FRAMED: Data-Driven Structural Performance Analysis of Community-Designed Bicycle Frames

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Abstract
This paper presents a data-driven analysis of the structural performance of 4500 community-designed bicycle frames. We present FRAMED — a parametric dataset of bicycle frames based on bicycles designed by bicycle practitioners from across the world. To support our data-driven approach, we also provide a dataset of structural performance values such as weight, displacements under load, and safety factors for all the bicycle frame designs. By exploring a diverse design space of frame design parameters and a set of ten competing design objectives, we present an automated way to analyze the structural performance of bicycle frames. Our structural simulations are validated against physical experimentation on bicycle frames. Through our analysis, we highlight overall trends in bicycle frame designs created by community members, study several bicycle frames under different loading conditions, identify non-dominated design candidates that perform well on multiple objectives, and explore correlations between structural objectives. Our analysis shows that over 75% of bicycle frames created by community members are infeasible, motivating the need for AI agents to support humans in designing bicycles. This work aims to simultaneously serve researchers focusing on bicycle design as well as researchers focusing on the development of data-driven design algorithms, such as surrogate models and Deep Generative Methods. The dataset and code are provided at http://decode.mit.edu/projects/framed/.

1 Introduction
The bicycle is one of the most ubiquitous consumer products in our modern society. Despite this fact, making bicycles accessible to more people has nu
numerous societal benefits, such as boosting public health\textsuperscript{[1]}, mitigating traffic congestion\textsuperscript{[2]}, and reducing emissions\textsuperscript{[3]}. These tantalizing prospects provide ample motivation to improve accessibility to bicycles and to improve their performance to increase appeal. With some estimates putting the number of privately owned bicycles at over 580 million\textsuperscript{[4]}, even incremental improvements in bicycle design methodology would undoubtedly have an immense impact.

One strategy to improve bicycle accessibility and ridership is to harness data-driven methods to accelerate the design process of customized bicycle frames, making them faster and cheaper to acquire. Data-driven methods have shown great promise in accelerating design tasks and enabling design automation across countless design domains. Data-driven approaches to design can tap into the immeasurable expertise captured within existing designs ranging from products on the market to rough prototypes to early-stage design concepts. Designers can leverage design principles implicitly embedded in quality data to accelerate their own design process. Additionally, tools like surrogate models trained on design data can help designers rapidly evaluate early stage design concepts without the need for expensive and time-consuming simulation or physical experimentation. The availability of quality data is an incredible asset in any design domain, and we aim to introduce and leverage this data for the bicycle frame design task.

In this paper, we pursue a data-driven approach to bicycle frame design and optimization. The key contributions of this work are summarized below:

- We introduce a dataset of 4500 bicycle frames inspired by bicycles designed by community members using the BikeCAD software. This dataset consists of a set of 37 design parameters for each frame and an associated 3D model for all frames that are geometrically valid.

- We provide a corresponding dataset of ten structural performance values under three load cases (in-plane, transverse, and eccentric loading) for each frame, consisting of seven deflections, two safety factors, and a weight value.

- We validate our structural simulations against results from physical testing of bicycle frames and show that our simulation results correlate with existing studies. We also validate our finite element mesh resolution with a mesh convergence study.

- We carry an in-depth exploration of bicycle design and performance data — We identify general trends, study several interesting frame designs in detail, identify a Pareto front of non-dominated designs,
and explore correlations between design parameters and performance values.

2 Structural Optimization of Bicycles Frames

Structural considerations of a bicycle frame, such as geometry, material, and size can drastically affect the rider experience. Typically, designers attempt to minimize weight and cost of the frame, but removing too much material could mean increasing the likelihood of the bicycle frame to fail under pressure, decreasing the power transfer of pedaling into forward acceleration, or amplifying the nerve damaging effects of vibrations in intense bicycle riding.

Since the inception of bicycles in the 1800s, people have sought to better understand how they work and how they can be improved upon. Recent studies [5, 6] have taken this search for an optimized bicycle to new extents through in depth analysis of what physical features of a bicycle are most influential to the rider experience. In general, it is important for a bicycle to be lightweight to allow fast acceleration and maneuverability, strong enough to resist failure under heavy loading, and to have a high stiffness to maximize the power transfer of pedaling into acceleration. These conflicting objectives are not always intuitive to understand, nor are they easily maximized.

Simulation of bicycle frames provides useful insight into how the rider experience can be improved. One of the earlier attempts at simulating the effects of varying loads on a bicycle frame Soden et al. [7] uses finite element analysis (FEA) and a representation of a bicycle frame as a set of linear beams connected at a series of nodes to predict the deflections a frame might see under different riding conditions. Since then, with the development of advanced CAD software and exponential growth in computational power, researchers have been able to represent more complex geometries [8], develop more accurate estimates for stresses in bicycle frames [9], and perform in-depth analysis of bicycle frame material selection [10].

Several studies have expanded on bicycle frame simulation with data driven approaches to structural optimization of bicycles. For example, Cung & Lee [11] simulate nearly 400 combinations of parameters for the 4 main tubes in the bicycle frame and their dimensions. They use these simulations to fit a model that determines the significance of each parameter in changing the structure of the bicycle frame. Cheng et al. [12] use FEA to optimize the bicycle frame by simulating drop frame testing. Their work aims to minimize the permanent deflection a bicycle frame experiences after drop frame testing while also minimizing the weight of the frame using compromise programming. Other studies seek to optimize the bicycle frame
by changing bicycle geometry. Lin et al. [13] creates a model that minimizes the deflection a frame experiences under various loading conditions by changing the angles that different tubes meet each other at. Covill et al. [14] fits a regression model to capture how influential parameters affect bicycle frame deflection after simulating loading cases on 82 frames.

Existing work at the intersection of numerical simulation and data-driven design for structural optimization of bicycles has shown great potential and paved the way for data-driven design to improve the rider experience. However, existing work has a few gaps — the designs considered are not based on real-bikes created by framebuilders and enthusiasts, they are limited in size by the number of bikes simulated, no large-scale publicly available bicycle frame dataset exists, and often the studies are limited to a small set of design parameters and load cases. To overcome these issues, FRAMED has the following advantages:

- We consider a significantly larger design space, parameterizing the bicycle frame across 37 parameters.
- We simulate bicycle frame models that are slightly modified from a collection of real bicycle designs, most of which are created by framebuilders and enthusiasts.
- We simulate over 4500 bicycle frame models, considerably more than previous data-driven design studies and release our dataset publicly for other researchers to use standardized loading conditions and datasets for data-driven design.

3 Methodology

In this section, we discuss the various methodology decisions behind the dataset including design parameterization, modeling, analysis of geometric feasibility, load cases, material selection, and meshing.

Parameterization and Modeling

We utilize a dataset named BIKED [15], which comprised of 4500 individually designed bicycle models sourced from hundreds of designers on the BIKECAD software. The BIKED dataset contains over 1300 design parameters, of which we identified 200 parameters that directly relate to the bicycle frame. To reduce the design space and ensure that 3D models can be reliably built from these design parameters, we make several key simplifications to these bicycle frame models:
Table 1: Summary of parameters used to dictate the bicycle frame design space

| Parameter Type                  | Data Type | Count |
|--------------------------------|-----------|-------|
| Frame Geometry Relations       | Continuous| 18    |
| Tube Outer Diameters           | Continuous| 9     |
| Tube Thicknesses               | Continuous| 7     |
| Frame Material                 | Categorical| 1     |
| Seat/Chain Stay Bridge Flags   | Boolean   | 2     |
| **Total**                      |           | **37**|

1. We only consider the “diamond” frame bicycle frame topology.
2. We assume all tubes have constant cross section and are straight.
3. We do not consider rounded junctions or fillets at the intersections of tubes.

These simplifications allow us to simplify the design space to 37 parameters. Most of these parameters are taken directly from BIKED, while a few are calculated deterministically by combining multiple BIKED design parameters. These 37 parameters can roughly be broken down into several groups, such as tube diameters, tube thicknesses, and dimensions of the high-level frame geometry. Additionally, we maintain two parameters from BIKED which serve as boolean flags indicating whether or not the frame has chain stay or seat stay bridges (bridges are crosspieces between the stays that add support). Finally, we use a single material parameter, which is discussed in more detail below in Section 3. A summary of the parameter types is included in Table 1. A side-by-side comparison of an original BIKED bicycle model, the same BIKED model with the frame isolated, and the corresponding 3D model generated based on this BIKED model is shown in Figure 1.

One of the key limitations acknowledged by BIKED’s authors is the limited diversity present in certain design parameters, largely due to peculiarities stemming from the BikeCAD software from which designs were sourced. BikeCAD has no 3D modeling feature or inbuilt simulation capabilities, so many parameters adding “depth” to the model are largely irrelevant in BikeCAD designs. This issue is especially pronounced in the tube thicknesses, with over 99% of all models having the same tube thickness values. To promote diversity of our dataset, we manually override the seven tube thicknesses parameters with randomly sampled thicknesses. We sample a 7D vector from a Sobol sequence, then logarithmically scale these vectors in an element wise fashion to a range of 0.5-10 mm. The resulting
bike models’ seven tube thickness values randomly lie between 0.5 and 10 mm, with a bias towards thinner tubes.

Using these parameters, we create an adaptive 3D bicycle frame model which automatically builds itself based on predefined geometric formulas, taking our 37 parameters as input variables. Figure 2 shows several views of the frame model after building itself using a set of parameters corresponding to a conventional road bike.

**Geometric Feasibility**

Our 37 variable parameterization makes for a diverse design space, but also introduces possibilities for infeasible combinations of parameters. To avoid geometrically infeasible models, we implement a list of geometric “checks.” A few of these checks are listed below:

- Tube thicknesses, diameters, and lengths must be positive
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- Seat stays and chain stays must intersect with the seat tube and bottom bracket respectively.
- Head tube and seat tube angles are between 0 and 180 degrees.

We find that 219 of 4512 of BIKED’s models fail these explicit feasibility checks. Despite these checks, 97 bicycle models still fail to build correctly when the parameters are fed into the adaptive 3D frame model, possibly due to geometric infeasibilities. Hence, there are 4101 geometrically valid frame designs remaining. A breakdown of overall design feasibility is included in Figure 6.

**Load Cases and Simulation Setup**

We seek to develop a concise set of tests which effectively evaluate a wide variety of structural considerations of the bicycle frame. We follow the methodology proposed in Vanwelleghem *et al.* [6] to evaluate in-plane, transversal, and eccentric stiffness. The authors propose three load cases to evaluate bicycle frames. Though Vanwelleghem *et al.* focus only on stiffness and don’t specify load magnitudes in their methodology, we require loads to roughly estimate maximum stresses and safety factors. Soden *et al.* [7] study forces applied to the bicycle during actual ridership in several road racing conditions (starting, climbing, braking, *etc.* ) and find a maximum pedal force of 1447 N across these conditions. We base our selected loads based on these findings and illustrate our load cases in Figure 3. Based on these studies and domain knowledge, we introduce three load cases which are applied to every bicycle frame. These cases are defined as follows:

1. In-Plane Stiffness: We apply 2000 N upwards to the dropouts and 2000 N downwards to the bottom bracket while holding the head tube fixed. We measure vertical and lateral displacements at the bottom bracket and dropouts as well as safety factor.

2. Transverse Stiffness: We apply 500 N laterally to the bottom bracket while holding the head tube fixed and preventing lateral deflection at the dropouts. We measure lateral displacement at the bottom bracket.

3. Eccentric Stiffness: We apply a 2000 N downward force and 140 Nm twist to the bottom bracket (representing a pedal 2000N force applied at an offset of 7 cm from the bottom bracket). We measure vertical displacement and twist of the bottom bracket as well as safety factor.
Six displacements and one rotation are measured across the three loading cases, which can be used to find various directional and rotational stiffnesses of the frame. Additionally, safety factors are measured for Simulations 1 and 3. Finally, we also note the weight of the frame model. We note that these forces may not cover extreme use cases. De Lorenzo et al.\cite{5} study forces on a bicycle during “aggressive off-road cycling”, including a 2.5 meter jump and find a maximum rear wheel loading of 4000 N.

Material Properties

BIKED provides a categorical “material” parameter consisting of one of six material classes. The breakdown of bicycle frames by material in the original dataset is shown in Figure 4. Three of these, steel, aluminum, and titanium are isotropic while carbon and bamboo are anisotropic. Since anisotropic materials are difficult to simulate without additional information about material orientation, we replace bamboo and carbon fiber, as well as the unspecified “other” category with aluminum. BIKED does not specify the alloy of steel, aluminum, and titanium used in bicycle models. Therefore, we select material properties of steel, aluminum, and titanium that are representative of common bicycle tube alloys. We select steel properties common of a heat-treated chrome-molybdenum steel such as AISI 4130 Steel, which is a rough average of the steels used in bicycle fabrication. We select aluminum and titanium properties of 6061-T6 alu-
Table 2: Selected material properties for steel, aluminum, and titanium used in simulation

| Material                  | Steel | Aluminum | Titanium |
|---------------------------|-------|----------|----------|
| Elastic Modulus (GPa)     | 205   | 69       | 105      |
| Poisson's Ratio           | 0.285 | 0.330    | 0.310    |
| Shear Modulus (GPa)       | 80    | 26       | 41       |
| Density (kg/m³)           | 7850  | 2700     | 4429     |
| Tensile Strength (MPa)    | 731   | 310      | 1050     |
| Yield Strength (MPa)      | 460   | 275      | 827      |

Figure 4: Breakdown of bikes by material in original BIKED data.

Mesh Resolution

In numerical simulations, mesh resolution is an essential parameter that balances the tradeoff between computation cost and simulation fidelity. Since this work simulates thousands of models, appropriately balancing computational cost and fidelity was essential. To study this balance, we randomly selected five bicycle frame models to test in each of our three simulation setups. For each study, we tested a logarithmic sweep of mesh resolutions with minimum cell size ranging from 0.01 mm to 1.28mm. Meshes are generated using SolidWorks’ “Blended curvature-based mesh.” In each test, the maximum cell size was set to 100 times the minimum cell size and the cell growth ratio between adjacent cells was set to 1.3. We examined convergence across mesh resolutions for each of our ten parameters of interest and documented two sample plots in Figure 5.

Although displacement values stabilize for fine mesh size, we observe in our studies that safety factors do not perfectly stabilize at even the finest of
Figure 5: Convergence study calculating two quantities of interest at different mesh resolutions across five different bicycle frame models. Mesh resolution is shown on horizontal axes and is measured in meters. The selected mesh resolution of 0.03 mm is indicated on the plots.

mesh resolutions tested. Qualitative analysis of simulation results indicates that the safety factors are reflecting extreme local stress concentrations at the junctions of the tubes. Thus, the low safety factors at finer resolutions can likely be attributed to imperfect modeling of the bicycle frame, particularly the infinite curvature at the tube junctions in the model. As such, we advise users of the dataset to expect some error in reported stress and safety factor values.

In general, displacement values are stable for mesh resolutions between 0.16 mm and 0.32 mm. Above 0.64 mm, displacement values are relatively unstable and simulations occasionally fail to converge. Displacement values are also relatively unstable for mesh resolutions between 0.04 and 0.16. We hypothesize that this range of mesh resolutions critically impacts fidelity since tube thicknesses may be as small as 0.5 mm and an accurate simulation should place several cells spanning the thickness of any key geometry. Below 0.04 mm, displacements are fairly stable.

We select a mesh resolution of 0.03 mm for our simulations to attain a reasonably precise estimate of displacements while avoiding the extreme cost and overestimates of stresses brought about by finer meshing.

4 Validation

To demonstrate that our frame model and meshing setup yield meaningful simulation results, we validate against existing published data. Validation using physical testing is usually a costly and time-consuming method, but
Table 3: Validation Study Results

|                | DeRosa SLX       | Casati Gold Line | Holland SL/SP  |
|----------------|------------------|------------------|----------------|
|                | Front            | Rear             | Model Defl.    | Front            | Rear             | Model Defl.    | Front            | Rear             | Model Defl.    |
| Actual Defl.   | 0.40             | 0.15             | 1.966          | 0.44             | 0.15             | 1.966          | 0.38             | 0.13             | 1.962          |
| Simulated Defl.| 0.297            | 0.116            | 1.69           | 0.3028           | 0.124            | 1.80           | 0.26             | 0.107            | 1.77           |
| Error          | 26%              | 23%              | 14%            | 31%              | 17%              | 8%             | 32%              | 18%              | 10%            |

is often the most rigorous. Fortunately, many existing studies have published results of physical experimentation on bicycle frames. Few of these, however, publish enough details on parametric data about the bikes they test for us to construct an accurate 3D bicycle frame model for simulation. We select a 1996 study by Damon Rinard [16] in which they physically tested over 70 bicycle frames for transverse deflection of the front and rear triangles. From their study, we select three frames for which we were able to find sufficient parametric data to approximate the 3D frame models: the DeRosa SLX, Casati Gold Line, and Holland SL/SP. Much of the parametric data comes from [17], which also provides estimates for frame mass. We mimic Rinard’s loading and measurement setup and compare simulated deflection values with reported values as well as frame model mass with reported frame mass. These results are presented in Table 3.

The comparison shows that our simulations have similar trends of deflection and mass as Rinard’s studies. However, our simulations tend to underestimate the front and rear deflections. This discrepancy is often expected between simulation and real-world testing and does not mean that the simulations are incorrect. There can be many reasons to explain the difference, a few of which we discuss here. First, the discrepancy in mass can largely be explained by the fact that our model does not include the frame’s fork while the experimental values do, attributing to the underestimation of mass values. Second, we suspect that measured deflections in Rinard’s studies fail to eliminate deflection caused by the compliance of his clamping scheme. This likely explains why the simulated values for front and rear deflections are consistently off by around the same amount of deflection, as the moment on the clamping mechanism is roughly the same for each test since the distance from the clamp to the front and rear parts of the bicycle do not vary a whole lot from test to test. For these reasons, we suspect that our simulations are accurate. Nevertheless, it is important to report these validation results against real-world experimentation. In future work, we will conduct our own physical validation to accurately model our bicycle frames.
5 Analysis

Model Validity

Overall, we find that a significant proportion of frame models fail to withstand the fairly demanding load cases. Taking a minimum Factor of Safety (FoS) of 1.0, we find that 3112 of 4198 frames simulated fail under at least one of the loading cases. Recall that 219 of the original 4512 models failed our geometric feasibility checks and 97 models failed to render due to geometry issues. The overall breakdown is shown in Figure 6. The relatively few frames that successfully accommodate the loading cases reflect the difficult balance of parameters and complexity of the bicycle design problem. Designers may often not anticipate that a particular bicycle design is structurally deficient until physically testing the frame.

![Figure 6: Breakdown of bikes by validity or type of infeasibility.](image)

Exploring the Performance Space

Through our simulations, we captured ten structural performance values for each of the 4101 geometrically valid bicycle frames. To make for easier visualization, we explore a subset of this space with five of these ten performance values: Dropout displacement during in-plane loading, bottom bracket displacement during transverse loading, bottom bracket rotation during eccentric loading, safety factor during in-plane loading, and weight. Additionally, we consider a subset of 780 models randomly selected from the 4101. Figure 7 shows a visualization of this subset, with histograms over each performance parameter and scatterplots over each pair of performance parameters. Additionally, points and histograms are organized based on bicycle frame model validity. In this case, we take a frame model to be valid if both safety factor values measured (one not shown) are greater than 1. Additionally, we label three bicycle frames on these plots to analyze in the following section. Based on these plots, we can make several observations. For example, looking at this histograms, we see that the distributions of deflections for valid bicycle frames are much more densely centered around 0 than for invalid frames (In general, valid frames have smaller deflection magnitudes). We can also see that the two distributions align very closely.
for mass and are drastically different for safety factors. Based on the scatterplots, we can also observe some correlations between objectives. For example, heavier models tend to have deflections with smaller magnitudes. We discuss these correlations in more detail below.

Figure 7: Plot showing: 1) Histograms over each performance parameter (diagonal plots). 2) Scatterplots over each pair of performance parameters (off-diagonal plots). 3) Labeling of bicycle frame models into feasible and infeasible models. 4) Three example frames that we discuss as case studies.
Case Studies

Here, we examine three sample frames that stand out for various reasons. Frame 1 has the highest vertical deflection during in-plane loading, highest deflection in transverse loading, and fourth highest rotational deflection in eccentric loading, each measured at the bottom bracket. Frame 2 has the highest safety factor during in-plane loading and fairly low displacements in each of the load cases. Frame 3 is the lightest valid model, boasting reasonable safety factors and modest deflections. Models of the three frames are shown in Figure 8.

Frame 1  This frame’s most noteworthy design characteristics are the unconventionally small diameter of the down tube and the large thickness of the seat tube. These two driving factors explain why the bicycle frame has exceptionally low vertical compliance as the seat tube prevents it from compressing much with its unusual stiffness. However, this frame still exhibits large transverse compliance, likely due to the small second moment of area of the major tubes. Being made of lightweight titanium, this frame is also one of the lightest in the dataset.

Frame 2  This frame is notable for its exceptionally high safety factor to mass ratio, which it achieves partially through the use of titanium, a material well known for its high strength and low weight. This frame model effectively optimizes two very important considerations in bicycle design. With consistently large tube outer diameters, yet relatively moderate thicknesses, this frame takes advantage of having a large second moment of area to increase its bending stiffness and resistance to failure under high stress.
riding conditions.

**Frame 3** This steel frame is similarly notable to Frame 2 for its high safety factor to mass ratio, but it achieves this while maintaining a very low mass in comparison to modern bicycle frames. An unconventionally short seat tube eliminates most of the accumulated mass a normal design would have, but does not cause for a large loss in vertical compliance. This difference in design does not have a large effect on transverse stiffness since the other tubes carry most of the load for out of plane forces, allowing the frame to still be reasonably stiff and safe yet light and desirable. In general, the diameter and thickness of the tubes carefully align to save weight without compromising too much.

**Pareto-Front**

Next, we explore optimality in the bicycle frame performance space. In our performance space, we have clear objectives: Minimizing the magnitude of deflections, maximizing safety factors, and minimizing mass. Highlighting non-dominated designs is a helpful design tool when searching for optimality. We say that one design “dominates” another if it outperforms that design in every single performance metric. Any design that is not dominated by any other design in the dataset is considered “non-dominated.” The collection of these non-dominated points is typically the subset of designs candidates that should be considered when selecting a final design and is called a Pareto front. Figure 9 repeats the scatterplots and histograms shown in Figure 7 except highlighting non-dominated (Pareto front) points. Additionally, since our in-plane loading case sees both positive and negative displacements and our goal is to bring deflections as close to 0 as possible, we plot the absolute value of deflections instead of the original values.

We determine that 57 of 780 designs are non-dominated, meaning that the vast majority of designs are inferior by all considered metrics to at least one other bicycle in the group. We can also appreciate that the distribution of objectives over non-dominated points are significantly more favorable than the distributions over the overall design space, confirming that these non-dominating points indeed constitute the kind of “elite” subset that we would expect. Manually examining the designs in such a subset may be a helpful tool for designers, especially after further filtering any infeasible designs.
Parameter-Performance Correlations

Here we delve into correlations between performance objectives. We compute Pearson Correlation Coefficient for each pair of objectives, using the absolute value for all displacements. Heatmap visualization of these correlations is shown in Figure 10. In general, displacements are highly correlated, but tend to negatively correlate with safety factors and bicycle frame model mass. Safety factors were positively correlated. Interestingly frame model mass was not strongly correlated with safety factor, potentially indicating that many bicycle frame models “waste” mass without putting it to good use.
Overall, we provide the performance and design parameter values for community members, researchers, and bicycle framebuilders to better understand these relationships and find key insights about their design choices.

6 Limitations

FRAMED is the first dataset that provides both parametric and performance values for a large set of community designed bicycle frames. However, it has a few limitations, which we discuss below. FRAMED inherits BIKED’s challenges with limited diversity in certain design parameters. We attempt to mitigate this by resampling these parameters. This resampling process makes FRAMED less suitable for studies about the existing bicycle design space and more suitable for surrogate models aiming to capture a wider portion of the design space.
FRAMED expands significantly on previous data-driven studies of bicycle frame design, with a considerably larger and more comprehensive design space. Nonetheless, FRAMED’s design space is still far more restricted than the real-world bicycle design space. For example, the design space only considers bikes with a conventional diamond frame, and excludes other bicycle frame configurations, such as bicycles with rear suspension mechanisms. It also excludes bicycle designs with non-cylindrical tubes and bicycles made from materials other than the three we support. We aim to expand FRAMED in future work, to include more types of geometries.

Though we validate FRAMED’s results, we acknowledge potential inaccuracy in the simulations, especially reported stresses and safety factors. Further validation against physical bicycle frames with better known sizing and parameters would help resolve this uncertainty. We also acknowledge that our frame modeling has a few assumptions. For example, we do not model curvature at the junctions of tubes since automating the parametrizations of these curves and fillets would be too complex and they make our simulations less robust.

7 Future Work

A natural extension of FRAMED is the fitting of surrogate models, which can drastically accelerate the early-stage conceptual design of bicycle frames by rapidly estimating design performance without the need for expensive and time-consuming simulation or physical prototyping. Another exciting extension of FRAMED would be to select an optimal performer to physically fabricate and test.

This research also has applications outside of bicycle design in the broader community of data-driven research. One of FRAMED’s core contributions is the introduction of a dataset of 4500 bicycle frame designs as well as associated structural performance values for these designs. FRAMED is therefore well positioned to support advancements in data-driven design tools like surrogate models. FRAMED may even support AI-based design tools such as performance-aware generative methods. Advanced AI-based design frameworks, such as Deep Generative Models (DGMs) have shown promising initial results on a variety of design problems. FRAMED is particularly well positioned to accelerate DGM development since not only do DGMs lack quality data and benchmark problems, most current DGMs do not account for design performance at all [18].
8 Conclusion

This study presents a data-driven approach to bicycle frame design, analysis, and optimization. To do so, we develop a dataset of 4500 individually-designed bicycle frames, simulate each in three loading conditions, and extract ten performance parameters of interest. We perform several validation studies on our data, such as comparing simulation results to physical experimental results on real bicycle frames, and demonstrating convergence at the selected mesh resolution. Through our analysis, we highlight general themes across bicycle designs in the dataset, study a selection of frames in greater detail, identify a non-dominated subset of the design space, and explore correlations between design objectives. Through our dataset and analysis, we aim to provide a resource for the bicycle design community, in particular, to help increase accessibility to custom bicycles and positively impact bicycle ridership. We simultaneously aim to support researchers in developing data-driven design methods like surrogate models or Deep Generative Models.
References

[1] P. Oja, S. Titze, A. Bauman, B. De Geus, P. Krenn, B. Reger-Nash, and T. Kohlberger, “Health benefits of cycling: a systematic review,” Scandinavian journal of medicine & science in sports, vol. 21, no. 4, pp. 496–509, 2011.

[2] T. L. Hamilton and C. J. Wichman, “Bicycle infrastructure and traffic congestion: Evidence from dc’s capital bikeshare,” Journal of Environmental Economics and Management, vol. 87, pp. 72–93, 2018.

[3] O. Edenhofer, Climate change 2014: mitigation of climate change. Cambridge University Press, 2015, vol. 3.

[4] O. Oke, K. Bhalla, D. C. Love, and S. Siddiqui, “Tracking global bicycle ownership patterns,” Journal of Transport & Health, vol. 2, no. 4, pp. 490–501, 2015.

[5] D. S. De Lorenzo and M. L. Hull, “Quantification of Structural Loading During Off-Road Cycling,” Journal of Biomechanical Engineering, vol. 121, no. 4, pp. 399–405, 08 1999. [Online]. Available: https://doi.org/10.1115/1.2798337

[6] J. Vanwalleghem, I. De Baere, M. Loccuier, and W. Van Paepegem, “Development of a multi-directional rating test method for bicycle stiffness,” Procedia Engineering, vol. 72, pp. 321–326, 2014.

[7] P. Soden, M. Millar, B. Adeyefa, and Y. Wong, “Loads, stresses, and deflections in bicycle frames,” The Journal of Strain Analysis for Engineering Design, vol. 21, no. 4, pp. 185–195, 1986.

[8] D. Covill, A. Blayden, D. Coren, and S. Begg, “Parametric finite element analysis of steel bicycle frames: the influence of tube selection on frame stiffness,” Procedia Engineering, vol. 112, pp. 34–39, 2015.

[9] D. Covill, P. Allard, J.-M. Drouet, and N. Emerson, “An assessment of bicycle frame behaviour under various load conditions using numerical simulations,” Procedia engineering, vol. 147, pp. 665–670, 2016.

[10] L. B. Lessard, J. A. Nemes, and P. L. Lizotte, “Utilization of fea in the design of composite bicycle frames,” Composites, vol. 26, no. 1, pp. 72–74, 1995.

[11] C.-P. Chung and C.-F. Lee, “Parameters decision on the product characteristics of a bike frame,” Procedia-Social and Behavioral Sciences, vol. 40, pp. 107–115, 2012.
[12] Y.-C. Cheng, C.-K. Lee, and M.-T. Tsai, “Multi-objective optimization of an on-road bicycle frame by uniform design and compromise programming,” Advances in Mechanical Engineering, vol. 8, no. 2, p. 1687814016632985, 2016.

[13] C.-C. Lin, S.-J. Huang, and C.-C. Liu, “Structural analysis and optimization of bicycle frame designs,” Advances in Mechanical Engineering, vol. 9, no. 12, p. 1687814017739513, 2017.

[14] D. Covill, S. Begg, E. Elton, M. Milne, R. Morris, and T. Katz, “Parametric finite element analysis of bicycle frame geometries,” Procedia Engineering, vol. 72, pp. 441–446, 2014.

[15] L. Regenwetter, B. Curry, and F. Ahmed, “Biked: A dataset for computational bicycle design with machine learning benchmarks,” Journal of Mechanical Design, vol. 144, no. 3, 2022.

[16] D. Rinard, “Frame deflection test,” 1996. [Online]. Available: https://www.sheldonbrown.com/rinard/rinard{fomtest.html

[17] E. Bicycle, “The bicycle info project.” [Online]. Available: http://www.equusbicycle.com/bike/columbus/columbuschart.htm

[18] L. Regenwetter, A. H. Nobari, and F. Ahmed, “Deep generative models in engineering design: A review,” arXiv preprint arXiv:2110.10863, 2021.