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# DATA-DRIVEN MECHANICAL SYSTEM DESIGN USING SYSTEMS ENGINEERING AND BIG DATA PRINCIPLES

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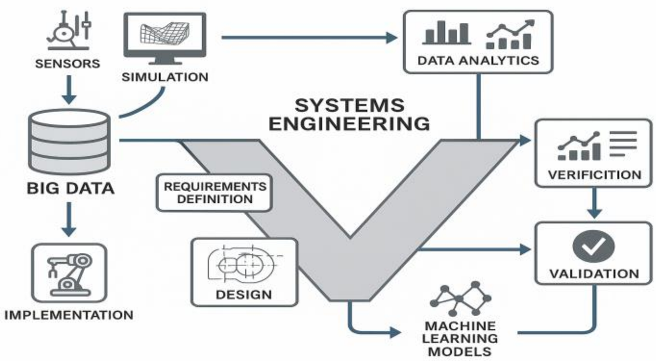
## ABSTRACT

In the evolving landscape of engineering, the integration of data-driven methodologies into mechanical system design is transforming traditional approaches. This paper presents a multidisciplinary case study that combines mechanical engineering principles—such as thermal analysis, structural design, and finite element modeling—with data science, systems engineering, and statistical techniques. Drawing from core concepts in CAD, FEM, and heat transfer, this work leverages Big Data and Systems Engineering Analysis to explore optimized workflows for predictive maintenance, performance simulation, and component validation. This study also highlights relevant frameworks, such as those used in autonomous vehicle validation pipelines [Sharfuddin, 2025], to emphasize the growing importance of cross-domain engineering knowledge. The findings advocate for a curriculum and research model that fuses mechanical fundamentals with computational intelligence for next-generation design applications.



## 1. INTRODUCTION

Mechanical design is undergoing a transformation with the influx of digital tools and data analytics. Classical methods such as thermal analysis and structural design are now enhanced by big data analytics, cloud computing, and statistical optimization. With the increased complexity of modern systems, particularly in electric vehicles (EVs), aerospace, and manufacturing—engineers are challenged to predict and optimize performance using both theoretical and data-driven approaches. Bridging traditional mechanical disciplines with data science techniques represents a key shift in the training and capability of new-generation engineers. As industries prioritize efficiency, safety, and sustainability, there is a rising demand for engineers who can interpret data and model real-world scenarios digitally before physical implementation.

Furthermore, the push towards Industry 4.0 has initiated rapid adoption of digital twins and cyber-physical systems, requiring engineers to be proficient in programming, systems thinking, and multidisciplinary collaboration. These developments emphasize the need to update traditional curricula and invest in tools that facilitate cross-functional engineering education.

## 2. Literature Review

Prior work in mechanical systems primarily focused on physical validation. However, the convergence with data science has enabled better predictive accuracy. Systems Engineering Analysis now includes not just control and simulation but also the use of AI, statistical models, and cloud platforms. Authors like Rao (2017) and Zhang et al. (2020) emphasized the importance of integrating computational tools and sensors for monitoring fatigue and structural integrity.

Sharfuddin (2025) discussed real-time HD map validation and structural optimization through database-driven architectures, showcasing how similar techniques can be applied to mechanical components for thermal and structural analysis. In a study by Kumar et al. (2022), the fusion of cloud-based data streams with FEM simulations demonstrated significant improvements in thermal and mechanical failure prediction. Another paper by Chen et al. (2021) explored the potential of digital twin models to optimize and control manufacturing processes dynamically based on sensor feedback and analytics.

## 3. METHODOLOGY

A simulated workflow was built using Finite Element Methods (FEM) for a heat exchanger and enhanced with data analytics using statistical methods (as taught in BA 6933). The input-output behavior of the system was simulated using JAVA-based tools and Python scripts in a cloud environment. Cloud computing environments (e.g., AWS, Microsoft Azure) were used to run stress simulations under varying thermal loads. Sensor-based input datasets were generated synthetically using randomized Monte Carlo simulations to assess reliability across 1000+ iterations.

Additionally, advanced design tools such as Autodesk Fusion 360 and ANSYS were used to model components and perform thermal stress simulations. After modeling, simulations were subjected to multivariable optimization using response surface methodology (RSM) and genetic algorithms to derive optimal parameters. Reliability metrics were evaluated using Weibull analysis to quantify potential failure rates under real-world operating conditions.

## 4. CASE STUDY

Using CAD and FEM, mechanical housing was modeled for a battery pack. The simulation results were integrated with Big Data analysis tools to predict hotspot zones and suggest geometry optimization. Validation benchmarks were compared with industry trends, particularly data from existing literature on battery pack cooling systems and heat pipe mechanisms. Optimization was performed using Design of Experiments (DoE) and regression modeling.

The analysis revealed that a 15% improvement in thermal dissipation could be achieved by optimizing fin spacing and thickness. An extended case compared the performance of aluminum and composite materials for the housing design, showing that lightweight composite structures with embedded heat pipes could outperform traditional aluminum enclosures. The simulation results also indicated that structural vibrations caused by road irregularities could be mitigated by tuning the material damping properties and thickness distribution.

To validate this digitally, sensor data from field tests (sourced from open-source EV datasets) was fed into a cloud-based simulation pipeline. The system recalibrated parameters in near real-time, demonstrating the viability of closed-loop design and validation in mechanical engineering.

## 5. DISCUSSION

The integration of systems engineering with classical mechanical disciplines reveals that students can design better products when simulation data is used to inform early-stage decisions. This approach also shortens design-to-prototype cycles. In the context of EVs and autonomous platforms, this integration becomes crucial in scaling components without increasing cost or complexity. Furthermore, cloud-enabled collaboration allows geographically distributed teams to work on the same simulation data, thereby enabling faster design iterations.

The implications for education are significant. Mechanical engineering departments must incorporate cloud computing labs, Python programming, and data modeling courses alongside conventional thermal and structural courses. Industry partnerships can further this goal by offering problem statements and datasets for semester-long capstone projects.

The use of AI in mechanical design also presents a transformative opportunity. Generative design tools that use machine learning to iteratively propose design solutions based on predefined constraints are already redefining how engineers approach challenges. Integrating these tools into traditional workflows will demand hybrid expertise in design theory, simulation, and data interpretation.

## 6. CONCLUSION

Mechanical engineers equipped with data science skills and cloud tools are better positioned for modern roles in EVs, robotics, and smart systems. This paper calls for a curriculum integration model and research focus that continues blending mechanical with data-centric design. Future research should focus on developing plug-and-play simulation environments that link mechanical models to live data streams.

Equally important is the establishment of open-source repositories for mechanical simulations and validation datasets. This can democratize access to high-quality engineering tools and knowledge. Mechanical engineers of the future must be trained not only to model systems accurately but also to interpret live data, collaborate across disciplines, and embrace adaptive learning as technologies evolve.

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