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The importance of educating dynamics for design techniques to improve the scientific level of graduate engineering students

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A B S T R A C T

The rapid evolution of engineering fields necessitates innovative design techniques and a deep understanding of dynamics. Graduate engineering students require advanced knowledge to tackle complex problems and drive mathematical models for complex mechanical systems. This study proposes an integrated approach, combining theoretical foundations with hands-on design experience and dynamic simulations. By incorporating industry-standard software and real-world case studies, graduate students can develop a deeper understanding of dynamic principles and their application in design and control. The expected outcomes include improved design skills, enhanced problem-solving abilities, and increased competitiveness in the job market. Furthermore, this research aims to provide educators with a comprehensive framework for teaching dynamics and design techniques, ultimately elevating the scientific level of graduate engineering students and fostering innovation in the field.

1. Introduction

In the last two decades, modelling and simulation have become general tools in the product development of mechanical systems [1]. The increasing requirement for high-speed and precise machines, mechanisms, and manipulators demands that joint clearances, friction, and the lubrication effect need to be considered when determining the dynamic model of the mechanical system, and these requirements need new modelling and design techniques [2]. Simulations of system models offer a cost-effective and safe way for the investigation of mechanical systems. Accordingly, this approach has gained increasing attention in the industry. Instead of using an expensive and complex test rig, a simulation program is used, which often saves time and money. Dynamics for Design (DFD) is the integration of recent advances in system dynamics, including nonlinearities, vibration analysis, and multibody systems with current design methodologies. The goal of integrating these subjects into one procedure is to obtain an efficient design cycle in terms of improved system reliability, optimal control of the system and consistent behavior across operating environments [3]. Mechanical design is the process of designing and/or selecting mechanical components. and putting them together to accomplish a desired function according to specific needs. Mechanical components transmit forces and motion from one point to another [4]. The transmission of force can be envisioned as a flow or force distribution. The force acting at a point on the surface could result in components in normal, tangential, and axial directions. These forces will produce stresses that define the relations between materials and dimensions of designed components. Lately, engineers have a great variety of tools and resources available to assist in the solution of design problems. Inexpensive microcomputers robust computer language packages and commercial software based on Dynamics for Design techniques provide tools of immense capability for the design, analysis, and simulation of complex mechanical components [5, 6].

2. Mathematical modeling in modern engineering design

Modelling and simulation have become general tools in the product development of mechanical products. The use of simulation enables the designers of the product to have feedback on the design and the interference of different sub-systems of the product. While the power and efficiency consumption of mechanical systems is increasing, the dynamics and thus also load, noise, and vibration problems are becoming more common due to lighter structures, higher loads, and faster operations. By using computer simulation from the early phase of the design process, many problems that arise from the dynamical interaction of different sub-systems of the product can be avoided with lower computational costs. Accordingly, this approach has gained increasing attention in the industry. Instead of using an expensive and complex test rig, a simulation program is used, which often saves time and money [2]. Building mathematical models of subsystems and components is one of the most important tasks in the analysis and design of any mechanical system [4]; see Figure 1. Developing such constitutive models to show mechanisms in real-life scenarios requires good knowledge of the system and its environment.

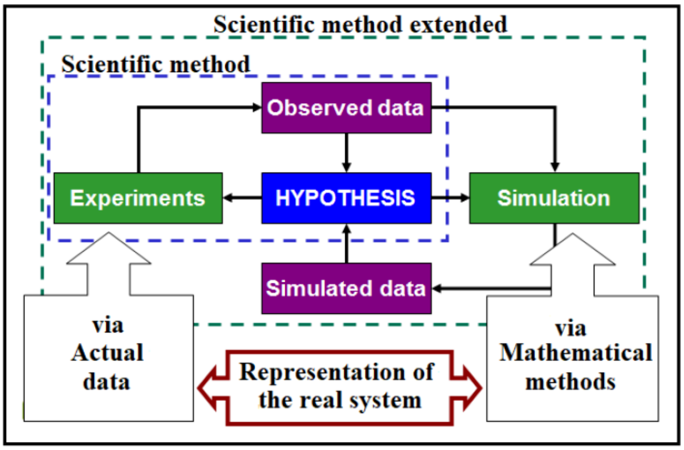

Fig. 1. Representation of mechanical system

The complexity of machines and multi-physics phenomena involved, environmental conditions, and the lack of information on how system parameters vary over time hinder the accurate construction of efficient physics-based models. In data science, there is a great possibility to integrate statistical learning concepts with classical approaches in applied mechanics and mathematics to discover sophisticated and accurate models of complex dynamical systems directly from data. Such data-driven models have been obtained using sparsity, time-series data, equation-free modelling, nonlinear regression, empirical dynamic modelling, modelling emergent behaviour, and automated inference of dynamics. Mathematical and computer-based models provide the foundation of most methods of engineering design and are of fundamental importance in many different areas of science. One important factor that influences research on modelling is the steady increase in complexity of the models required for new and existing applications [7]. For example, one common factor in the investigation of physiological systems and the analysis and design of modern engineering systems is the fact that in both these fields there has been rapid growth, in recent years, in our understanding of the importance of integrated systems and the benefits of system integration within design. To study the dynamics of a system it is necessary to understand the equation of motion and its components. On top of that, the value of system parameters used in the theoretical models of the mathematical models plays a very important role in accurately predicting the response of a physical system. Knowing the dynamic equations of a system, linear regression methods are employed to estimate such system parameters. However, in the case that the developed physics-based model does not consider either the physics of the problem fully or the environment of a given system due to the lack of knowledge, the system parameters estimated from such biased mathematical models cannot represent the system accurately. Figure 2 shows the mathematical modelling procedures. [8].

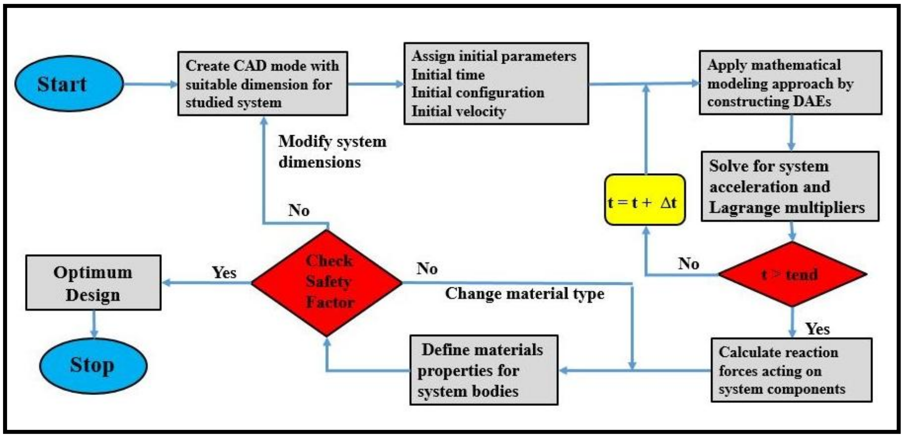

Fig. 2. Mathematical modeling flowchart

Several general-purpose computer programs exist, which allow engineers to model complex mechanical systems and evaluate the dynamic characteristics of potential designs before building prototypes [9]. This reduces cost and lead time in designs. The symbolic manipulation as well as the computational work of solving the obtained equations of motion can be carried out using a commercial simulation tool that is applied to different systems. The mathematical model is finally represented by either a set of ordinary differential equations (ODE) or a set of differential-algebraic equations (DAE). The most modern mathematical modelling techniques, which are being used widely in the mathematical modelling of mechanical systems, can be divided into several groups: first, finite element methods (FEM) and second, approaches based on multibody dynamics (MBS). Additionally, approaches based on boundary elements, finite differences, and finite volume schemes in this context may be mentioned in [10].

3. Finite Element Analysis

Finite element methods were introduced to deal with problems of structural analysis. FEM is, without a doubt, the most powerful numerical method in the field of modelling complex mechanical systems [11]. Although it is well suited for particularly high accuracy requirements, it is a very high computational effort that causes practical difficulties such as very long simulation times. Finite Element Analysis (FEA) is a numerical method used to simulate and analyze the behavior of complex systems, structures, and materials under various physical loads, such as mechanical, thermal, electrical, and magnetic forces. The term "finite element" refers to the process of dividing a complex system or structure into smaller, discrete elements, such as nodes, edges, and faces, to create a finite element mesh. This mesh is then used to approximate the behavior of the system or structure under various loads [12]. The "Analysis" part of FEA refers to the process of solving the equations that govern the behavior of the system or structure, using numerical methods, such as Gaussian elimination or iterative solvers. In such situations, MBS can often efficiently model the contact with acceptable accuracy and considerably less computational effort compared to FEM. In contrast to the FEM, approaches based on multibody dynamics can deal with the effect of contact forces on the overall motion of the system for long simulation times [13]. Symbolic manipulation can be used to speed up the solution procedure. This is because some terms in the final equations can be factored out or cancelled out in some situations. Thus, if the symbolic expression of the output can be obtained and then simplified, the number of arithmetic operations needed to obtain an output can be considerably reduced. Typically, in rigid multibody systems, a reduction in the number of arithmetic operations by a factor of five can be achieved using the symbolically simplified final expressions. The manipulation and simplification of the symbolic expressions are done using a symbolic processor. Generally, the final symbolic equations are integrated numerically in time because the resulting differential equations are nonlinear, and, therefore, it is very difficult to obtain closed-form expressions. Symbolic manipulation has been extensively developed and used in rigid multibody systems [15] but has only been recently applied to flexible multibody systems. One major advantage of the symbolic generation approach appears when data such as some vector components vanish for a specific application. Symbolic generation of equations of motion can speed up the solution process since, by simplification of the symbolic expression of the output, the number of arithmetic operations needed for evaluation can be considerably reduced. However, the final symbolic equations are integrated numerically since the resulting differential equations are generally highly nonlinear, and therefore, it is sometimes impossible to obtain closed-form solutions [16].

We should underline right away that all FEM models and solutions are approximations. Their accuracy is heavily dependent on knowing the behavior of the system being simulated, the modelling assumptions, and the initial user limitations. In actuality, the solution to the problem is not straightforward since the number of equations involved is vast; thus, we rely on ample computer memory to store all the numbers and data and solve the equations. Finally, an overview of the finite element analysis process is illustrated in Figure 3, and the following are the primary phases in the development of any finite element model for most types of analysis:

- Analysis type selection
- Material property idealization
- Model geometry creation
- Application of support or constraints
- Loads application
- Optimization of the solution

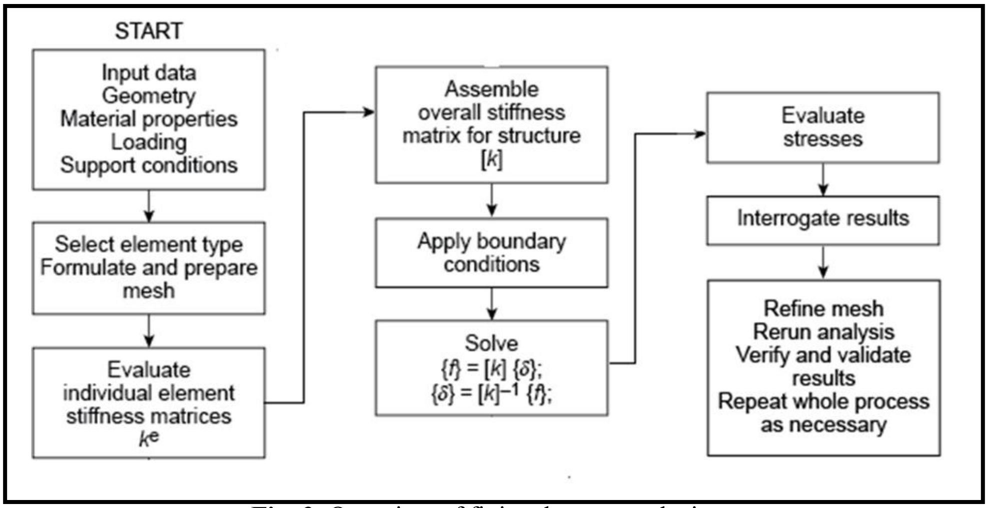

Fig. 3. Overview of finite element analysis process

4. Multibody System Dynamics

Multibody systems serve as a basis for many modern models of mechanical systems and have been applied in many areas of science. The field of Multibody System Dynamics (MBS) has its roots in classical and analytical methods of dynamics to meet the growing demands in the modelling and simulation of complex and advanced mechanical systems in industry and engineering [17]. The mechanical components, which can be modelled as rigid or flexible, are constrained by a kinematic pair of different types. Additionally, bodies can be actuated upon by force elements and external forces due to interaction with the environment to increase design reliability. The widespread diffusion of multibody dynamics software calls for attention. MBS technology can accurately simulate a system containing rigid and flexible bodies [18]. It is possible to simulate nonlinear elastic cases, including contact and large deformation, as well as linear elastic cases. There are a lot of important things when using MBS in the modelling and simulation of complex mechanical systems that cover all required design aspects; see Figure 4.

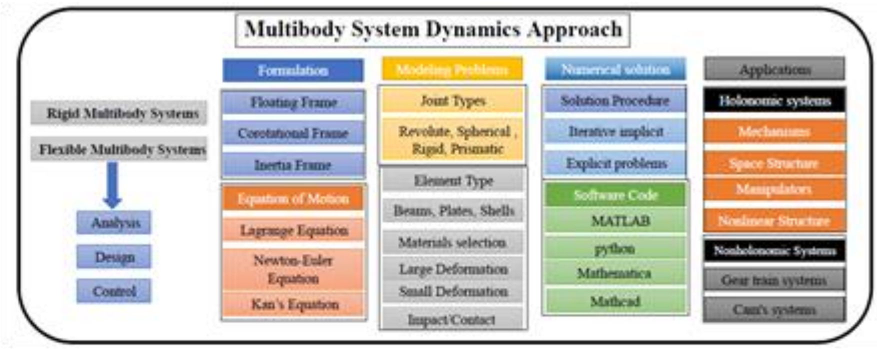

Fig. 4. Multibody system dynamics approach terms

Multibody dynamics modelling is applied to a greater extent within industrial companies or consulting firms. Thus, a significant portion of current mechanical engineering graduates are potential users of such software without having minimal knowledge of its theoretical bases. Moreover, many current users, although familiar with the graphic interface, lack a basic understanding of the theory behind the code. Unfortunately, software packages without a detailed theoretical manual are not rare, and the courses organized by the companies, due also to time constraints, usually focus on the working features of the code and not on its theory [19]. A correct interpretation of the results obtained from software requires a deep understanding of the theoretical bases used for its development and of the numerical methods used. This is a widely accepted opinion in engineering. Errors and inaccuracies in data input, dynamic formulation limits, improper modelling, and failure of numerical methods are common pitfalls for the user of multibody dynamics software. A formal education on multibody dynamics theory and software may reduce the probability of errors. However, considering the status of mechanical engineering curricula, many users of multibody dynamics software may not be fully aware of the limits of their models. The potential danger of the above-described situation requires some action from the multibody dynamics research community when you have completed your bullet list [20]. After analyzing the system well using one of the modelling methods, the results can be obtained, which are an essential part of the design and control process [21]. Mathematical modeling plays a crucial role in controlling systems by providing a framework for understanding, analyzing, and predicting the behavior of complex systems. By applying mathematical modeling techniques, control engineers can design and implement effective control systems that ensure stable, efficient, and optimal system performance.

5. Parameter Estimation Procedure

The discipline of parameter estimation deals with the determination of such parameters using a numerical simulation based on a model of the system under consideration. The typical process for determining the parameters with a model of a system is by using optimization methods [22]. The objective functions represent the difference between measured data from an experiment and simulated data from a model. Furthermore, computations and analyses are implemented for selected mechanical systems. The symbolic manipulation as well as the computational work of solving the obtained DAEs can be carried out using a commercial simulation tool. Once the preliminary design of the mechanical structure has been attained, the stress distribution of system components in the complex mechanical system is examined, including system stability and structural design aspects. Kinematics simulation results include system velocities and positions concerning simulation time, which can be used in the parameter estimation process [23]. The most important parameter affected by the selected mechanical system to apply parameter estimation is the method used to measure the degree of freedom. The parameter estimation procedure is used to obtain optimal design parameters by comparing the simulated model output with experimentally measured data. The estimated parameters are used in the optimization of the design of mechanical systems and improved reliability of the systems considered. Figure 5 shows the main object of parameter estimation in optimization processes [24].

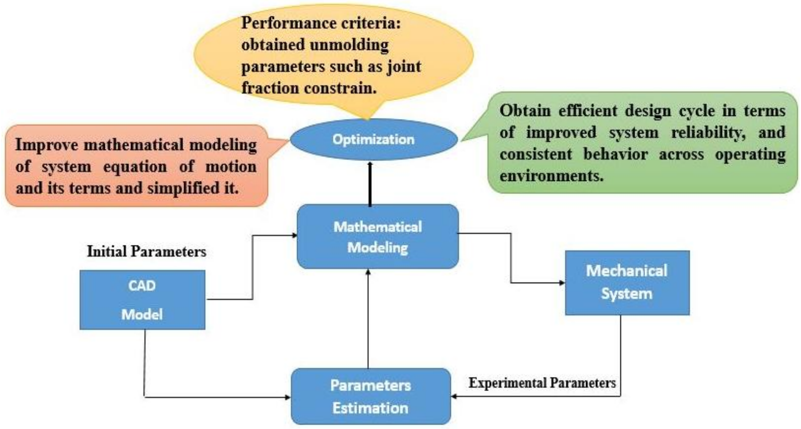

Fig. 5. Parameter estimation objectives

If experimental measurements are available for a mechanical system, the parameters in the corresponding mathematical model can be identified by minimizing the error between the model response and the experimental data. Parameter estimation problems in differential equations are often treated by simply coupling an integrator with an optimization procedure [25]. Several general-purpose computer programs exist, which allow engineers to model complex mechanical systems and evaluate the dynamic characteristics of potential designs before building prototypes [26]. The design method based on the Dynamics for Design (DFD) procedure proposed provides new ideas and methods for the design and control of complex mechanical systems. These general-purpose simulation packages have several drawbacks. They need to be operated by experienced engineers and are numerically inefficient. As a result, extensive research efforts should be directed to develop more efficient and easy-to-use modelling methods, which requires expanding the teaching of dynamic for design techniques to graduate students. Also, the large amount of data obtained from the mathematical model can be used by artificial neural networks to be optimized parameter estimation procedures.

6. Artificial neural networks

Mathematical modeling plays a crucial role in the development of neural networks as it provides a framework for understanding the relation between inputs and outputs and hidden layers. Neural network simulation is an important research and development area extending from biological studies to artificial applications. Artificial neural networks are constructed using experimental data to solve modelling and control application challenges. Artificial neural networks (ANNs) are mathematical equation-based models of brain components such as neurons and their connections, as well as network input, control parameters, and network dynamics. Artificial neural networks learn and make decisions by commenting on similar events, and they are capable of parallel processing.

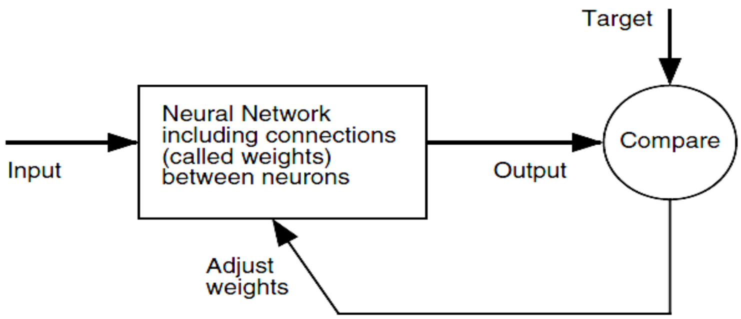

Fig. 6. Neural networks theory

Artificial neural networks can readily predict and replicate non-linear behavior for complex systems if training data is available [27,28]. The benefits of artificial neural networks may be described as follows: Information is stored throughout the network rather than in a database. Following the training process, the data may generate output with partial information. By commenting on comparable events, artificial neural networks learn events and make choices. Capability for parallel processing. The following are some of the drawbacks of artificial neural networks: inexplicable network behavior. The structure of artificial neural networks is determined by no explicit rule. Experience and trial and error are used to determine the best network structure. Before being introduced to the neural network, problems must be transformed into numerical values. The length of network training is not known [29]. By combining ANNs with mathematical modeling, researchers and engineers can develop powerful tools for analyzing and predicting complex system behavior, leading to advancements in various fields. Figure 7 shows the importance of mathematical modeling for engineering graduates in describing engineering problems found in practical life mathematically and the importance of learning different methods of modeling and controlling the inferred data and how to transform them into results that benefit humanity [30].

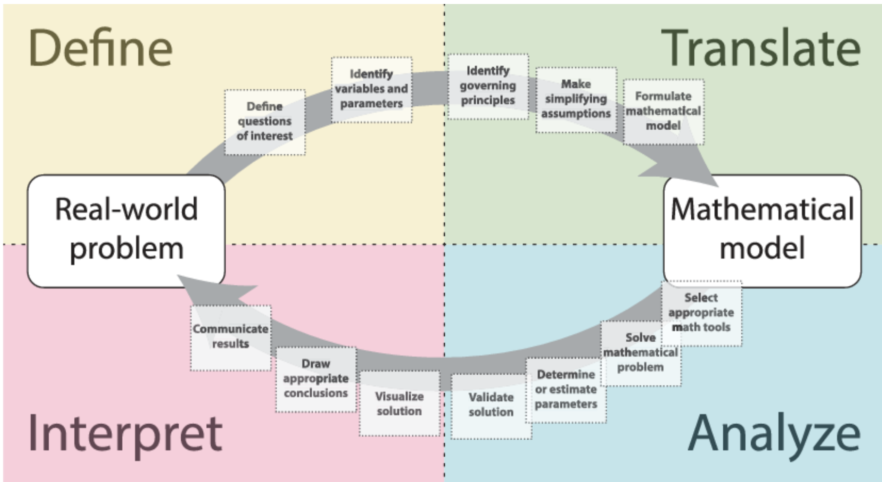

Fig. 7. Schematic representation of the mathematical modelling process cycle

7. Conclusion

Teaching graduate students' dynamics for design techniques is crucial for their success in today's complex engineering opportunity. By mastering mathematical modeling, graduate students can develop a powerful toolset to analyze, design, and optimize complex systems, making them more competitive in the job market and better equipped to tackle real-world challenges. The integration of mathematical modeling techniques into graduate engineering curricula can have a profound impact on students' ability to think critically, solve problems creatively, and communicate complex ideas effectively. Furthermore, it can foster a deeper understanding of the underlying physical principles, enabling students to make more informed design decisions and drive innovation in their respective fields. Also, learning artificial neural networks is a crucial topic for graduate students in various fields, providing a framework for understanding complex systems, practical applications in machine learning and deep learning, and career opportunities in research and development, data science, and artificial intelligence. By doing so, we can empower the next generation of engineers to address the most pressing challenges of our time and create innovative solutions that serve the industry and help accelerate development.

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