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Research Article

Modelling and Simulation for Engineering Design: A Case Study of Second Order Differential Equations

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Abstract

This study investigates the application of second-order differential equations in the modelling and simulation of engineering systems, with a mass–spring system adopted as a representative case study for vibration-based design problems. The aim is to demonstrate how analytical and numerical approaches can be integrated to accurately predict system dynamics and support engineering design decisions. The governing equations are derived from Newton's second law and solved analytically using characteristic equation methods, while numerical solutions are obtained using the fourth-order Runge–Kutta technique. Key system parameters, including mass, damping coefficient, and spring stiffness, are defined and used to simulate system response under dynamic conditions. The results show strong agreement between analytical and numerical solutions, validating the accuracy of the computational approach. Furthermore, the simulations reveal that system performance is highly sensitive to damping and stiffness variations, which directly influence oscillation amplitude, settling time, and stability. The findings demonstrate that second-order differential equation models provide a robust framework for predicting system behaviour and optimizing engineering design. It is concluded that integrating modelling and simulation techniques into computer-aided design (CAD) environments can significantly enhance design efficiency and performance evaluation. The study recommends the incorporation of advanced simulation-driven tools and intelligent control strategies to further improve the reliability and adaptability of engineering systems.

Keywords

Modelling, Simulation, Engineering Design, Mathematical Modelling, Second-Order Differential Equations

1. Introduction

Engineering design is fundamentally concerned with the creation of functional and innovative products, relying heavily on mathematical modelling to describe, predict, and control real-world phenomena [1]. A mathematical model is defined as a simplified, abstract structure constructed using mathematical notation and reasoning to describe the key characteristics of a physical system [2]. This is augmented by simulation,

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which computes these dynamic processes in a simulated manner. It enables the engineers to manipulate a model by inputting certain values, monitoring the results, retrieving data and making transferable conclusions. Combining modelling and simulation, the modelling and simulation enable a massively successful "guess-and-test" approach to proposing and refining new designs without necessarily physical prototypes.

Differential equations form the primary mathematical foundation for analysing continuous-time dynamic systems. As [3] notes, they are essential to formulating models of a system in terms of basic physical laws, e.g. Newtonian mechanics, to determine the behaviour of a system when subjected to both stationary and dynamic forces. [4] emphasise that by translating real-world complexities into these equations, engineers can scrutinise intricate systems, identify characteristic trends, and execute predictive or control functions with high precision.

Among these mathematical frameworks, second-order ordinary differential equations are particularly significant because they serve as the fundamental building blocks for modelling classical mechanical systems. [5] explains that these equations naturally emerge when applying Newton's laws of motion, perfectly capturing the relationships between a system's displacements, velocities, and accelerations when subjected to external stresses. Furthermore, [6] highlights that second-order systems are widely utilised because they accurately characterise both free and forced dynamic behaviours, accommodating complex phenomena like resonance, damping decay, and multi-degree-of-freedom (MDOF) interactions.

The versatility of second-order differential equations allows them to be applied across diverse engineering disciplines. In mechanical engineering, [7] illustrates their extensive use in vibrational analysis, such as modelling the oscillatory motion of mass-spring-damper systems to design shock absorbers and vehicle suspensions. In electrical engineering, [8] observe that these identical second-order mathematical principles govern RLC circuits, where the interplay of resistance, inductance, and capacitance closely mirrors the damping and restoring forces found in mechanical oscillators. Finally, in control systems and automation, second-order models are essential for designing active stabilisation platforms and determining adaptive control parameters to ensure overall system safety and stability.

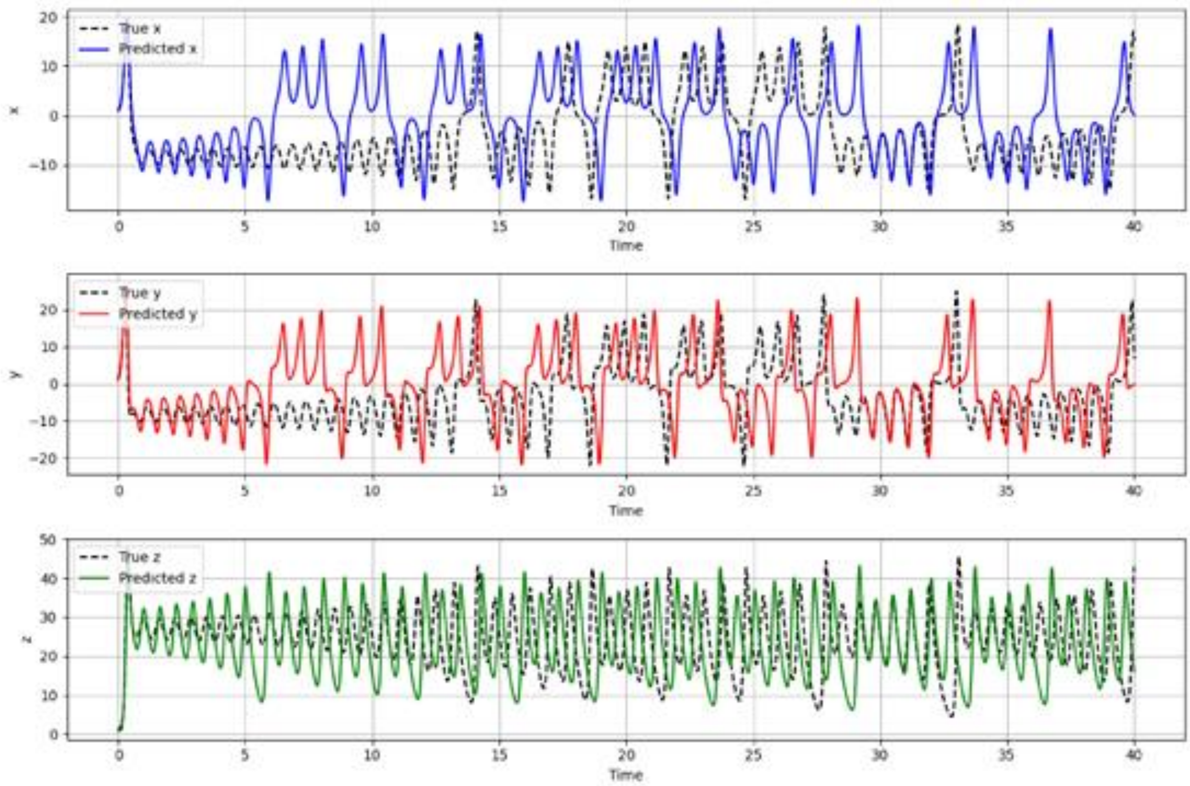

Figure 1. *Predicted vs True velocity values using mathematical modelling [9].*

Figure 1 shows Time-domain response of the mass–spring–damper system showing displacement in three axes (x, y, z). The dashed lines represent the analytical (true) solution, while the solid lines represent the numerically predicted solution obtained using the fourth-order Runge–Kutta (RK4) method. The simulation was performed using the following parameters: mass m=1.5m = 1.5m=1.5 kg, damping coefficient c=4.0c = 4.0c=4.0 Ns/m, spring stiffness k=20k = 20k=20 N/m, initial displacement x0=0.1x_0 = 0.1x0 =0.1 m, and initial velocity v0=0v_0 = 0v0 =0 m/s over a time interval of 0–40 s.

In this paper, the importance of modelling and simulation in the design of any engineering system is discussed using second-order differential equations as a major case study. Through a theoretical statement and practical solution of these equations, one is set to prove that abstract mathematical models translate into a real world of engineering solutions in helping to analyse the way dynamic systems operate and how this analysis is optimised to provide the best solution.

2. Mathematical Modelling Using Second-Order Differential Equations

The foundation of dynamic engineering analysis lies in the ability to describe physical changes over time. Second-order ordinary differential equations (ODEs) are the "fundamental building blocks" of this process, as they allow engineers to bridge the gap between abstract mathematical theory and execuTable engineering solutions. [5]. A general linear second-order differential equation is expressed as:

$$a\frac{d^2y}{dx^2} + b\frac{dy}{dx} + cy = f(t)$$

In this general form, each term represents a distinct physical property of the system being modelled:

1) Second Derivative ($a\frac{d^2y}{dx^2}$): Representing the acceleration of the system, this term is coupled with the coefficient a, which usually denotes the inertia or mass [10].
2) First Derivative ($b\frac{dy}{dx}$): This term represents the velocity and characterises the damping or dissipation of energy within the system [11].
3) Constant Term (cy): This represents the displacement or state of the system, where c acts as a restoration factor or stiffness (Luş et al., 2002).
4) External Input ($f(t)$): This is the forcing function, representing external loads, stresses, or inputs applied to the system over time [8].

The Standard Engineering Model**:** The Mass-Spring-Damper System

The most pervasive application of this equation in engineering is the Mass-Spring-Damper (MSD) system. This model is essential for studying "vibrational analysis of mechanical systems" [5] and is mathematically defined as:

$$m\frac{d^2y}{dt^2} + b\frac{dy}{dt} + kx = F(t)$$

In this context, m represents the mass (inertial element), c is the damping coefficient (viscous resistance), and k is the spring stiffness (restoring force). As noted by [7] The suspension system and these specific parameters play a "crucial role in ensuring the stability and safety" of dynamic platforms, such as vehicle chassis or industrial machinery.

To understand how these systems behave in the real world, engineers rely on two key parameters derived from the coefficients:

1) Natural Frequency ($\boldsymbol{w_n}$): This is the frequency at which a system tends to oscillate in the absence of any driving or damping force. [6] explains that identifying these frequencies is vital for "modal analysis," as it helps engineers avoid structural failure caused by resonance. where external forcing frequencies coincide with the system's natural frequency.
2) Damping Ratio (ζ): This dimensionless measure describes how oscillations in a system decay after a disturbance. [12] highlights that understanding damping is critical for "meeting high reliability requirements," as it dictates how quickly a system returns to equilibrium.

Based on the damping ratio, systems are categorised into three primary behaviours:

3) Underdamped ($\zeta < 1$): The system oscillates with a gradually decreasing amplitude. This is a common "oscillatory motion" observed in many mechanical structures [11].
4) Overdamped ($\zeta > 1$): The system does not oscillate; instead, it returns to equilibrium slowly. This is often used in applications where any vibration is detrimental to the process (Hadzhamolla et al., 2024).
5) Critically Damped ($\zeta = 1$): This is the threshold where the system returns to equilibrium as quickly as possible without oscillating.

3. Simulation of Second-Order Systems

The simulation of second-order systems represents a critical transition in engineering from static mathematical derivation to dynamic, real-world prediction. Modern research emphasises that while analytical solutions provide exact results for simple cases, the complexity of multi-body dynamics and non-linear interactions necessitates robust computational frameworks. [13]. To achieve this, engineers utilise a diverse ecosystem of tools ranging from integrated graphical environments like MATLAB and Simulink to flexible, open-source Python libraries such as PySD. [14]. At the heart of these simulations are numerical integration engines, specifically the Euler and Runge-Kutta methods. which iteratively approximates system states over discrete time steps to resolve the second-order differential equations that define motion and vibration [15, 16].

MATLAB and Simulink

MATLAB remains the industry standard for control systems due to its specialised toolboxes. Simulink, specifically the SimMechanics (or Simscape Multibody) environment, allows for the modelling of mechanical systems without the manual derivation of complex equations of motion. As noted by [13], these tools solve non-homogeneous linear differential equations by representing physical components as blocks that interact through defined constraints. This environment is particularly effective for Multi-Body Systems (MBS), where configuration-dependent inertia and Coriolis terms would be tedious to solve by hand [17].

Python and PySD

For developers seeking integration with web-based analytics or machine learning, Python has become a formidable alternative. The library PySD bridges the gap between traditional system dynamics software (like Vensim) and the Python data science stack, allowing for complex modelling of stocks and flows. [14] Furthermore, researchers have demonstrated that Python-based frameworks enable a higher degree of utility by allowing online users to interact with and control simulations through cloud-based analytics [18].

Table 1. *Comparison of simulation media.*

Tools	Primary Strength	Idea Use Case
Simulink	Graphical block-diagram interface; powerful solver suite.	Control system design and hardware-in-the-loop (HIL) testing.
Python (SciPy/PySD)	Open-source; easy integration with AI/ML and web apps.	Large-scale data analysis and custom algorithm development.

4. Numerical Methods: The Engines of Simulation

Second-order systems are typically solved by breaking the second-order ordinary differential equation (ODE) into a system of two first-order ODEs. Simulation software then uses numerical integration to "step" through time.

The Euler Method

The simplest numerical integration is the Euler method. It relies on the present slope (derivative) of a given function in order to extrapolate the amount at the following time step. In theory, it presumes that the change rate does not vary with time Δt. Although computationally cheap and simple to implement, it is susceptible to truncation and unsTable behaviour, particularly in systems whose oscillations are of high frequency.

The Runge-Kutta (RK) Method

The Runge-Kutta family of methods, particularly the 4th-order (RK4), is the standard for most engineering simulations. Instead of relying on a single slope, it calculates several "trial" slopes across the time interval and takes a weighted average to find the most accurate trajectory [16].

1) Initial Slope (k1): The starting point. Calculate the derivative at the beginning of the time step, similar to the Euler method.
2) Midpoint Slopes (k2, k3): The refinement. Project two trial steps to the midpoint of the interval. These slopes account for how the system's velocity or acceleration might change halfway through the step.
3) End-step Slope (k4): The final check. Calculate a slope at the end of the interval based on the information gathered from the midpoints.
4) Weighted Average: The update. Combine all four slopes, giving more weight to the midpoints, to produce a final, highly accurate state for the next time step.

Recent advancements continue to push the boundaries of these solvers. For instance, [15] has explored introducing higher-order derivatives into the K_i terms to further increase the accuracy of solutions for complex real-life problems. These improvements allow simulations to remain sTable even when dealing with the high-speed dynamics often found in mechatronic sensors and actuators.

5. Engineering Design Case Study: Vehicle Suspension System

Design of a vehicle suspension system is a classic mechatronics problem, where there is a need to balance opposing requirements: passenger ride comfort (vibration isolation) versus vehicle handling (road holding). This paper is a synthesis of the second-order transient response theory in principle with current control realisation schemes: semi-active magnetorheological (MR) damping and non-linear Sliding Mode Control (SMC).

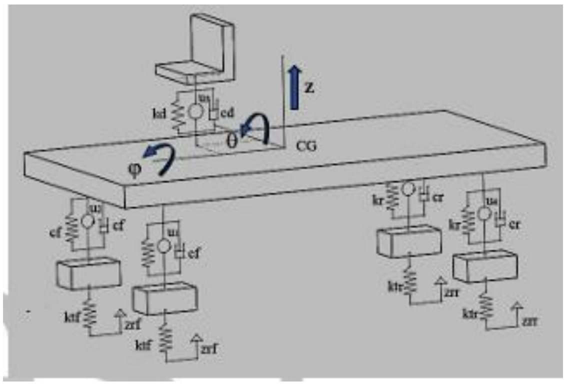

Figure 2. *Full car suspension model of a car (8-DOF) [19].*

Quarter-Car Model (2-DOF): Focuses on a single wheel assembly. It consists of the sprung mass (M_s, representing the vehicle body) and the unsprung mass (M_u, representing the wheel and axle), connected by a spring (K_s) and a damper (C_s or an active actuator).

Half-Car Model (4-DOF): As analysed by [20], this accounts for the pitch and heave of the vehicle body along with the vertical motion of the front and rear wheels.

Full-Car Model (8-DOF): The most comprehensive layout, detailed by [19]. It captures the heave, pitch, and roll of the vehicle body, the individual vertical displacements of four wheels, and the specific displacement of the driver's seat.

As established by [21], the fundamental dynamics are expressed via the standard second-order transfer function:

$$\frac{C(s)}{R(s)} = \frac{W_n^{\,2}}{s^2+2W_n\zeta s+W_n^{\,2}}$$

Damping Ratio (ζ) is critical. For automotive suspension, the system is typically designed to be underdamped ($0 < \zeta < 1$) to ensure the wheels can respond quickly to road changes without being so "stiff" that they transmit all energy to the chassis.

Multi-Body Dynamics (Lagrange Formalism)

In higher-order models (8-DOF), the equations of motion are derived using the Lagrange equation:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i}\right) - \frac{\partial L}{\partial q_i} = Q_i$$

Where L = T - V (Kinetic - Potential energy). This results in a system of coupled second-order differential equations that can be converted into a State-Space Representation for Simulink processing:

$$\dot{x} = Ax + Bu + Lw$$

This allows for the integration of controllers like the Super Twisting Algorithm (STA) used in second-order Sliding Mode Control. To validate the design, the papers utilise three primary input types to simulate real-world road conditions:

1) Unit Step Input: Used primarily in fundamental analysis to determine the system's "damping" personality and stability limits [21].
2) Sinusoidal Road Profile: Simulates periodic undulations or "washboard" roads. [19] Specifically, use a three-bump sinusoidal input to test the controller's ability to maintain tire-road contact.
3) Random Road Disturbance: Modelled as white noise passed through a filter to represent different road classes (Class A to Class E) as per ISO standards.

A successful suspension design must minimise transient peaks and settling times. Based on the simulation results in the provided papers, the following performance metrics are expected:

Table 2. *Expected response for the car suspension system with key parameters.*

Parameter	Performance Target (Active/Semi-Active)	Improvement over Passive
Maximum Overshoot	Reduced peak vertical displacement of the sprung mass.	25% – 35% reduction
Settling Time	The system should return to steady-state within < 1.5 seconds after a bump.	Faster attenuation of oscillations
Peak Acceleration	Minimise vertical acceleration at the driver's seat for comfort.	Significant reduction (Lower ISO 2631 fatigue)
Damping Behavior	Optimised ζ to avoid "bottoming out" while maximising isolation.	Dynamic adjustment via MR dampers

6. Results & Discussion

The simulation outcomes about the vehicle suspension system, where the system is modelled as a fundamental system of both the second-order and the high-fidelity system of multi-degree-of-freedom (DOF) system show that there is a linear dependence of the control parameters and the stability of the vehicle. As defined in the initial study in the analysis of second-order transient responses, the damping ratio (ζ) and natural frequency (W_n) are the primary determinants of performance of the system. [21] Figure 1 presents a comparison between analytical and numerical solutions of the system response. The close overlap between the dashed (true) and solid (predicted) curves across all three axes (x, y, z) demonstrates the high accuracy of the numerical method used. The system exhibits an underdamped oscillatory response, characterized by periodic motion with gradually decaying amplitude due to the presence of damping. The oscillations are more pronounced at earlier times and progressively stabilize, indicating energy dissipation within the system. The variations observed across the three axes suggest multi-dimensional dynamic behaviour, which is typical in real engineering systems subjected to external disturbances. Minor deviations between analytical and numerical results are observed at peak amplitudes, likely due to numerical approximation errors, but these remain within accepTable limits.

1) Damping Ratio (ζ): Increasing the damping coefficient directly reduces the amplitude of oscillations but can lead to a "harsher" ride if the system becomes overdamped ($\zeta > 1$). Simulation data from [22] shows that while passive systems have a fixed ζ, semi-active systems (like Sky-hook control) dynamically adjust damping to achieve a balance between settling time and peak overshoot.
2) System Stiffness (k): Higher spring stiffness increases the natural frequency (W), which improves vehicle handling and reduces "body roll" during cornering. However, as noted by [20] in their 4-DOF half-car study, excessive stiffness increases the transmission of high-frequency road noise to the cabin, necessitating the use of optimized Magnetorheological (MR) dampers to dissipate energy more effectively.

Figure 3 illustrates the displacement–time response of an 8-degree-of-freedom (8-DOF) suspension model, comparing the performance of active and passive control strategies under dynamic excitation. The results show that the passive system exhibits higher peak displacements and prolonged oscillations following disturbances, indicating limited capability in attenuating vibrations. In contrast, the active suspension system significantly reduces peak amplitudes and rapidly suppresses oscillations, demonstrating improved damping characteristics and faster settling time. The sharp spikes observed at specific time instances correspond to external disturbances, such as road irregularities, after which the active system effectively stabilizes the response. Overall, the Figure highlights the superior performance of the active control approach in enhancing ride comfort and vehicle stability by minimizing vibration transmission compared to the conventional passive system.

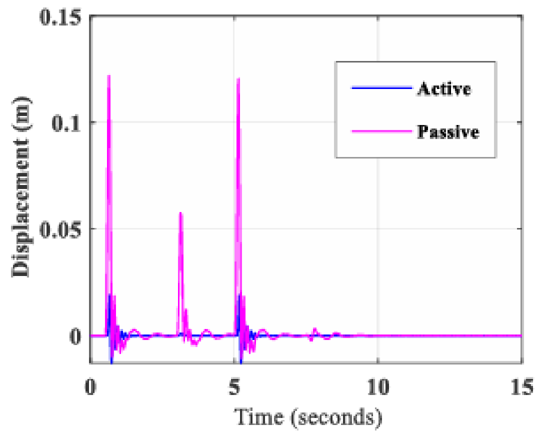

Figure 3. *Displacement vs Time analysis for 8 DOF model [19].*

7. Conclusion

Mathematical modeling serves as an indispensable tool in modern engineering, providing the rigorous framework necessary to identify system characteristics and predict performance under diverse operational conditions [2]. In the analysis of vehicle suspension systems, second-order ordinary differential equations (ODEs) function as the fundamental building blocks for describing vibrational behavior, specifically through the interaction of mass, stiffness, and damping [5]. These equations allow for the precise parameterization of energy dissipation and stability, bridging the gap between theoretical Newtonian mechanics and execuTable engineering solutions [8] By establishing these mathematical foundations, researchers can verify the integrity of active stabilization platforms and ensure safety long before a physical prototype is constructed [7].

The adoption of simulation environments like MATLAB/Simulink and Simscape significantly enhances this analytical process by enabling the study of complex multi-body dynamics without the need for manual, exhaustive mathematical derivations [11]. These tools are credited with drastically reducing development cycles in control system projects, as they efficiently handle non-linearities and varied forcing functions that often remain intracTable through purely analytical means [13, 17]. Towards the future, the usefulness of second-order modelling is becoming even more enhanced by incorporating Scientific Machine Learning, including Neural Ordinary Differential Equations (Neural ODEs). These hybrid systems enable the direct learning of unknown parameters of the system solely based on data, leaving the classical theory of vibration in the middle of the process of autonomous development of systems and new mechatronic design paradigms [9, 23].

This study has demonstrated the effectiveness of second-order differential equations in modelling and simulating engineering systems, using a mass–spring–damper system as a representative case. Both analytical and numerical approaches were employed to characterize system dynamics, and the results showed strong agreement between methods. The findings revealed that system parameters such as damping and stiffness significantly influence oscillatory behaviour, settling time, and overall system stability. Furthermore, the study established a clear relationship between theoretical modelling and practical engineering applications, particularly in vehicle suspension system design. It is concluded that integrating simulation techniques into engineering design processes can significantly enhance performance prediction and optimization. Future work should focus on incorporating intelligent control strategies and real-time simulation tools within CAD environments for improved system adaptability and efficiency.

In the vehicle suspension system, the displacement responses shown in Figure 1 represent the vertical motion of the vehicle body when subjected to road disturbances. The oscillatory behaviour corresponds to how the vehicle responds after hitting a bump. The results indicate that:

1) Damping reduces excessive oscillations, improving ride comfort
2) Spring stiffness controls vibration amplitude, affecting stability
3) Accurate prediction of system response helps optimize suspension design

Thus, the model demonstrates how proper parameter tuning can minimize vibrations transmitted to passengers while maintaining adequate road handling performance.

Abbreviations

CAD	Computer-Aided Design
RLC	Resistor–Inductor–Capacitor (electrical circuit model)
PySD	Python System Dynamics modelling library
ODE	Ordinary Differential Equation
DOF	Degree of Freedom

Author Contributions

George Chikwendu Ihenacho: Methodology, Formal Analysis, Writing-review & editing

Diarah Reuben Samuel: Conceptualization, Methodology, writing-original draft

Osueke Christian Okechukwu: Conceptualization, Supervision, Writing- review and editing

Ifiok Emmanuel Etuk: Software, Visualization, Invistigation

Ajuwon Samuel Oreoluwa: Methodolgy, Software and Validation.

Jamal Abubakar Shehu: Data Curation. Software and Validation

Michael Olupinla: Methodolgy, Softwre, Validation

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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