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# FROM SOUND AND VIBRATION MEASUREMENTS TO SIMULATION INTELLIGENCE IN MUSICAL ACOUSTICS

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Measurement techniques in acoustics and vibration science have matured over decades, giving us high-fidelity recordings and detailed structural responses. At the same time, physical modeling methods such as finite-difference schemes and digital waveguides have enabled real-time simulation of musical instruments and other vibro-acoustic systems. This paper outlines a vision of simulation intelligence that fuses these traditions to produce predictive, interactive and adaptive digital twins for sound and vibration applications. We first revisit measurement-driven studies on historical instruments, exemplified by an acoustical analysis of the Turkish tanbur; that study combined time-frequency analysis of recordings with physical insight into resonator geometry and string dynamics. The lessons from such work highlight how linear and nonlinear vibration features extracted from data can inform modeling assumptions and parameter estimation. We then survey advances in real-time simulation with finite-difference time-domain models for plucked and bowed strings, membranes and plates, designed for interactive performance. The associated SIVE toolkit demonstrates how these models can be integrated in virtual environments, and how control, haptics and perceptual feedback create convincing sonic interactions. Building on these examples, we propose a framework that uses measurement data to calibrate, validate and adapt physical models in operation, leveraging machine learning to map complex parameter spaces and handle uncertainties. Simulation intelligence thus involves continuous assimilation of sensor data into simulation, enabling real-time tuning, anomaly detection and design optimization. Potential applications include the preservation and virtualization of rare instruments, structural health monitoring of bridges and vehicles, and immersive XR experiences. By bridging detailed measurements with physically-informed simulation, the field moves toward systems that not only replicate past behavior but also anticipate future dynamics. This integration invites collaboration across acoustics, signal processing, computer graphics and artificial intelligence.

*Keywords: physical modeling, digital twin, simulation intelligence, machine learning*

## 1. Introduction

Sound and vibration measurements form the foundation of acoustics research and the design of audio systems. Advances in sensor technology and signal processing have made it possible to acquire high-quality data from microphones, accelerometers, laser vibrometers and embedded devices, covering frequency ranges from infrasonic vibrations to ultrasonic phenomena. These measurements not only provide insight into the underlying physical processes but also drive calibration and validation of numerical models used in engineering and creative applications. Simultaneously, physical modeling techniques such as digital waveguide synthesis and finite-difference time-domain (FDTD) schemes have matured into powerful tools capable of reproducing the dynamical behavior of strings, membranes, plates and full mechanical structures [1] . They allow researchers to predict how modifications to geometry or material properties will affect the sound and vibrational response before prototypes are built.

The digital twin concept extends these ideas by coupling a physical system to a virtual counterpart that updates itself in real time using measurements from sensors, enabling state estimation, control and predictive maintenance [2,3] . However, connecting measurement data with models in a way that yields continuous improvements remains a challenge. Models often rely on simplifying assumptions that break down under changing environmental conditions or non-linear behaviors, while real-world measurements can be noisy, incomplete or subject to drift.

This paper investigates how to bridge these domains through *simulation intelligence* [3] : the integration of measurement techniques, physical modeling, data assimilation and machine learning. We first review the state of the art in measurement and modeling, highlighting successes and shortcomings. We then propose a framework for simulation intelligence that emphasizes feedback loops between data and models, inspired by early work in instrument analysis and recent developments in interactive simulations. Case studies involving the analysis of the tanbur, real-time simulation of other musical instruments in virtual environments and addressing their lifecycle management are presented to illustrate the potential of this approach.

# 2. Background

## 2.1 Sound and Vibration Measurement Techniques

Measurement techniques in acoustics encompass an array of sensors and analytical methods. Microphones capture airborne sound pressure with remarkable fidelity across wide dynamic ranges. Accelerometers and contact pickups measure vibrational acceleration or velocity in solids, while laser Doppler vibrometers and optical scanning systems provide non-contact measurements of displacement. These sensors feed into data acquisition systems with high sample rates and bit depths that preserve subtle details of the signal. Once captured, signals are analyzed using time-domain and frequency-domain methods.

For example, when analyzing the vibration and sound characteristics of the Turkish tanbur [4] , time–frequency analysis (see Fig. 1) revealed not only the fundamental frequencies but also nonlinear behaviors due to string tension modulation and sympathetic coupling.

## 2.2 Physical Modeling of Vibrating Systems

Physical modeling seeks to derive discrete representations of the equations of motion governing vibrating systems. In the one-dimensional case of a string, the wave equation describes how transverse displacement evolves in space and time. Digital waveguide synthesis solves this equation by decomposing the solution into left- and right-propagating waves that travel along delay lines [1] . The delay lines are terminated with reflection filters that represent the boundary conditions and incorporate frequency-dependent losses. More complex systems, such as membranes and plates, require two- or three-dimensional waveguide meshes or banded waveguide models to capture dispersion and anisotropy. Digital waveguides provide physically accurate simulations with reduced computational cost and can now be optimized with modern machine learning and differentiable digital signal processing techniques [5,6] .

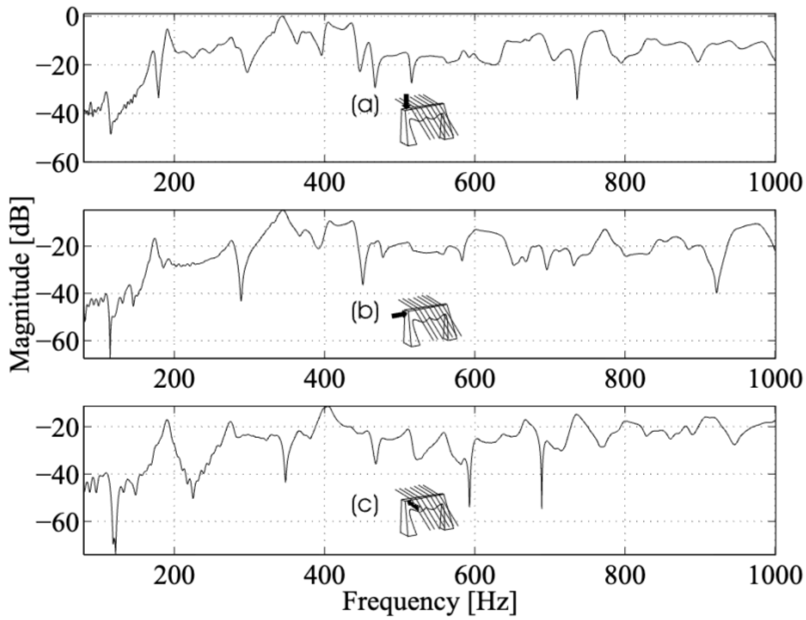


Figure 1: Low-frequency range of the normalized magnitude spectra of a tanbur: a) The vertical impulse response b) The horizontal impulse response c) The longitudinal impulse response. After [4].

Finite-difference time-domain methods provide an alternative approach by discretizing both time and spatial derivatives directly [7] . They are particularly well suited to irregular geometries and higher dimensions, at the cost of stricter stability conditions and increased computational load. In the Emulated Ensemble project, FDTD models were developed for a variety of instruments, including plucked and bowed strings, drum membranes and complex resonators. Real-time performance was achieved by optimizing the update equations and exploiting parallelism in modern processors and graphics processing units. Coupling digital waveguide and FDTD models allows flexible hybrid schemes in which, for instance, a string is modelled by a waveguide while its interaction with a membrane is handled by FDTD. Such models can be extended to include non-linearities, collision terms, and damping effects. Physical modeling not only offers high audio quality but also provides parameters that relate directly to physical properties, making it attractive for digital twins. By adjusting tension, stiffness, damping coefficients or boundary conditions, one can simulate how changes in material or structural design impact the acoustic response. However, these models require accurate parameter estimates and may become unstable when driven by strong non-linearities.

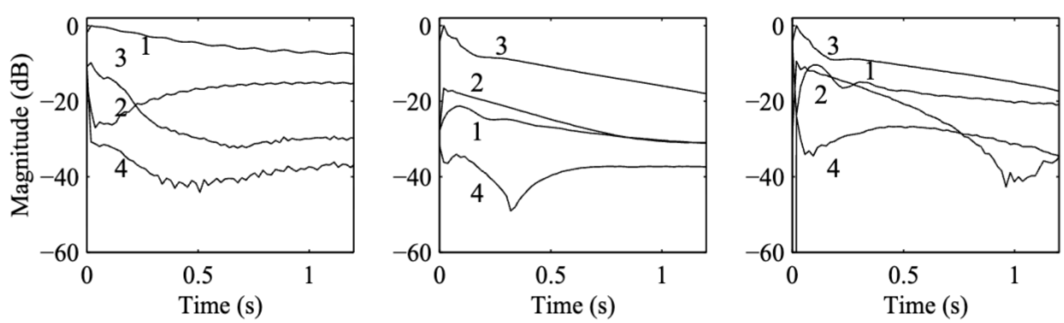


Figure 2: Amplitude envelopes of the four first harmonics of a tanbur tone plucked in the middle of the string, as detected in string vibration (left), in vibration of the soundboard (middle), and in the radiated sound (right).

### 2.3 Digital Twins and Data Lifecycle Management

The digital twin concept originates from engineering domains such as aerospace and manufacturing and refers to a digital model of an existing or intended physical system that remains synchronised with it through real-time data [8,9] . Unlike traditional simulations, a digital twin evolves alongside its physical counterpart and can be used for monitoring, diagnostics, optimization and control. Authoritative definitions require dynamic interaction between the two: measurement data must continuously inform the model, and updates in the virtual domain must be able to influence the physical system.

In the context of sound and vibration, digital twins have begun to appear in applications such as structural health monitoring of bridges, predictive maintenance of rotating machinery and virtual acoustics of concert halls. For instance, accelerometers mounted on a bridge can feed data into a finite-element model that predicts stress concentrations and alerts maintenance teams if abnormal patterns are detected. Similarly, digital twins of musical instruments could support luthiers in optimizing designs or preserving historical instruments without invasive interventions.

The digital twin paradigm also encourages integration of machine learning, which can learn complex mappings between measurements and physical parameters or predict system evolution based on historical data. Graph neural networks, recurrent neural networks and Gaussian processes have been explored to approximate dynamic models or to augment physics-based simulations. Nevertheless, these methods often require large, labelled datasets and may lack interpretability. A simulation intelligence approach [3] seeks to blend data-driven and physics-based models, using machine learning to handle uncertainties and non-linearities while retaining the structure and explainability of physical models.

## 3. Simulation intelligence framework

The proposed simulation intelligence framework consists of three layers: *measurement*, *model optimization*, and *data operations (DataOps)*, as depicted in Fig. 3. The *measurement* layer encompasses sensor selection, placement, data acquisition, and basic signal processing. It produces features such as modal frequencies, mode shapes, spectral envelopes, and temporal envelopes. These features feed into the model calibration layer, where physical models are adjusted to reflect the current state of the system. *Calibration and optimization* involve solving inverse problems: given observations, we seek the set of model parameters that minimize the discrepancy between measured and simulated responses. Techniques such as least-squares optimization, Bayesian inference, and machine-learning surrogate models are employed. For example, in the tanbur study, a dual-polarization waveguide model was calibrated by matching its output to measured plucked-string sounds, revealing the importance of nonlinear tension modulation. In the SIVE Toolkit, parameters such as string tension, membrane density, and plate stiffness were tuned to achieve realistic timbres. The *DataOps* layer operationalizes the data lifecycle (ingestion, curation, metadata, and versioning). In the SIVE Toolkit, this layer includes 3D assets, recorded sounds, processed/analyzed sounds, and metadata.

The simulation intelligence framework integrates these measured and optimized models, together with their datasets and metadata, into a digital twin that evolves over time. It incorporates algorithms that update state variables using new measurements: ensemble Kalman filters, extended Kalman filters, and variational methods are common choices. Machine learning components assist by learning model errors, predicting parameter drift, or modeling complex boundary interactions. The simulation intelligence layer also provides outputs for monitoring, control, and user interaction. In an interactive music application, for instance, a performer could pluck a virtual string while the digital twin updates its parameters based on audio input, creating an instrument that learns from the performer. The framework emphasizes modularity, allowing components to be replaced or updated as new sensor technologies or modeling methods emerge.

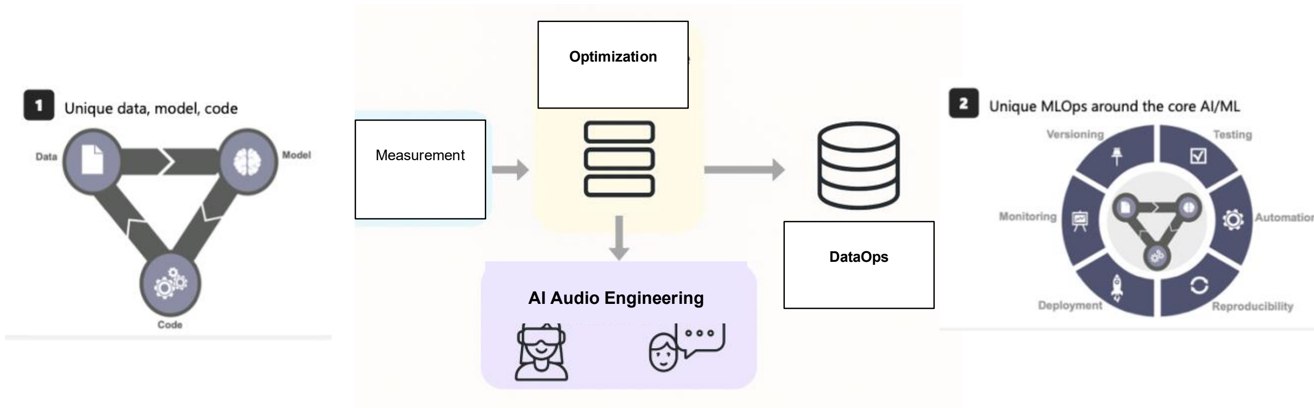


Figure 3: Simulation Intelligence Framework.

# 4. Case Studies

## 4.1 Digital Twins of Historical or Ethnic Instruments

The acoustical analysis of the tanbur combined all components of the simulation intelligence framework. The instrument's wooden hemispherical body and paired strings contribute to a rich spectrum of partials. Recordings obtained in an anechoic chamber were subjected to spectral and time–frequency analysis to identify fundamental frequencies, overtones and non-linear phenomena. The data revealed that sympathetic string coupling and tension modulation create missing harmonics, produce beating patterns and a slowly varying spectral envelope, which must be incorporated into physical models [4] . A dual-polarization digital waveguide model with nonlinear tension modulation was calibrated using these measurements and the physical parameters of the instrument components, adjusting for string tension, termination reflectivity and resonator coupling. The real-time model reproduced the measured spectra with high fidelity and allowed exploration of how changes in string gauges or bridge geometry would alter the sound. A similar approach has been followed in [10] for the Finnish zither *kantele.* These studies exemplify how measurement-driven calibration enhances model realism and informs design of the simulation intelligence, albeit a full deployment to virtual environments could be established many years later, as described in the sequel.

## 4.2 Towards Simulation Intelligence in Virtual Environments

Silvin Willemsen developed FDTD models for strings, membranes, plates, and resonators during his doctoral studies, with the goal of creating interactive musical instruments [11] . Efficient update equations and careful memory management enabled real-time execution of hundreds of coupled grids. These models were integrated into a performance system with force-feedback controllers and visual display. Measurements of real instruments were used to validate the models and to map gesture inputs to model excitations. Musicians reported that the system was responsive and expressive, illustrating that high-fidelity physical models can be used in performance when paired with efficient computation. He prepared the SIVE Toolkit (https://github.com/SilvinWillemsen/SIVEtoolkit) as an open-source framework to facilitate experimentation with and life-cycle management of these models. The toolkit offers physically based sound synthesis modules for the Unity game engine, with multimodal interaction and sound spatialization modules. Each module is built upon digital waveguide and FDTD principles and can be parameterized in real time. By mapping user actions, such as collisions, strokes, or squeezes, to model excitations, developers can create immersive soundscapes that react naturally to interactions.

Measurement data, such as hand motion captured by VR controllers, can be used to calibrate model parameters online, embodying simulation intelligence. The toolkit demonstrates how advanced physical models can be packaged for use in interactive applications and points towards broader adoption in virtual reality and gaming.

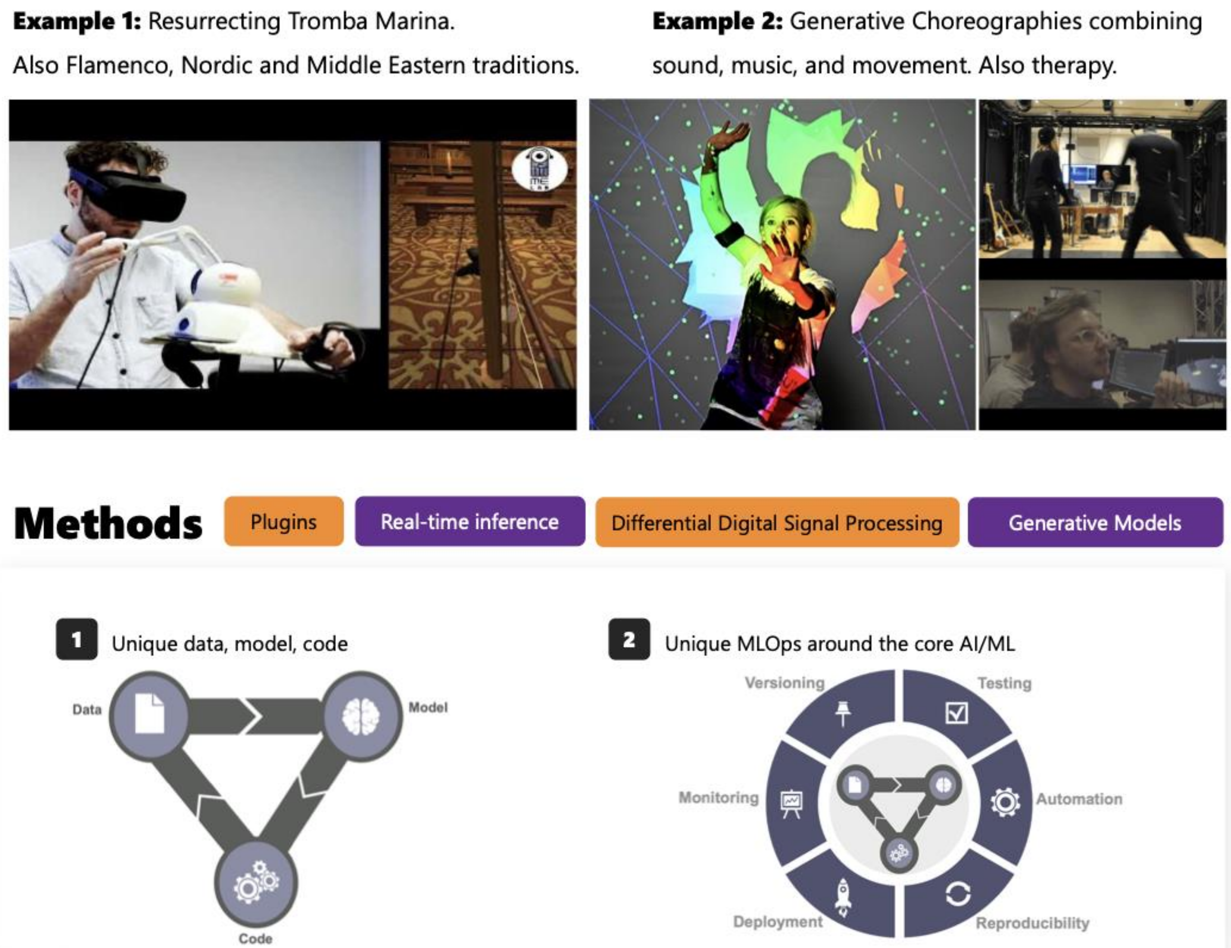


Figure 4: Simulation intelligence framework integrating measurements, physical modeling, and AI-driven digital twins for adaptive acoustical and structural applications, combining controllers, motion sensors and generative AI models. The methods used in SI include real-time inference with streaming audio plugins.

The framework integrates measurement, model calibration, and simulation intelligence layers to bridge real-world data with digital twin models. Example 1 in Fig. 4 is based on the acoustical analysis of the *tromba marina*, a historical bowed string instrument that sounds similar to a brass instrument; here, the analysis informs a calibrated digital waveguide model of the bow, string, and trembling bridge, enabling non-invasive study and optimization. Another example is an interactive virtual musical performance, which enables users to play virtual instruments through body movement without a dedicated physical interface. The methods illustrated in these examples include sensor placement, signal processing, inverse problem solving with machine-learning surrogates, and real-time inference with streaming audio plugins. The framework also emphasizes AI engineering to ensure robust deployment, monitoring, and continuous improvement of machine-learning components that predict system evolution or model error within the digital twin, supporting adaptive and scalable solutions across sound and vibration domains.

# 5. Current work in progress

To implement the proposed simulation intelligence framework in a reproducible and scalable, we are building a structured experimental pipeline that integrates measurement data acquisition, model calibration, adaptive simulation, persistent storage, and omniverse streaming serving. A key design objective is to support continuous synchronization between physical measurements and digital twin simulations while ensuring that datasets, artifacts, and derived models remain traceable and accessible.

## 5.1 Data Acquisition and Storage Architecture

All experimental data were collected using multimodal sensing configurations consisting of high-fidelity microphones, accelerometers, and laser vibrometers. Signals were recorded at multiple excitation positions across a set of plucked and struck musical instruments, including the Turkish tanbur, Finnish kantele, tromba marina, classical guitar, harpsichord, clavichord, vibraphone, and handheld percussion instruments. For each recording session, time-domain signals, derived spectral envelopes, and modal parameters were extracted and stored together with contextual metadata describing sensor placement, environmental conditions, and instrument configuration.

To support scalable storage and reproducibility, all datasets and intermediate artifacts are being stored using a MinIO object storage system configured as the central datastore for the experimental pipeline. Each recording session generated a structured data bundle containing raw sensor signals, processed spectral and modal features, calibrated model parameters, simulation outputs, experiment metadata and configuration logs. These bundles are being versioned and stored as immutable objects in MinIO buckets. Object naming followed a hierarchical structure encoding instrument type, excitation configuration, and timestamp. This design allowed efficient retrieval of historical data and enabled repeatable re-execution of calibration experiments under identical conditions. Furthermore, MinIO supported distributed access across simulation nodes, facilitating parallel evaluation and long-term dataset preservation. Our SI framework will thus benefit from the coordinated integration of measurement data, physics-based modeling, machine learning, and persistent data infrastructure. The use of MinIO as a centralized datastore will enable structured experiment management, version control, and scalable access to historical data, supporting reproducibility and collaborative experimentation.

# 6. Discussion

The case studies highlight both the potential and the challenges of simulation intelligence. Incorporating measurement data into physical models improves realism and enables adaptation to changing conditions. However, the accuracy of the resulting simulations depends heavily on sensor quality, calibration procedures and model assumptions. For instance, nonlinearities in string instruments can be difficult to capture with simple digital waveguide or FDTD models. The inclusion of nonlinear tension modulation, collision terms and hysteresis effects increases computational cost and may compromise real-time performance. Machine learning methods offer a means to model such complexities, but they require substantial training data and may behave unpredictably outside the range of the training set. Another challenge lies in parameter estimation. Inverse problems are often ill-posed: multiple parameter sets can produce similar observable behavior.

Regularization techniques and prior knowledge must therefore be incorporated. Data assimilation algorithms can become unstable if the model or measurement uncertainties are not properly specified. Moreover, the integration of multiple sensory modalities (audio, vibration, haptics) demands careful synchronization. Despite these difficulties, the benefits of simulation intelligence are evident. In cultural heritage preservation, digital twins enable non-invasive study of rare instruments, allowing virtual performances that capture their characteristic timbres without subjecting them to wear. In structural engineering, continuous monitoring combined with predictive simulation can detect damage before catastrophic failure. In interactive media, simulation intelligence provides responsive, expressive virtual instruments and environments. The framework also encourages interdisciplinary collaboration: acousticians, computer scientists, control engineers and machine learning specialists must work together to develop robust systems. The role of user perception and cognition in evaluating simulation quality is a fertile ground for future research.

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