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Vibration monitoring of historical towers: New contributions from data science

Maria Girardi[1] [0000–0002–7358–5607], Gianmarco Gurioli[2] [0000–0003–0922–8119], Nicola Messina[1] [[0000–0003–3011–2487], Cristina Padovani[1] [[0000–0002–2467–569X], and Daniele Pellegrini[1] [[0000–0002–3416–771X]

[1] Institute of Information Science and Technologies "A. Faedo", ISTI-CNR, Italy
https://www.isti.cnr.it

[2] Dipartimento di Matematica e Informatica "U. Dini", University of Florence, Italy,
https://www.dimai.unifi.it

Abstract. Deep neural networks are used to study the ambient vibrations of the medieval towers of the San Frediano Cathedral and the Guinigi Palace in the historic centre of Lucca. The towers have been continuously monitored for many months via high-sensitivity seismic stations. The recorded data sets integrated with environmental parameters are employed to train a Temporal Fusion Transformer network and forecast the dynamic behaviour of the monitored structures. The results show that the adopted algorithm can learn the main features of the towers' dynamic response, predict its evolution over time, and detect anomalies.

Keywords: Historical constructions · Structural health monitoring · Deep neural networks · Time series forecasting · Anomaly detection.

1 Introduction

Artificial intelligence represents a new paradigm in many fields such as science, technology, and industry, and Deep Learning (DL) techniques are increasingly being used in various applications. The growing availability of big data recorded by sensor networks and computing power allows scientists and technicians to train data-driven models that can help understanding the complexity of the real world.

Heritage structures are complex systems characterised by nonlinear mechanical behaviour, varied geometric schemes, constituent materials and building techniques. This complexity is heightened by the difficulty in getting accurate information on the materials' mechanical properties due to the scarcity of documentation and the need to limit destructive in-situ tests.

For these reasons, Structural Health Monitoring (SHM) has become increasingly attractive for safeguarding architectural heritage [1]-[8]. Long-term SHM based on ambient vibration tests can effectively increase the comprehension of the structure's mechanical behaviour and reveal possible anomalies in the loads acting on the structure or in its dynamic response. A crucial point in designing these monitoring systems concerns the availability of algorithms able to process large data sets automatically, possibly in real time. Artificial intelligence naturally fits this framework since the collected data can be used as training data sets to extract relevant features and predict the dynamic properties at future time instants. This approach uses DL techniques for time series forecasting and anomaly detection. The interested reader can refer to [9] and [10] for a comprehensive review of the software architectures involved.

Applications of DL to SHM of heritage structures are still relatively recent and limited [11]-[18]. The present paper shows the application of deep neural networks to analyse and predict the ambient vibrations of medieval masonry towers. The study relies on two large data sets recorded in the historic centre of Lucca on the San Frediano bell tower [19] and the Guinigi Tower [20], [21] to train a Temporal Fusion Transformer (TFT) network [22], predict the dynamical behaviour of the buildings (in the frequency domain) and perform anomaly detection. TFT has been experimented on electricity, traffic, retail and volatility problems; the studies summarised in this paper and described in detail in [23] and [10] represent the first applications of TFT to SHM.

2 The TFT network

The TFT network introduced in [22] is an attention-based deep neural network for multi-horizon forecasting. Figure 1 (from [10]) depicts the TFT's forecasting scheme. In the figure, input data are split into observed inputs $\mathbf{z}_t$, measured at each $t \in [0, T]$ by the sensors, and inputs $\mathbf{x}_t$ that are known without measurements (known inputs, such as the date at a prescribed time t). Input data and past targets are used to train the TFT model, which is then employed to predict the scalar targets $y_{i,t}$ (e.g. the i-th natural frequency) from t on. TFT can simultaneously predict various percentiles (e.g. the 1st, 50th and 99th) of the targets at each future time step of interest (hence the name multi-horizon forecasting). Each quantile forecast can be written as

$$\hat{y}_i(q, t, \tau) = f_q(\tau, y_{i,t-k:t}, \mathbf{z}_{t-k:t}, \mathbf{x}_{t-k:t+\tau}; \omega). \tag{1}$$

In equation (1) $\hat{y}_i(q, t, \tau)$ is the predicted q-th quantile (e.g. 0.01, 0.5, 0.99) of the i-th target referred to the τ-step ahead the starting time t, $f_q(\cdot; \omega)$ is the model induced by the TFT architecture depending on the parameters ω, $y_{i,t-k:t}$ and $\mathbf{z}_{t-k:t}$ represent the past target values and the observed input from the starting time t up to k time steps before, $\mathbf{x}_{t-k:t+\tau}$ are known inputs across the entire range. The parameters vector ω is calculated by the TFT network solving a minimisation problem on the domain of the input training data: such a minimisation procedure represents the so-called model's training. Typically, a portion of the input data is set aside in the training procedure and reserved for further model refinement (validation). Finally, the network test is performed on a third portion of the input data set, called the test set. We refer to the original work [22] for more details on TFTs and related issues.

Exploiting its prediction capability, TFT can detect possible anomalies or unexpected events by inspecting how much the observed targets deviate from the predicted ones. Once the TFT has been trained on a set of non-anomalous data, the prediction $\hat{y}_i(0.5, t, \tau)$ of the i-th target value along with the 1st and the 99-th percentiles $\hat{y}_i(0.01, t, \tau)$ and $\hat{y}_i(0.99, t, \tau)$ are obtained. An anomaly occurs at time $t + \tau$ if the observed value $y_{i,t+\tau}$ lies outside the confidence interval $[\hat{y}_i(0.01, t, \tau), \hat{y}_i(0.99, t, \tau)]$ predicted by the network.

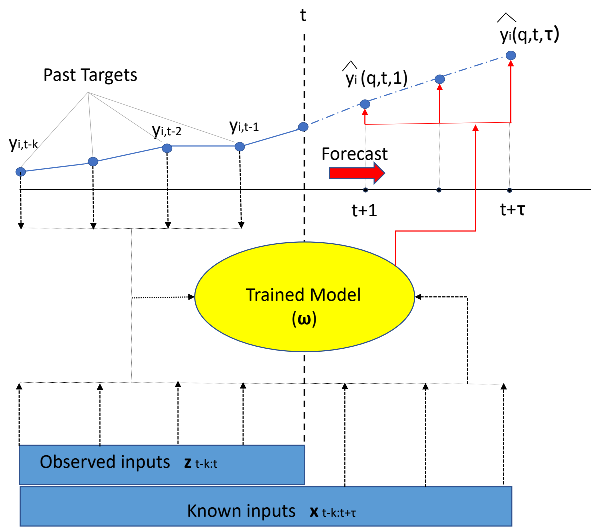

Fig. 1. Illustrative diagram of multi-horizon forecasting using past and observed inputs [10].

3 Application to the ambient vibrations of two historical masonry towers

In this section, we apply the TFT network to the San Frediano bell tower and the Guinigi Tower, two of the most iconic monuments in the historic centre of Lucca (Figure 2). Both towers have been continuously monitored via three-axial high-sensitivity seismic stations for more than one year. The velocities recorded have been split into hour slots and processed via the Stochastic Subspace Identification (SSI) method [24] to extract the vibration frequencies of the towers. These frequencies and other environmental parameters (temperature, humidity, etc.) measured on the towers or in their proximity (*www.sir.toscana.it*) constitute the input database on which the TFT algorithm has been trained, validated and tested. More specifically, the input database of the San Frediano bell tower includes data from 28 Oct 2015 to 16 Oct 2016, while that of the Guinigi Tower goes from 1 Aug 2021 to 31 Jul 2022. Along with the frequencies and the environmental parameters, other inputs were considered, such as the date and hour slot, the weekend days and, for the Guinigi Tower, the hourly number of visitors and the Root Mean Square (RMS) values of the velocities recorded.

Fig. 2. Historic centre of Lucca: the San Frediano bell tower (left) and the Guinigi Tower (right).

Two seismic events measured on the towers have been considered to test the sensitivity of the algorithm to potential anomalies: the Amatrice earthquake (M 6.0, about 400 km from Lucca) occurred on 24 Aug 2016 at 1:36 UTC for the San Frediano bell tower and the Viareggio earthquake (M 3.7, about 20 km from Lucca) occurred on 6 Feb 2022 at 1:36 UTC for the Guinigi Tower. The two events were recorded by the sensors installed on the buildings. Fig. 3 and 4 show anomaly detection results when the testing of the TFT network is conducted over a period containing the earthquakes. In the figures, τ introduced in equation (1) is set to 1. The green line represents the measured (experimental) frequencies, the continuous red line is for the 50th percentile predicted by TFT and the two red dashed lines represent the predicted confidence interval between the 1st and 99th percentiles. According to the damage detection criterion introduced at the end of Section 2, an anomaly occurs when at least one experimental frequency exceeds this predicted interval. The network can capture the seismic event as an anomaly for both case studies. In particular, the Amatrice earthquake affects only the first two frequencies, while the effects of the Viareggio earthquake are visible in all the three frequencies shown in the figure. The algorithm can also detect the vibrations of the San Frediano bell tower induced by the swinging bells (Fig. 3). This anomaly involves the second frequency (related to the swinging direction) and corresponds to the main religious ceremonies held in the Cathedral, particularly on Saturday (20 Aug at 17:00) and Sunday (21 Aug at h 10:00).

It is worth noting that the frequencies of the San Frediano bell tower exhibit a very marked oscillatory behaviour over the day; this behaviour is due to the daily temperature variations and is very well predicted by the TFT network.

The Guinigi Tower shows different behaviour, which does not exhibit a clear correlation between frequencies and temperature [20]. On the other hand, the Guinigi Tower is open to the public every day from 10:00 a.m. to 5:00 p.m. while the San Frediano bell tower was close to visitors during the monitoring period and the instruments could measure the tower's vibrations in undisturbed conditions.

To visualise the anomalies identified by TFT over the test set, we can mark each anomaly with a vertical bar and use an appropriate colour map to distinguish the anomaly score - i.e. the magnitude of the event (see [10] for the rules adopted to calculate such a score). Fig. 5 shows the anomaly plots of the Guinigi Tower when three simulated damage scenarios are considered, in which the values of the six experimental frequencies $f_1 < f_2 < ... < f_6$ are lowered according to the following rules and starting from the Viareggio earthquake hour slot:

- **Scenario 1**: by $2\%, 1\%, 0.5\%, 0.5\%, 0.5\%$ and 0.5%, respectively. This damage scenario is inspired by that observed on the Gabbia tower in Mantua after the Emilia earthquake of May 2012 [25].
- **Scenario 2**: by $4\%, 2\%, 1\%, 1\%, 1\%$ and 1%, respectively.
- **Scenario 3**: by 4% (uniform reduction of all frequencies).

The figure shows that the network can highlight the change in the tower's dynamic properties after the earthquake and the magnitude of the detected anomalies increases as the damage intensity increases from Scenario 1 to Scenario 3. The anomaly is permanently highlighted after the earthquake in all the cases considered.

Conclusions

This paper describes an application of the TFT network to the SHM of two medieval masonry towers in the historic centre of Lucca, the San Frediano bell tower and the Guinigi Tower. The algorithm is trained over the natural frequencies of the towers, extracted from the velocity data recorded by high-sensitivity seismic stations and other relevant input variables describing the environment (temperature, humidity) and the loads acting on the structures (wind, number of visitors, swinging bells, etc). The algorithm has been employed to predict the vibrational features (natural frequencies) and detect possible anomalies or unexpected events by inspecting how much the actual frequencies deviate from the predicted ones. In particular, TFT has been tested on two seismic events measured on the towers during the monitoring periods and on simulated damage scenarios, in which the frequencies of the Guinigi Tower are permanently lowered to model structural damage. The network has shown good accuracy in predicting the towers' frequencies and sensitivity in anomaly detection.

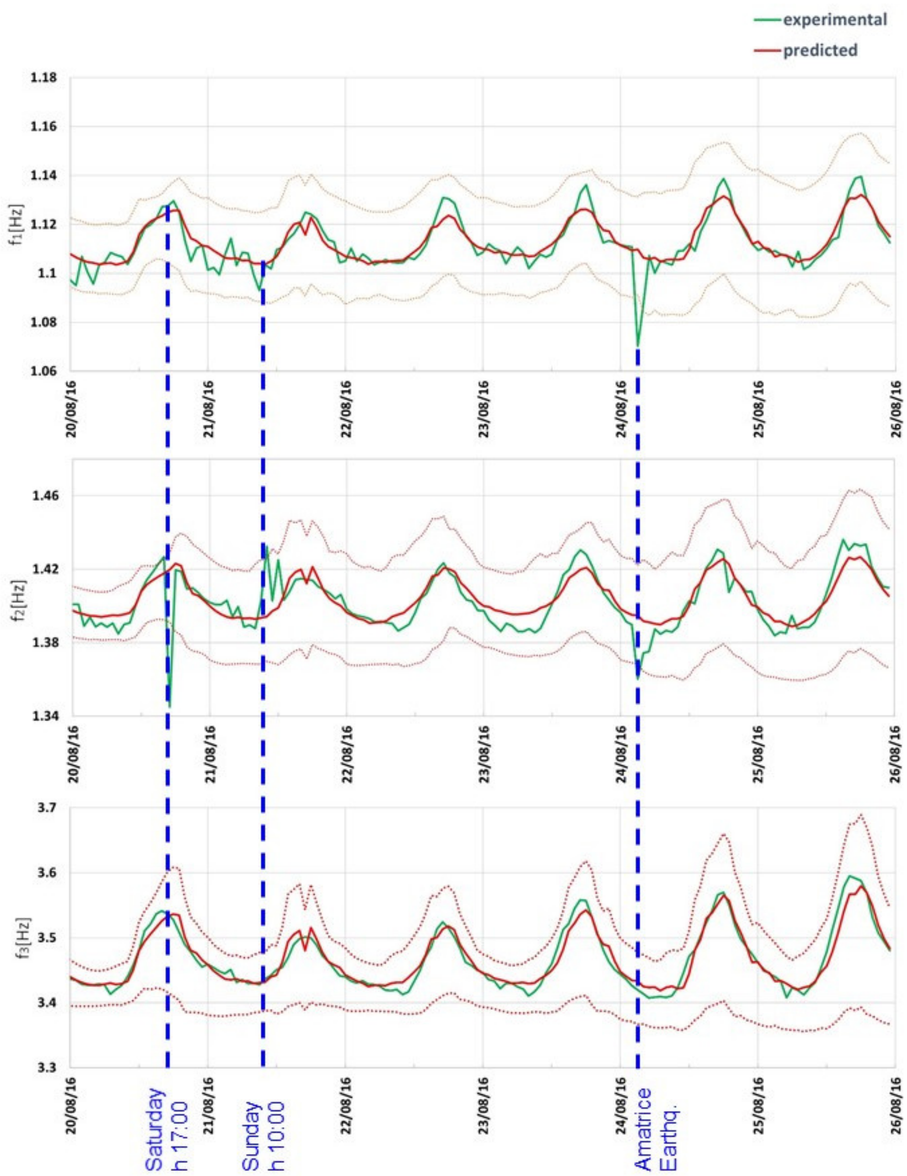

Fig. 3. San Frediano bell tower, Amatrice earthquake (24 August 2016, 3:36 a.m.). First three predicted (red line) and experimental frequencies (green line). The dashed lines represent the 1st and 99th percentiles predicted by the model.

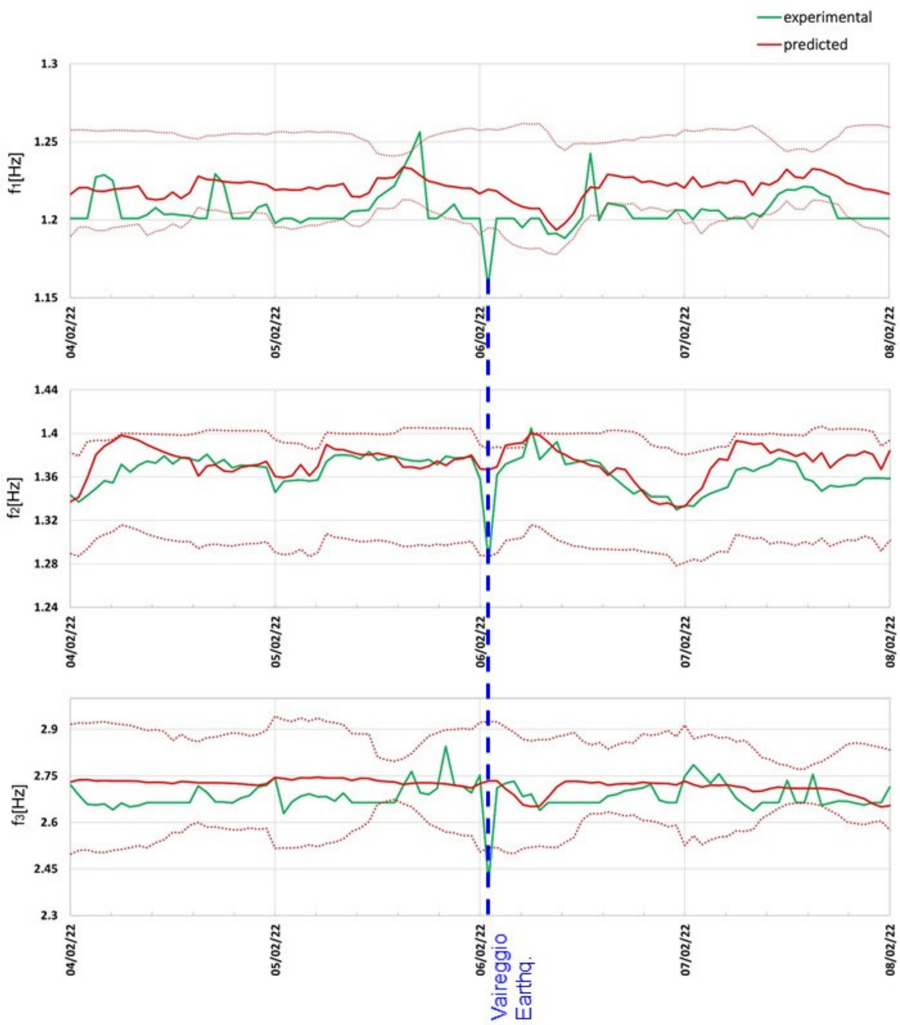

Fig. 4. Guinigi Tower, Viareggio earthquake (6 February 2022, 1:36 UTC). First three predicted (red line) and experimental frequencies (green line). The dashed lines represent the 1st and 99th percentiles predicted by the model.

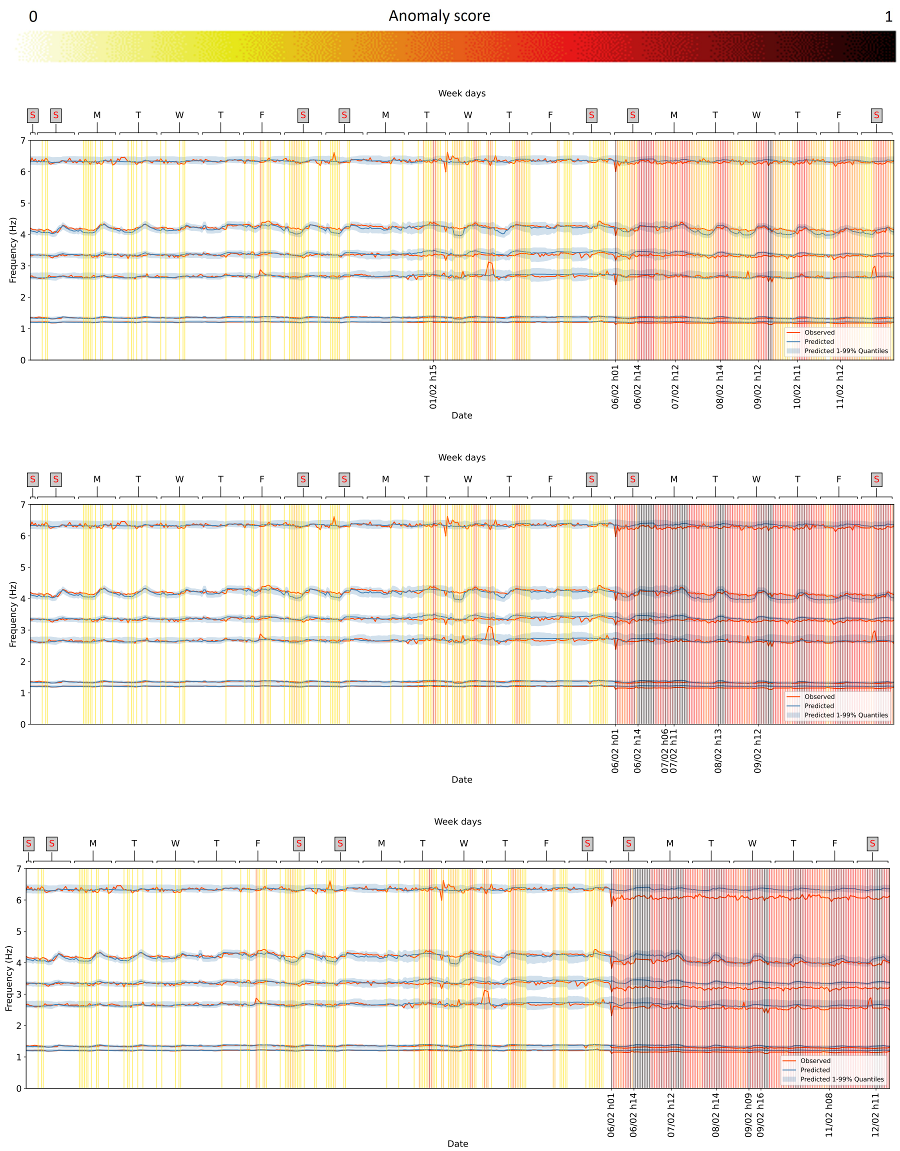

Fig. 5. Guinigi Tower, anomaly plots for **Scenario 1** (top), **Scenario 2** (middle) and **Scenario 3** (bottom).

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