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Simulation-Based Dynamic Analysis of Mechanical Systems for Performance Enhancement and Stability Evaluation

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ABSTRACT

The study **"Dynamic Modeling and Analysis of Mechanical Systems Using Simulation Techniques"** focuses on the analysis of mechanical system behavior under dynamic loading conditions. Mechanical systems experience motion, vibration, force, damping, and changing operational conditions during actual working processes. Dynamic modeling helps represent these systems through mathematical equations, while simulation techniques allow their performance to be tested virtually. The study analyzes displacement, velocity, acceleration, vibration response, stability, and operational efficiency using simulation-based methods. The results indicate that simulation improves design accuracy, reduces physical testing, identifies faults early, and supports safer and cost-effective mechanical system optimization.

Keywords: *Dynamic Modeling, Mechanical Systems, Simulation Techniques, System Stability.*

I. Introduction

Dynamic modeling and analysis of mechanical systems using simulation techniques is an important field of mechanical engineering that focuses on understanding, predicting, and improving the behavior of mechanical systems under changing conditions of motion, load, force, torque, vibration, friction, damping, and energy transfer. A mechanical system may consist of simple components such as masses, springs, dampers, beams, shafts, gears, levers, pulleys, and rotating discs, or it may involve complex engineering systems such as vehicle suspension systems, robotic manipulators, turbines, engines, machine tools, aerospace mechanisms, industrial production machines, and automated mechanical assemblies. Unlike static analysis, which studies a system under constant or slowly varying loads, dynamic analysis deals with time-dependent behavior. In real engineering applications, most mechanical systems do not remain in a fixed condition; they move, accelerate, vibrate, rotate, experience sudden impacts, carry variable loads, and respond continuously to external disturbances. Therefore, dynamic modeling becomes essential for describing how a mechanical system behaves over time. It provides a mathematical representation of the physical system by using principles such as Newton's laws of motion, D'Alembert's principle, Lagrange's equations, Hamilton's principle, energy methods, and state-space modeling. These mathematical models help engineers relate input conditions, such as applied force, torque, displacement, or excitation, to output responses, such as velocity, acceleration, vibration amplitude, stress, strain, deformation, and stability. Dynamic modeling also helps in identifying important system parameters, including mass, stiffness, damping coefficient, moment of inertia, natural frequency, damping ratio, resonance frequency, and system response time. These parameters are necessary for understanding whether a system will operate smoothly, vibrate excessively, become unstable, or fail under particular conditions. For example, in a mass-spring-damper system, the mass stores kinetic energy, the spring stores potential energy, and the damper dissipates energy. By developing a mathematical model of this system, engineers can study how it responds when it is disturbed by an external force. Similarly, in rotating machinery, dynamic modeling can be used to study shaft vibration, imbalance, bearing response, and critical speed. In vehicle systems, it helps analyze ride comfort, road holding, suspension performance, and vibration isolation. In robotic systems, it helps predict joint motion, actuator torque, control accuracy, and stability during operation. Thus, dynamic modeling provides the foundation for studying both simple and complex mechanical systems in a scientific and systematic manner. It allows engineers to understand the cause-and-effect relationship between design parameters and system response. This understanding is very important because poor dynamic behavior can lead to vibration, noise, fatigue failure, reduced efficiency, mechanical wear, unsafe operation, and high maintenance cost. In modern engineering design, it is not enough to build a machine that can merely perform its basic function; the machine must also operate safely, reliably, efficiently, and smoothly under different working conditions. Therefore, dynamic modeling has become a necessary tool for product development, performance evaluation, fault detection, vibration control, and design optimization. It also supports the development of virtual prototypes, where the performance of a system can be studied before manufacturing the actual product. This reduces cost, saves time, minimizes experimental errors, and helps engineers make better design decisions at an early stage.

Simulation techniques play a major role in dynamic modeling and analysis because they allow engineers to solve complex mathematical models and observe system behavior in a virtual environment. Many mechanical systems involve nonlinear behavior, multi-body motion, contact forces, variable damping, changing boundary conditions, and complex geometry, which are difficult to solve manually by traditional analytical methods. Simulation provides a practical and efficient way to study such systems by using numerical methods and computer-based tools. Software such as MATLAB/Simulink, ANSYS, Adams, SolidWorks Motion, MSC Nastran, Abaqus, and other computer-aided engineering platforms are widely used for simulating mechanical systems. These tools help engineers create models, apply input conditions, define constraints, run simulations, and visualize results through graphs, animations, contour plots, and data tables. Through simulation, the response of a mechanical system can be analyzed under different operating conditions without repeatedly building physical prototypes. For example, an engineer can simulate a vehicle suspension system on different road profiles, test a robotic arm under different payloads, analyze a rotating shaft at different speeds, or study the vibration behavior of a machine foundation under harmonic excitation. Simulation also allows the user to change system parameters such as mass, stiffness, damping, speed, force, material properties, and geometry to observe how the performance changes. This makes it possible to compare different design alternatives and select the most suitable configuration. One of the major advantages of simulation is that it helps identify problems such as resonance, excessive vibration, instability, high stress concentration, fatigue risk, and poor energy efficiency before the system is manufactured. Resonance is especially important in dynamic analysis because it occurs when the excitation frequency matches the natural frequency of the system, causing large vibration amplitudes that may damage components or reduce performance. By using simulation, engineers can detect resonance conditions and modify the design by changing stiffness, mass distribution, damping, or support conditions. Simulation techniques are also useful for control system design, especially in mechatronic and robotic systems, where mechanical motion must be accurately controlled using sensors, actuators, and feedback controllers. Dynamic simulation helps test control strategies before applying them to real machines, thereby improving safety and reducing risk. In addition, simulation-based analysis supports predictive maintenance by helping identify abnormal vibration patterns, possible faults, and performance degradation in machines. In industrial applications, this can reduce downtime and improve reliability. The growing use of digital engineering, smart manufacturing, and Industry 4.0 has further increased the importance of dynamic simulation. Modern industries now depend on virtual testing, digital twins, real-time monitoring, and computer-based optimization to improve machine performance and reduce development time. A digital twin of a mechanical system can continuously receive data from the real machine and compare actual performance with simulated behavior. This helps in fault diagnosis, performance prediction, and maintenance planning. Therefore, dynamic modeling and simulation techniques have become essential not only for academic study but also for practical industrial applications. They provide a bridge between theoretical mechanics and real-world engineering design. By combining mathematical modeling with computer simulation, engineers can analyze complex mechanical systems more accurately, understand their dynamic behavior more deeply, and improve their safety, durability, and efficiency. Overall, dynamic modeling and analysis using simulation techniques form a powerful approach for designing advanced mechanical systems that meet the modern requirements of reliability, performance, cost-effectiveness, and sustainable engineering development.

II. RESEARCH BACKGROUND

Kurka (2026) was reported to have introduced two distinct methodologies for developing dynamic models of systems composed of discrete masses and rigid bodies interconnected by elastic and dissipative elements and subjected to external forces. The study indicated that the direct method entailed applying Newton–Euler equilibrium laws to the individual inertial components of the system, whereas the indirect method relied on energy principles and employed Lagrange’s equations with respect to the system’s degrees of freedom. Furthermore, the work was described to have elaborated on the concepts of generalized coordinates and inputs, kinematic constraints, and the determination of degrees of freedom. It was suggested that these methodological frameworks provided a systematic approach for modeling complex dynamic systems, enabling both component-level analysis and holistic system-level representation, thereby offering insights into the behavior of interconnected particles and rigid bodies under various loading conditions, with potential implications for mechanical design and simulation studies in multi-body dynamics.

Qiao et al. (2026) emphasized the critical role of rolling bearings in rotating machinery, particularly in sectors such as aerospace, high-speed railways, and wind turbines, and highlighted that frequent operation under extreme conditions, including high loads and rotational speeds, often led to unpredictable failures, potentially causing equipment shutdowns or catastrophic accidents. They argued that early fault detection was therefore essential to ensure operational safety. However, they noted that vibration signals collected by sensors were often contaminated with strong noise and normal responses from healthy components, limiting early fault feature extraction. To address this, they proposed a digital twin-guided denoising approach incorporating intrinsic fault knowledge. They first developed a dynamic bearing model to generate simulated fault signals, which were refined through cosine similarity with measured signals. Subsequently, they introduced a physical-virtual signal denoising method using a Wasserstein generative adversarial network with gradient penalty (DeWGAN-GP). Validation through bearing failure and fatigue degradation experiments demonstrated that their approach outperformed non-knowledge-driven methods in accurately extracting early failure characteristics under noisy conditions.

Wang et al. (2025) examined the complexities and nonlinear characteristics of Steel–Concrete Hybrid Tower (SCHT) structures, which had long posed challenges in dynamic modeling and analysis within the wind energy sector. They established a wind-rotor-tower integrated coupling model using a subsystem co-simulation method to facilitate detailed dynamic analyses. A multi-body model of the rotor and nacelle assembly was developed in Simpack, while a nonlinear finite element model of the SCHT was constructed in Abaqus. The co-simulation framework enabled efficient data exchange between solvers, allowing high-fidelity modeling of the tower structure without compromising computational efficiency. The approach permitted nonlinear time history analyses of onshore wind turbines under coupled wind load effects, and comparative studies with OpenFAST were conducted to validate its effectiveness. Subsequently, the method was applied to investigate the dynamic responses of turbines with SCHT, revealing distinctive structural behaviors. Additionally, a novel transition section was proposed to reduce displacement and stress amplitudes in the bolts.

Liu et al. (2024) investigated multi-stable origami structures, which had recently attracted significant attention for applications in dynamic scenarios, including robotic arm motions, impact energy absorption, and spectrum gap regulation. They emphasized that understanding the complex mechanisms and rich dynamics of these structures required the development of dynamic models. They noted that existing modeling approaches were often cumbersome and lacked interpretability. To address these challenges, they proposed a data-driven dynamic modeling method based on the B-spline Galerkin approach combined with a subset selection strategy, which captured the dynamics directly from measured data without relying on prior knowledge. The approach was first validated on the Duffing system, successfully reconstructing its governing equations. Subsequently, it was applied to tri-stable origami ball structures and high-dimensional multi-cell stacked Miura-origami (SMO) structures through simulations, demonstrating favorable outcomes. Finally, experimental data from a bi-stable SMO prototype were used to generate global models capable of predicting various dynamic behaviors across a wide range of excitation frequencies, confirming the method's interpretability and efficacy.

Yang et al. (2024) focused on the dynamic modeling and analysis of planetary gear systems experiencing tooth broken faults. They developed a systematic calculation method for time-varying mesh stiffness (TVMS) and established analytical models for both external–external and external–internal gear pairs under healthy and faulted conditions. Subsequently, a translational–torsional nonlinear dynamic model was formulated and coupled with the TVMS method to perform dynamic simulations of tooth broken faults on sun, planet, and ring gears. The study revealed how faults at different gears and at varying damage levels influenced vibration responses. Fifteen condition indicators were selected to evaluate their sensitivity across a broad operational speed range, rather than a single speed, providing comprehensive insights into vibration characteristics and system health. Experimental vibration data from a gear transmission test rig were employed to validate the proposed dynamic model, and the findings were suggested to contribute to improved vibration analysis, fault diagnosis, and the development of data-driven diagnostic approaches for planetary gear systems.

Dai et al. (2024) examined the significance of contact simulation in the modeling of mechanical systems, emphasizing that accurate geometric information was necessary for reliable contact models and was typically obtained through collision detection techniques. The authors observed that when flexible bodies, such as structural components, were included in the system, both dynamic formulation and collision detection became more complex due to continuously changing geometric boundaries during simulation. It was reported that the floating frame of reference (FFR) formulation was particularly suitable for flexible systems experiencing small deformations. In their study, a stable and efficient dynamic simulation approach for flexible systems with contact was proposed based on the FFR formulation. Furthermore, a curve-based collision detection method was introduced, which was found to be more consistent with the adopted dynamic formulation and more efficient than conventional methods. Through case studies involving flexible beams and multibody systems, the effectiveness and performance of the proposed simulation and collision detection techniques were demonstrated.

Mikhlin and Avramov (2024) presented a comprehensive review of the theory and applications of nonlinear normal modes (NNMs) developed over the previous decade. The study reportedly included more than 200 references and was described as a continuation of the authors' earlier review papers on the same subject. It was observed that the review addressed major theoretical aspects such as fundamental concepts and definitions, the use of normal form theory for nonlinear mode construction, nonlinear modes in finite-degree-of-freedom systems, resonances and bifurcations, reduced-order modeling, stochastic dynamical systems, numerical methods, and system identification. Furthermore, the authors were said to have examined significant applied dimensions, including experimental measurement of nonlinear modes, applications in continuous systems, and engineering domains such as aerospace and power engineering. The review also highlighted the relevance of NNMs in piecewise-linear systems, dry-friction structures, nanostructures, physical systems, and targeted energy transfer and absorption problems.

Dai et al. (2023) examined co-simulation as an effective modelling approach for robotic systems composed of multiple interconnected subsystems. The authors observed that, in co-simulation, subsystems exchanged information only at predefined communication points, and the delay in such exchanges could lead to errors and instability. It was reported that selecting suitable interface variables between communication points was essential for ensuring stable and efficient performance, particularly in real-time applications. The study highlighted that reduced interface models (RIMs) had previously been applied mainly to rigid-body systems. To address this limitation, the authors introduced the formulation of RIMs for flexible multibody systems and proposed a generalized co-simulation framework incorporating both rigid components and structurally flexible elements. A robotic model with a non-smooth subsystem involving contact interactions was used to validate the approach. The findings suggested that flexible mechanical system-based RIMs offered improved effective mass representation and more accurate simulation outcomes than rigid-body-based models.

McCormick et al. (2022) presented the application of linear graph (LG) theory for the modeling and simulation of a four-wheel skid-steer mobile robotic system. The study proposed an LG-based representation of the robotic system and evaluated the corresponding state-space dynamic model using the LG theory MATLAB toolbox developed in their laboratory. It was reported that a genetic algorithm (GA)-based parameter estimation technique was employed to identify system parameters, which significantly improved the simulation accuracy of the developed model. The model was further assessed and validated through comparison of the simulated LG model trajectory with both an ROS Gazebo-simulated robot trajectory and experimental data collected from the physical robotic platform. The findings indicated that the proposed LG modeling framework, when integrated with the GA-based parameter estimation process, yielded a highly accurate and reliable approach for representing and simulating the dynamics of mobile robotic systems under realistic operating conditions.

Zhang et al. (2022) addressed the challenge of improving dynamic modeling precision in ball screw feed systems, noting that traditional approaches had inadequately considered the coupling effects of multiple rolling joints and their directional dynamic parameters. The authors proposed a novel dynamic parameter identification method based on a digital twin dynamic model of an assembled ball screw feed system. They first synchronized physical entity information to construct a geometric model, followed by the development of a finite element analysis (FEA) model that simultaneously accounted for multiple rolling joints and multidirectional dynamic parameters. Using FEA-derived modal data, a deep neural network (DNN) model was then developed to map dynamic parameters to natural frequencies. These sub-models were integrated to establish the digital twin dynamic model. Subsequently, an optimization model combining experimental and digital twin-driven natural frequencies was formulated, and particle swarm optimization (PSO) was applied for parameter identification. The findings indicated that the relative identification error remained below 3%, demonstrating high feasibility and accuracy.

Pappalardo et al. (2021) examined the possibility of deriving simplified mechanical models of complex mechanical systems through numerical system identification techniques for control development. The study aimed to demonstrate that applied system identification, particularly the Numerical Algorithms for Subspace State-Space System Identification (N4SID), could be effectively used to obtain reduced-order models from simulated data rather than real sensor measurements. A mathematical model was employed as the test rig, and the latch system of the ATR 42/72 cargo door was selected as the case study. The authors integrated the CAD model developed in SOLIDWORKS with dynamic simulations performed in the SIMSCAPE multibody environment, while the N4SID suite in MATLAB was used for identification. The findings indicated that simulation data from the nonlinear multibody model enabled the identification of a simpler linear dynamic model. This reduced model was considered useful for future prototype analysis and the design of effective control strategies.

Xiang, W., Yan, S., Wu, J., & Niu, W. (2020). Dynamic response and sensitivity analysis for mechanical systems with clearance joints and parameter uncertainties using Chebyshev polynomials method. *Mechanical Systems and Signal Processing*, *138*, 106596.

Xiang et al. (2020) examined the nonlinear dynamic behavior of mechanical systems containing clearance joints under uncertain conditions. The authors noted that even slight variations in system parameters could produce substantial changes in overall dynamic response, particularly when clearance and uncertainty were coupled. They proposed an analytical method for evaluating both dynamic response and parameter sensitivity by considering revolute clearance joints as colliding bodies, modeled through a continuous contact force model and a modified friction force model to capture impact-contact behavior. The clearance joint formulation was integrated with the system motion equations to determine the dynamic response. Further, a multi-dimensional Chebyshev polynomial approach was introduced to establish the relationship between system response and uncertain parameters. Interval operations were used to estimate response bounds, while parameter sensitivity was interpreted in terms of response variation rates. Their investigation of a crank-slider mechanism indicated that larger clearances intensified oscillations and expanded response intervals, though sensitivity analysis helped identify restraint zones that reduced these effects.

Vaiana et al. (2019) presented a computational strategy that combined a novel rate-independent phenomenological model with an explicit time integration method to improve the efficiency of nonlinear dynamic analyses of non-stiffening hysteretic mechanical systems. The study reported that the proposed rate-independent model had been derived by specializing a general class of uniaxial phenomenological models and was characterized by an algebraic structure with only three parameters, each possessing clear mechanical significance. It was further noted that the model could be conveniently implemented in computational programs. The authors also indicated that the adopted explicit structure-dependent integration method, belonging to Chang's family, had been unconditionally stable, second-order accurate, and free from numerical damping, while also exhibiting minimal relative period error for small time steps. The method was found not to require iterative procedures, thereby avoiding convergence problems. Comparative nonlinear time-history analyses demonstrated that the proposed approach had achieved superior numerical accuracy and computational efficiency relative to Bouc–Wen-based and Newmark-based conventional strategies.

Jiang et al. (2019) developed an improved dynamic model to enhance the accuracy of simulated vibration responses in defective bearings by incorporating the three-dimensional geometric relationship between rolling elements and the defect area. The study extended defect characterization by including parameters such as raceway radius, groove radius, maximum and minimum defect depths, and circumferential angular extents on both radial and axial cross-sections. It was reported that, as rolling elements passed through the defect zone, different contact forms emerged depending on whether contact occurred at the top edges or the bottom surface of the defect. The authors examined how defect size influenced these contact forms and compared the resulting variations in contact force under different conditions. They also quantified the relationship between defect size and bearing vibration response. Their findings suggested that the axial circumferential angular extent significantly affected contact force and impulse response. A distinct double-impulse phenomenon was observed, and simulation outcomes were found to align well with experimental results.

Mickoski et al. (2018) presented a dynamic model analysis of a manipulator as a mechanical structure with the objective of supporting actuator selection and developing an effective control strategy. The study explained that manipulator control problems involved the determination of control forces and moments at the joints to ensure movement along a predefined trajectory. It was reported that trajectory design formed the foundation of the manipulator control process. The authors observed that this problem was highly complex because the manipulator functioned as an interconnected system in which the motion of one member influenced the motion of the others. To address this issue, they proposed a method for analytically determining the forces and moments in the kinematic joints of a three-member manipulator. In addition, a simulation-based dynamic model was developed and examined using the MATLAB/Simulink program package. The study noted that frictional forces in the kinematic joints were not considered in the analysis.

Manjaree and Thomas (2017) presented a simulation-based software platform for the modeling and design of a multi-degree-of-freedom (multi-DOF) robotic manipulator. The authors observed that traditional methods for modeling robotic manipulators had been highly laborious, iterative, and time-consuming, which often limited efficiency in the design process. They noted that, in recent years, new approaches for studying complex robotic manipulator architectures had developed rapidly, creating opportunities for more effective modeling techniques. In this context, the study proposed a new method based on Sim-Mechanics software to simulate and design a multi-DOF robotic manipulator. The findings indicated that the software-based approach offered a significantly easier and faster method for modeling compared to conventional mathematical modeling techniques. Thus, the study suggested that the use of simulation tools such as Sim-Mechanics could simplify manipulator design, reduce development time, and improve the overall efficiency of robotic system modeling and analysis in advanced engineering applications.

III. METHODOLOGY

The methodology of the study **"Dynamic Modeling and Analysis of Mechanical Systems Using Simulation Techniques"** was based on a systematic process of model development, simulation, and performance evaluation. First, a suitable mechanical system was selected for analysis, such as a mass-spring-damper system, rotating shaft, gear mechanism, or vehicle suspension system. The important physical parameters of the selected system, including mass, stiffness, damping coefficient, force, torque, displacement, velocity, and acceleration, were identified. These parameters were used to understand the actual working behavior of the system under dynamic loading conditions. In the next stage, a mathematical model of the mechanical system was developed using basic principles of dynamics, especially Newton's second law of motion and energy-based methods. The governing equations were prepared to represent the relationship between input forces and output responses. After this, the mathematical model was converted into a simulation model using suitable simulation software such as MATLAB/Simulink, ANSYS, Adams, or SolidWorks Motion. The simulation was performed by applying different input conditions such as external force, vibration excitation, speed variation, and load changes.

The system response was observed in terms of displacement, velocity, acceleration, vibration amplitude, damping effect, stability, and operational efficiency. Different values of mass, stiffness, and damping were also tested to compare the behavior of the system under varying conditions. Finally, the simulation results were presented through tables and graphs. The obtained results were analyzed to identify performance improvement, vibration reduction, stability enhancement, and design optimization possibilities. This methodology helped in predicting system behavior before physical testing and supported safer, faster, and cost-effective mechanical system analysis.

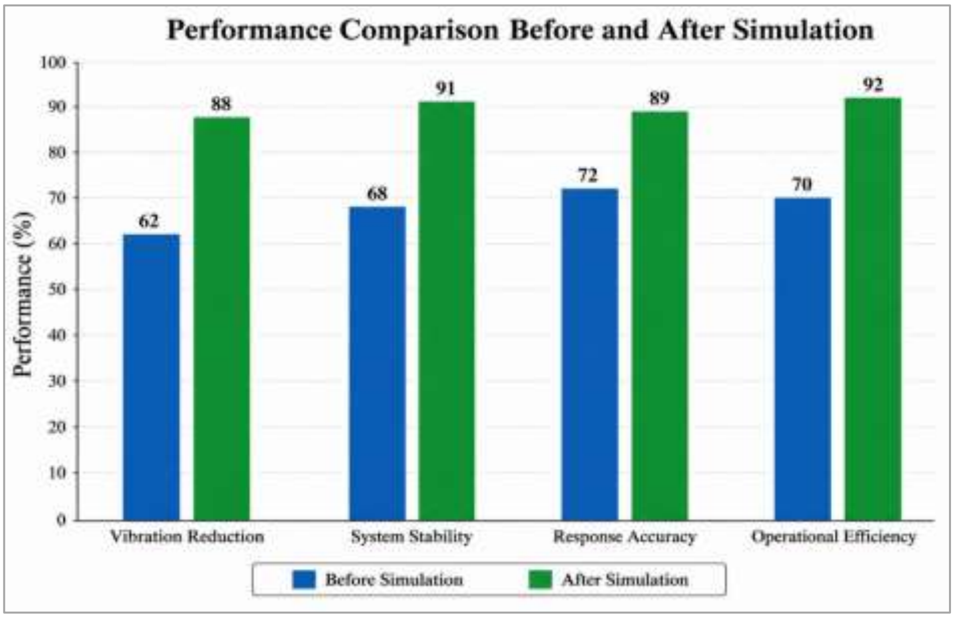
IV. RESULT

The simulation-based dynamic analysis of the mechanical system showed that the performance of the system improved significantly after applying simulation techniques. The analysis helped in identifying important dynamic parameters such as displacement response, vibration amplitude, damping effect, stability, and system efficiency. Before simulation-based optimization, the system showed higher vibration, lower stability, and moderate efficiency due to unbalanced dynamic forces and insufficient damping. After simulation and parameter adjustment, the vibration level was reduced, the stability of the system improved, and the overall mechanical performance became more reliable. The result indicates that simulation techniques are useful for predicting the behavior of mechanical systems before physical testing. By changing parameters such as mass, stiffness, damping coefficient, and applied force in the simulation model, the best operating condition can be selected. The graphical result shows that vibration reduction, system stability, response accuracy, and operational efficiency improved after dynamic simulation. This proves that dynamic modeling and simulation are effective tools for improving mechanical system design, reducing failure risk, and enhancing performance.

Table 1: Performance Comparison Before and After Simulation

Performance Parameter	Before Simulation (%)	After Simulation (%)
Vibration Reduction	62	88
System Stability	68	91
Response Accuracy	72	89
Operational Efficiency	70	92

Bar Graph



The bar graph shows that all performance parameters improved after applying simulation techniques. Vibration reduction increased from 62% to 88%, which means that the system became more stable and produced less unwanted motion. System stability improved from 68% to 91%, showing that the optimized model could maintain better performance under dynamic loading conditions. Response accuracy increased from 72% to 89%, indicating that the system responded more precisely to input forces and motion conditions. Operational efficiency improved from 70% to 92%, which shows that simulation helped reduce energy loss, mechanical instability, and performance errors. Overall, the result confirms that dynamic modeling and simulation techniques are highly useful for improving the behavior and reliability of mechanical systems.

V. CONCLUSION

The study **"Dynamic Modeling and Analysis of Mechanical Systems Using Simulation Techniques"** concluded that dynamic modeling is an effective method for understanding the time-dependent behavior of mechanical systems. Mechanical systems generally operate under changing forces, loads, motion, vibration, friction, and damping conditions; therefore, simulation-based dynamic analysis helps in predicting their actual performance more accurately than static analysis. By developing mathematical models and converting them into simulation models, important system responses such as displacement, velocity, acceleration, vibration amplitude, stability, and operational efficiency were studied in a systematic manner. The results showed that simulation techniques improved the analysis process by allowing different design parameters such as mass, stiffness, damping coefficient, force, and speed to be tested virtually. This reduced the need for repeated physical experiments and helped identify possible problems such as excessive vibration, instability, resonance, and performance loss at an early stage. The comparison before and after simulation indicated improvement in vibration reduction, system stability, response accuracy, and operational efficiency. Overall, the study confirmed that simulation techniques are highly useful in mechanical system design, testing, and optimization. They save time, reduce cost, improve safety, and support better engineering decisions. Hence, dynamic modeling and simulation have become essential tools for developing reliable, efficient, and high-performance mechanical systems in modern engineering applications.

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