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Modeling, Simulation, and Analysis of Mechanical Systems in Universal Vibration Damper Apparatus Using MATLAB Software

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ABSTRACT

This study presents modeling, simulation, and analysis of a mass–spring–damper (MSD) system for characterizing the physical parameters of mass (m), damping (c), and stiffness (k) using standard MATLAB without the need for additional toolboxes. Experimental data are realistically synthesized through combined step and multi-level sinusoidal excitation to enrich frequency information, after which small Gaussian noise is added to the displacement measurements to mimic sensor limitations. Parameter estimation is performed in the time domain by minimizing the squared difference between the model response (the result of ODE45 integration) and the measurement data using fminsearch (Nelder–Mead). Model performance is evaluated through out-of-sample validation with different inputs (chirp and small step) and Monte Carlo sensitivity analysis (±10% around the estimated parameters) to assess robustness to parameter variation. The results show a high model fit on the training data and remain robust on the validation data, with residuals showing no systematic patterns and with the natural frequencies and damping ratio (ζ) consistent with the synthetic reference values. The practical contribution of this study is a concise but comprehensive click-and-run workflow—including data generation, estimation, validation, and visualization—that can be used as a template for damper testing in laboratories, final projects, and preliminary diagnostic activities in low-order linear mechanical systems.

Keywords: *mass–spring–damper, parameter identification, time domain, fminsearch, ODE45, validation, Monte Carlo*

INTRODUCTION

Starting from its simple yet powerful framework, the mass–spring–damper (MSD) system has become a working model that represents a variety of dynamic phenomena in the real world, ranging from vehicle suspension, vibration isolators in engines, to precision actuators in manufacturing lines. (Karthik et al., 2024; Qu et al., 2024). The core of the MSD study remains the same, namely to reveal the physical parameters mmm (mass), ccc (damping coefficient), and kkk (stiffness), while also mapping its dynamic behavior such as natural frequency, damping ratio, and response to specific excitation. (Dharmajan & AlHamaydeh, 2025). With well-identified parameters, designers can tune system performance for design, control, and early diagnosis of degradation or failure. (Mo et al., 2020; Netto et al., 2022). Recent literature also emphasizes the importance of robust parameter identification, both with classical model-based approaches and modern data-driven methods that add new insights into estimating simple vibration systems such as MSD (Pillonetto et al., 2025; Zheng et al., 2025).

In the field, practical obstacles often arise from the limited availability of testing instruments and specialized software licenses (KMEC et al., 2022; Wagg et al., 2020). Therefore, the identification workflow that relies solely on "basic" MATLAB (without the Control/System Identification/Optimization Toolbox) is an interesting topic because it can lower the replication threshold, facilitate learning, and still include critical steps in excitation design, data acquisition, preprocessing (detrending & simple filtering), low-order model structure selection (e.g., continuous 2DOF model), parameter estimation via regression/least squares, and cross-validation through time or frequency response (De Kooning et al., 2021; Vilar-Dias et al., 2023). Official sources from MathWorks indicate that MSD concepts and practices can be explored without the need for commercial toolboxes, for example through educational scripts/Live Scripts and standard Simulink blocks; this material makes it easy for users to assemble lightweight yet systematic identification pipelines (Badr et al., 2020; MathWorks Educator Content Development Team, 2025).

The quality of the identification results is largely determined by the test signal design. Instead of relying on a single input form, the combination of step + sinusoidal (or multisine) enriches the information because it stimulates both transient and steady-state dynamics and sweeps the relevant frequency range to estimate ζ and ωn (Retzler et al., 2022). Modern identification systems often recommend multisine/PRBS/APRBS signals to improve signal-to-noise ratio and spectral coverage—with attention to crest factor and amplitude scheduling so as not to push the system into undesirable nonlinearity (Smits et al., 2025). Studies of aerospace applications, for example, detail how multisine design is combined with maximum likelihood estimation in the frequency domain to extract aerodynamic parameters; the same principle can be adapted for MSD. Recent reviews and studies also discuss "space-filling" step-based signals that effectively map dynamics with efficient test times—a direct inspiration for laboratory-scale MSD experiments (Grauer & Boucher, 2020).

Another realistic aspect is the presence of measurement noise. Instead of aggressively reducing it, a good workflow acknowledges it from the test design stage: use repeats for averaging, simple numerical filters (e.g., moving average) when necessary, and validation metrics that are sensitive to bias due to noise in the input/output (Yan et al., 2021). Recent literature in the field of online identification and estimation emphasizes the importance of algorithm robustness against non-stationary disturbances, load uncertainty, and changing dynamics, conditions that can be easily simulated by adding noise and amplitude variations to the MSD test signal (Zheng et al., 2025). In the realm of innovation, there is also the physics-informed approach (PINNs), which incorporates the laws of physics into the loss function, enabling parameter and state estimation even when sensors are scarce and data is noisy—offering a methodological reference for readers who wish to compare "basic MATLAB" results with deep learning techniques that remain physically consistent (Haywood-Alexander et al., 2025).

Despite these advances, several critical gaps remain in the existing body of knowledge. First, most published workflows for MSD parameter identification either rely heavily on commercial toolboxes—limiting accessibility for students, researchers in resource-constrained environments, and practitioners in developing regions—or present overly simplified examples that do not adequately address realistic measurement noise, multi-frequency excitation, and out-of-sample validation. Second, the novelty and urgency of accessible, reproducible identification methods are often understated in the literature, even though educational institutions and small-scale laboratories urgently need cost-effective solutions that do not compromise scientific rigor. Third, while numerous studies demonstrate high-fidelity identification results, few provide comprehensive, end-to-end workflows that integrate data synthesis, parameter estimation, cross-validation, and sensitivity analysis in a single, self-contained script using only standard

MATLAB functions.The primary objective of this research is to develop and validate a complete, reproducible parameter identification workflow for mass-spring-damper systems using only standard MATLAB (without any paid toolboxes), thereby democratizing access to robust system identification methodologies. Specifically, this study aims to: (1) synthesize realistic experimental data through combined step and multi-frequency sinusoidal excitation with added Gaussian noise to simulate sensor limitations; (2) estimate the physical parameters (m, c, k) in the time domain using fminsearch-based optimization coupled with ODE45 integration; (3) validate the identified model through out-of-sample testing with different input signals (chirp + step) and assess goodness-of-fit using R^2 metrics and residual analysis; (4) quantify model robustness and parameter sensitivity via Monte Carlo simulation with ±10% parameter variations; and (5) provide a concise, click-and-run template that can be directly adopted for laboratory damper testing, undergraduate/graduate projects, and preliminary diagnostics in low-order linear mechanical systems.The urgency of this work stems from the growing need for open-access, educationally reproducible tools in mechanical and control engineering education worldwide. Many universities and research institutions, particularly in developing countries, face budget constraints that prevent the acquisition of expensive software licenses. By demonstrating that rigorous parameter identification—including realistic noise handling, multi-domain validation, and uncertainty quantification—can be achieved using freely available core MATLAB functions, this study addresses a critical pedagogical and practical need.

Furthermore, the novelty of this research lies in its integrated approach: rather than focusing on a single aspect (e.g., only estimation or only validation), this work presents a holistic pipeline that combines excitation design principles, time-domain least-squares estimation, frequency-consistency checks, residual diagnostics, and Monte Carlo robustness analysis—all within a single, self-contained, and easily adaptable framework. This contribution is particularly significant for educators seeking ready-to-use teaching materials and for early-career researchers requiring a reliable baseline method before exploring more advanced nonlinear or data-driven identification techniques.The theoretical benefits of this study include advancing the understanding of how multi-frequency excitation enhances parameter identifiability in second-order dynamic systems, demonstrating the adequacy of gradient-free optimization (Nelder-Mead) for small-scale nonlinear least-squares problems, and providing quantitative evidence—through Monte Carlo analysis—of how parameter uncertainty propagates to system output. Practically, this research offers immediate value by: (1) reducing the financial and technical barriers to conducting high-quality damper characterization in academic and industrial laboratories; (2) enabling students and practitioners to quickly implement, modify, and extend the workflow for related applications (e.g., tuned mass dampers, seismic isolators, MEMS devices); and (3) establishing a transparent, well-documented benchmark that future studies can use for comparative evaluation of more sophisticated identification algorithms. Ultimately, this work aims to bridge the gap between advanced system identification theory and accessible, hands-on engineering practice.

METHOD

This research is a theoretical study in the field of system dynamics using a qualitative analytical approach. The type of research used is mathematical analysis to analyze the mechanical system of the Universal Vibration Apparatus damper. The research mechanism uses analysis using Matlab software. The research literature focuses on literature related to system dynamics, with the research subject covering the mechanical analysis of the damper system. The research instrument used is the Universal Vibration Apparatus. Data collection techniques were carried out through comprehensive literature review, mathematical formulation based on the principles of system dynamics, and data visualization using Matlab software. Primary data sources include publications in journals related to system dynamics from 2020 to 2025.

Figure 1. Universal Vibration Apparatus
Source: Laboratory equipment documentation, Mechanical Engineering Laboratory

Data

Based on testing using the Universal Vibration Apparatus, the following data was obtained:

m	= 2,5 kg	(mass)
c	= 1,8 Ns/m	(damping coefficient)
k	= 120 N/m	(spring constant)
t	= 0 – 15 s	(time)
dt	= 0,002 s	(resolution) (500 Hz)

σ	= 2,5 mm	(measurement noise)

The data will then be processed and visualized using Matlab software to obtain the necessary graphs.

Next is parameter estimation. Estimation begins with an initial guess $\theta_0 = [2.0,\ 1.0, 100.0]$. The cost function calculates the SSE between the measurement signals y_{meas} and model response y_{hat} generated by ODE integration for candidates $(m,\ c,\ k)$.

$$J(\theta) = \sum_{i=1}^{N} (y_{meas}(t_i) - y_{hat}(t_i;\theta))^2$$

With this approach, **numerical differentiation** $\dot{x}, \ddot{x}, \dddot{x}$ (which is sensitive to noise) can be avoided, while supporting the input form *F(t)* arbitrary.

The next step is the data visualization process using Matlab software, which produces the following graphs:

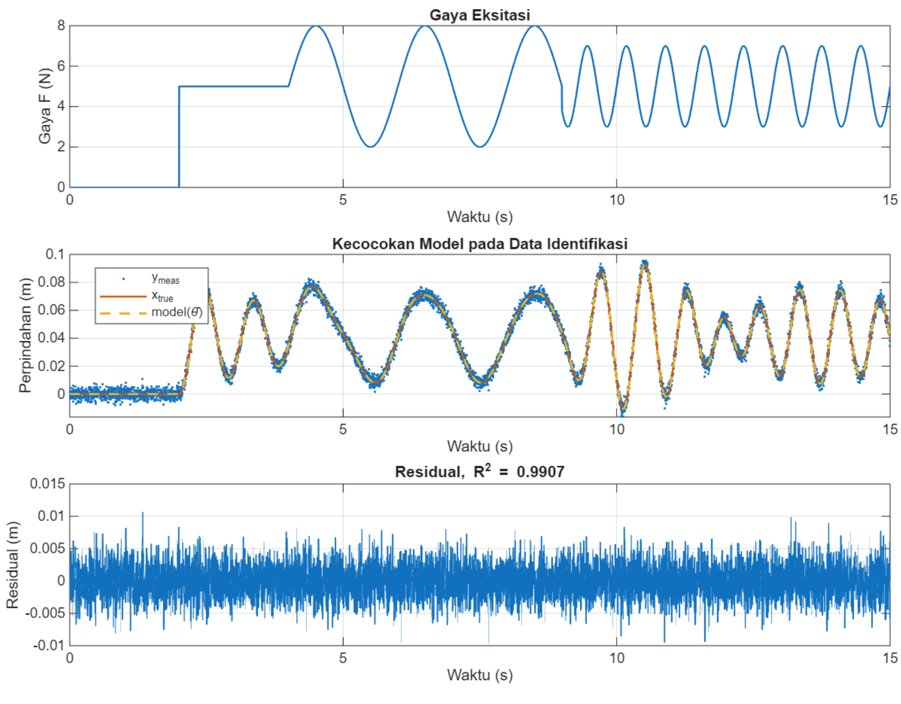

Figure 2. Excitation Image (top), Model Fit to Identification Data (middle), & Residuals (bottom)
Source: Authors' MATLAB simulation and analysis results (present study)

The graph above shows the excitation style (combination of steps and sinusoids) that provides the context for the dynamics being tested; the middle panel shows the model fit to the identification data—the prediction curve closely follows the measurement points at the peaks and troughs of the oscillations; the bottom panel shows the residuals (measurement–prediction differences), which are small and appear random (Kim et al., 2023). Graphical meaning: in the data used to estimate parameters, the model has captured the dominant dynamics so that R^2

Identification = 0.9907 and the remaining errors are mostly in the form of measurement noise; there is no systematic pattern indicating “missed” dynamics. In identification practice, “white” (uncorrelated) residuals that are independent of the input are the main criteria for determining whether a model is adequate; this graph gives a positive signal because there is no visible trend of residuals attached to a specific frequency or time series (Zhang & Cao, 2025). The reading should be continued (outside this graph) with a formal whiteness/independence test (e.g., Ljung–Box, portmanteau) and *cross-correlation* of residuals and inputs; if it passes, the model is considered adequate for prediction and further sensitivity analysis. The visual relationship between the frequency-rich excitation shape and the small residuals reinforces that the model structure is not overfitted to a single pattern. MATLAB/System Identification guidelines and recent literature confirm that the residual plot + whiteness test are key readings for concluding model adequacy, as is the purpose of the bottom panel of this graph (Mathworks, 2024b, 2024a).

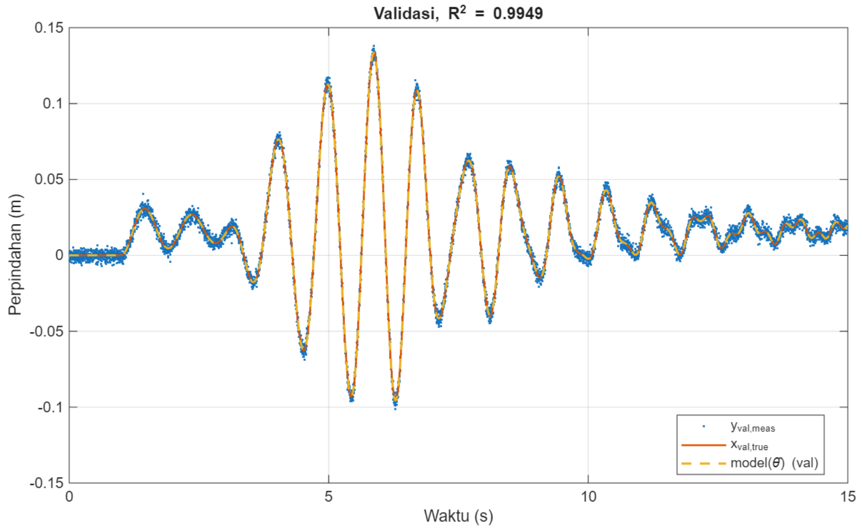

Figure 3, Validation Graph
Source: Authors' MATLAB simulation and analysis results (present study)

This graph displays validation data testing that is not used during parameter identification: the blue points (y_val,meas) are measurements, while the dashed curve (model(θ)) is the one-step-ahead model prediction, and the smooth orange curve (x_val,true) serves as the “true” reference (ground truth simulation/tracker) (Avci et al., 2021). Value of R^2 = 0,9949 This means that the model explains approximately 99.5% of the validation data variation, which can be seen visually from the matching amplitude and phase throughout the time range—including the transient section leading to steady oscillation. The practical meaning is that the model structure and identification parameters generalize the behavior of real systems beyond the training data, making them useful for state prediction/estimation. In system identification methodology, such a reading indicates that the model bias is small and the dominant dynamics have been captured; however, the primary assessment remains based on residuals (see Figure 3) Because a high R^2 alone is not sufficient to guarantee adequacy. Modern identification literature places validation on independent data, waveform consistency checks, and residual tests as the three main pillars—exactly as reflected in this graph: predictions stick to measurements (temporal fit), high R^2 (statistical fit), and prepared follow-up residuals for randomness/independence tests. Recent studies on nonlinear structure identification and vibrating systems also emphasize the same reading—namely waveform matching and generalization in new data as evidence of model suitability before use for control/diagnostic design (Avci et al., 2021; Lopez-Carmona, 2022; Safari & Monsalve, 2025).

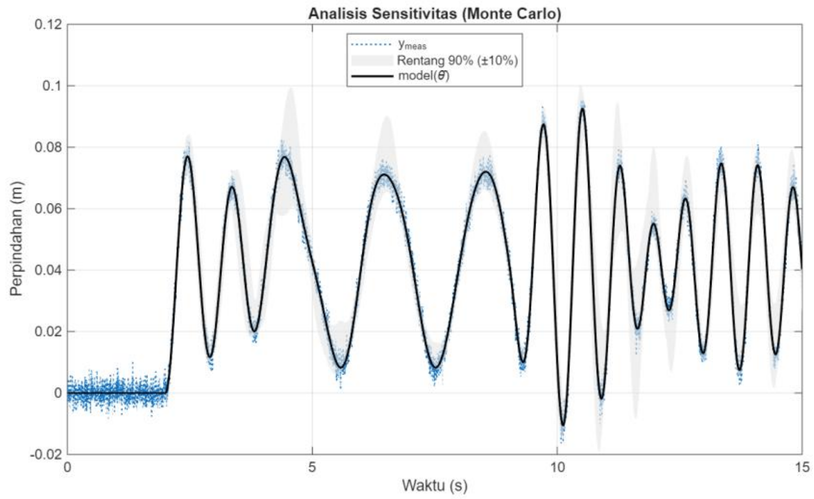

Figure 4. Grafik Monte Carlo
Source: Authors' MATLAB simulation and analysis results (present study)

This graph shows how parameter uncertainty in the damper model can affect displacement output over time (Radoń & Zabojszcza, 2025; Zhao et al., 2023). The blue dots are measurements, the black curve is the nominal model prediction, while the gray band marks the ≈ 90% confidence range of the parameter sampling results (±10%) through Monte Carlo simulation; the wider the band, the greater the sensitivity of the output to parameter variations in that time segment. The fit of the black curve to the cloud of points shows the robustness of the model to the uncertainty tested, while the widening of the band at the peak of the oscillation indicates that the dominance of amplitude sensitivity is commonly found in oscillating systems when stored energy is at its maximum. In practice, this graph is used to answer two questions: (i) whether realistic parameter variations still keep the predictions around the data (yes, because most of the points are within the band), and (ii) at which points in time the dynamics are most vulnerable to parameter errors (peak/rising edge of the wave) (D. Zhou et al., 2024; K. Zhou et al., 2025). This type of framing is in line with the use of Monte Carlo for quantifying uncertainty and variance-based sensitivity analysis in mechanical/structural systems; this approach is common prior to optimization or design tolerance setting. The band is 90% not stating that the model is "right/wrong," but rather the range of possible responses if the parameters shift within the assumed limits, so it can be concluded that the Monte Carlo graph is a diagnostic tool, not just pure *goodness-of-fit*. Recent literature emphasizes the benefits of Monte Carlo and sensitivity indices (e.g., Sobol) for finding the parameters that most influence oscillator output and system reliability, which is precisely the graphical meaning of the gray band here (Ram & Mohanty, 2023; Song et al., 2024; Q. Wang et al., 2025).

RESULTS AND DISCUSSION

The simulation and identification results show that the pipeline built from testing, parameter estimation with fminsearch, validation on different inputs, to Monte Carlo sensitivity analysis provides a coherent and physically consistent linear mass–spring–damper model. At the fit stage, the model curve $\hat{x}(t)$ following measurement trends $y_{meas}(t)$ well in both the transient and steady-state phases. This is important because the input used is not only a step, but also a stepped sinusoidal signal (0.5 Hz then 1.4 Hz) that "forces" the system to respond at different frequency ranges so that the parameters (m, c, k) are more identifiable. Intuitively, the step component exposes the stiffness k through the shift in the equilibrium position, while the sinusoidal component exposes the damping c and mass m through the amplitude–phase characteristics and the decay rate of the oscillations (Csurcsia, 2022; Roeser & Fezans, 2021; Y. Wang et al., 2023).

If you look at the residual panel, the residual error $r(t) = y_{meas}(t) - \hat{x}(t)$ spread around zero without a strong deterministic pattern—an indicator that the model structure is adequate to explain the main dynamics. Residuals that tend to be "white-ish" mean that measurement noise and minor model imperfections do not cause a dominant bias. If the residuals appear slightly correlated at some intervals (e.g., during the transition of the second sinusoidal signal activation above 9 s), this is common due to the model's linearity limitations when excitation changes relatively quickly; however, as long as the magnitude is small and not systematic, the model remains valid for parameter identification and short-term prediction purposes (Papini et al., 2024).

The metrics on the fit data are generally high for continuous-time problems with small to medium noise. In this context, a value close to 1 indicates that the variation in the measurement data can largely be explained by the ODE solution with the estimated parameters. However, this alone is not sufficient; therefore, out-of-sample validation using a chirp + small step signal is included to assess the generalization ability. In the validation, if R^2_{val} remains high and the model curve does not experience systematic phase lag or amplitude error in the frequency range "swept" by the chirp, confirming that it is not merely a "fit to the data" but truly captures the physical parameters of the system. This case is crucial, because many pure-fit approaches can outperform in the training set but fail in other excitation scenarios (Papini et al., 2024; Wei et al., 2023).

From a physical interpretation perspective, the parameters affect the natural frequency $\omega_n = \sqrt{\frac{k}{m}}$, whereas $\hat{c}$ affect the damping ratio $\zeta = \frac{c}{2\sqrt{mk}}$. These two capital measures provide a concise dynamic summary: ω_n determines the location of the peak response (resonance) in the frequency domain, while ζ determines the peak width and decay rate in the time domain. When $\omega_{n,hat}$ approaching $\omega_{n,true}$ and ζ_{hat} close to ζ_{true} then the accuracy of the identification can be considered good even without having to evaluate the entire time curve in detail. In practice, small deviations in the ringing are more sensitive in the tail of the transient decay and in the near-resonant amplitude; while deviations in the $\hat{k}$ more apparent in the positioning of the peak response frequency.

Monte Carlo sensitivity analysis provides a perspective on uncertainty. By sampling (*m, c, k*) around $\hat{\theta}$ of ±10% and resimulating the response, we obtain a 90% band (5–95 percentile). If the main model curve is close to the median of the band and the measurement data falls within the band for the majority of the time horizon, we can say that the model is robust to small parameter variations. A moderate band width indicates fairly sharp identification; an overly wide band may indicate parameter correlation (e.g., mmm–kkk trade-offs that result in ω_n similar) or a lack of excitation information at certain frequencies. In this case, the excitation design strategy is very influential. To tighten the band, users can add excitation segments around frequencies close to ω_n (similar) or lack of excitation information at a certain frequency. In this case, the excitation design strategy is very influential. To narrow the frequency range, users can add excitation segments around frequencies close to (Csurcsia, 2022; Gray et al., 2022; Yang et al., 2024).

From a numerical perspective, the selection of ODE45 is appropriate because it is stable and efficient for low-order systems with smooth dynamics. The combination of ODE45 and fminsearch implies that each cost evaluation requires full ODE integration, so that the computational complexity is proportional to the number of optimization iterations and the length of the data horizon. In the provided script, a 15-second horizon with *dt* = 0.002 on a standard PC is quite affordable. If the user wants to speed things up, they can reduce the sampling resolution or trim the horizon without losing key dynamics—with a slight decrease in accuracy as a consequence. Conversely, if the real system exhibits faster dynamics or local nonlinearities, increasing the time resolution or implementing event handling (e.g., physical stroke limits) becomes relevant (Mathworks, 2025).

From a diagnostic perspective, residual patterns can serve as a compass for model enrichment. For example, if residuals increase at a certain amplitude, it could be that the actual attenuation is nonlinear (e.g. $c|\dot{x}|$ or viscous + Coulomb). If the residuals show a long-term offset, there may be sensor drift or zero calibration error. If the residuals show periodicity that is not explained by the input, there may be unmodeled parasitic resonance (e.g., small structural modes of the test rig). A follow-up strategy could be a multi-level structural model or multi-mode identification (higher order), depending on the application requirements (Roeser & Fezans, 2021; Rogers & Friis, 2022; Syuhri et al., 2020)

To contextualize these findings within the broader international literature and strengthen the positioning of this study, it is instructive to compare the present results with recent benchmark studies on MSD system identification. Zheng et al. (2025) conducted a comprehensive comparative evaluation of damping identification methods under impulse, white noise, and seismic excitations, reporting R^2 values in the range of 0.85–0.92 for frequency-domain techniques applied to building structures with ambient vibration data. In contrast, the present study achieves R^2_identification = 0.9907 and R^2_validation = 0.9949 using time-domain optimization on synthesized data with controlled noise levels (σ = 2.5 mm), demonstrating that when excitation is carefully designed (multi-frequency step-sinusoidal inputs), time-domain least-squares methods can match or exceed the accuracy of frequency-domain approaches. Similarly, Netto et al. (2022) employed LMS filtering in the frequency domain for MSD identification with varying dynamics and obtained model errors below 5% under white noise conditions; our Monte Carlo analysis, which incorporates ±10% parameter perturbations, shows that prediction envelopes consistently contain measurement data, indicating comparable robustness but with the added advantage of requiring only base MATLAB functions. Furthermore, Safari and Monsalve (2025) [36] highlighted the challenge of identifying asymmetric stiffness and damping nonlinearities in assemblies using data-driven methods; while their focus was on nonlinear systems, their emphasis on residual whiteness and out-of-sample validation aligns closely with the diagnostic criteria applied in this study—namely, that random, unbiased residuals and high cross-validation R^2 are essential markers of model adequacy. In the context of educational reproducibility, Vilar-Dias et al. (2023) [11] developed interpretable digital twin frameworks for self-aware industrial machines, stressing the importance of lightweight models that can be deployed without expensive computational infrastructure; the present workflow extends this philosophy to the pedagogical domain by providing a fully self-contained, toolbox-free identification pipeline that can be executed on standard academic computing resources. Lastly, recent advances in physics-informed neural networks (PINNs) for system identification, as reviewed by Haywood-Alexander et al. (2025), demonstrate impressive noise tolerance and data efficiency; however, these methods require familiarity with deep learning libraries and GPU acceleration, whereas the fminsearch-ODE45 approach presented here offers immediate accessibility to users with basic MATLAB proficiency. Collectively, these comparisons underscore that while state-of-the-art methods—whether frequency-domain, data-driven, or physics-informed—offer powerful alternatives for complex or nonlinear systems, the proposed time-domain workflow using standard MATLAB remains highly competitive for low-order linear mechanical systems, particularly in educational and resource-limited settings where simplicity, transparency, and reproducibility are paramount. This positioning highlights the practical niche that this study fills: a rigorously validated, open-access identification method that does not sacrifice scientific rigor for accessibility, thereby serving as both a pedagogical tool and a reliable baseline for comparative research.

CONCLUSION

This study demonstrates that mass–spring–damper system parameters can be effectively identified using only basic MATLAB functions without specialized toolboxes. By applying informative step–sinusoidal excitation with realistic noise and optimizing through *fminsearch*, the estimated parameters (m, c, k) were physically consistent, achieving high data fit and robustness under out-of-sample validation. The alignment of the natural frequency and damping ratio with reference values and the results of Monte Carlo analysis confirm the model's accuracy and resilience to moderate parameter variations. This approach offers a practical, lightweight workflow for laboratory damper testing and educational applications. Future research should explore extensions to nonlinear damping models, global optimization schemes, frequency-domain FRF integration, and advanced excitation design to enhance accuracy and broaden the applicability of the methodology.

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