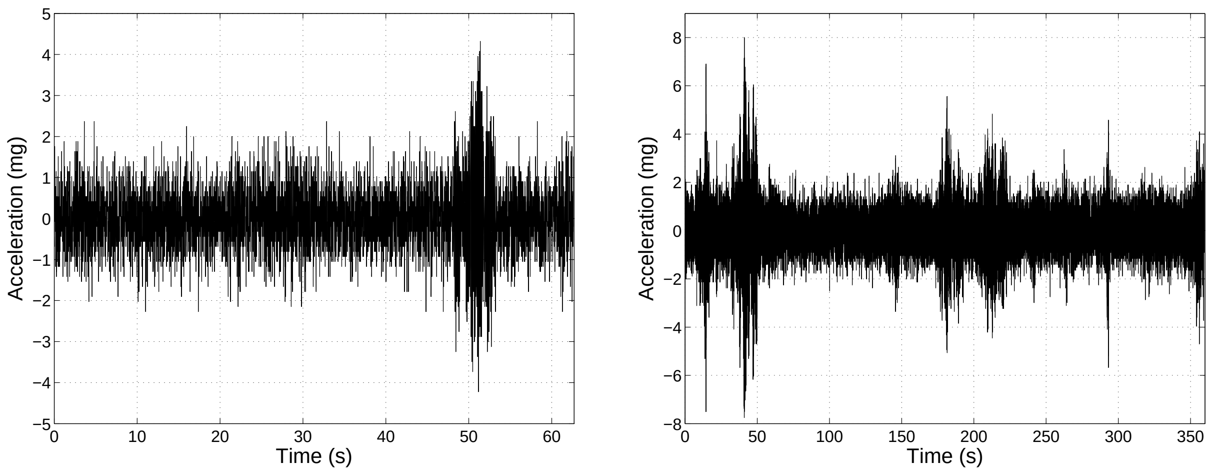

Figure 5: Tower response to urban traffic

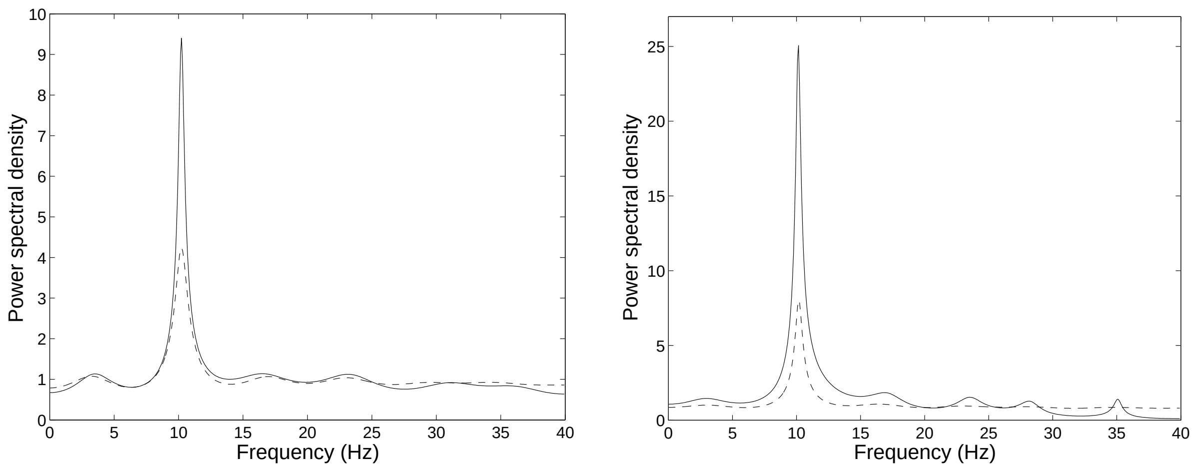

Figure 6: Power spectra of AR (dashed) and AR+noise (solid) models (urban traffic)

spectra (solid line) of the AR + noise models. A peak at 10 Hz can be clearly observed in all plots. The plot associated with the first AR model shows also a small peak at 3.5 Hz.

The plots concerning AR + noise models show a large peak at 10 Hz; the first plot shows also modest peaks at 3.5 Hz, 17 Hz and 23 Hz, the second one shows small peaks at 17 Hz, 28 Hz and 35 Hz.

5 Concluding remarks

This paper has described some results concerning the modal analysis of a medieval tower now included in a more recent building and located in Bologna, Italy. The analysis has been performed by means of MEMS–based sensors TSM02 endowed with local computational capabilities. The purpose of these tests has been the evaluation of the performance of a new SHM system and the comparison of the results obtained by identifying AR and AR + noise models. Both models have given congruent results; AR + noise models, however, lead to more detailed analyses when the data are characterized by poor signal to noise ratios as happens with urban traffic excitation.

References

[1] Bonelli A, Bursi O, Ceravolo R, Santini S, Tondini N. Dynamic identification and structural health monitoring of a twin deck curved cable-stayed footbridge: the “Ponte del Mare” of Pescara in Italy, *Proceedings of the V European Conference on Structural Health Monitoring*, Sorrento, Italy, 2010.

[2] Rainieri C, Fabbrocino G, Cosenza E. Structural Health monitoring systems as a tool for seismic protection, *Proceedings of the XIV World Conference on Earthquake Engineering*, Beijing, China, 2008.

[3] Vincenzi L, Mazzotti C, Savoia M. Modal identification of a TAV viaduct using subspace models, *2nd International FIB Congress*, Naples, Italy, 2006.

[4] Mazzotti C, Vincenzi L. Structural identification of a steel structure by forced vibrations, *ICOSSAR - International conference of structural safety and reliability*, Rome, Italy, 2005.

[5] Farrar CR, Doebling SW, Nix DA. Vibration-Based Structural Damage Identification. *Philosophical Transactions of the Royal Society: Mathematical, Physical & Engineering Sciences* 2001; **359**: 131–149.

[6] Fib Task Group 5.1. Monitoring and Safety Evaluation of Existing Concrete Structures. State–of–the–Art Report, Final draft, 2002.

[7] ISO/DIS 18649:2002(E). Mechanical vibration - Evaluation of measurement results from dynamic tests and investigations on bridges, 2002.

[8] Guidorzi R. *Multivariable System Identification: From Observations to Models*. Bononia University Press: Bologna, Italy, 2003.

[9] Ljung L. *System Identification – Theory for the User* (2nd edn). Prentice Hall:Upper Saddle River, NJ, U.S.A., 1999.

[10] Pagano M. Estimation of models of autoregressive signal plus white noise. *The Annals of Statistics* 1974; **2**:99–108.

[11] Kay SM. The effects of noise on the autoregressive spectral estimator. *IEEE Transactions on Acoustics, Speech and Signal Processing* 1979; **27**:478–485.

[12] Diversi R, Guidorzi R, Soverini U. Identification of autoregressive models in the presence of additive noise. *International Journal of Adaptive Control and Signal Processing* 2008; **22**:465–481.