

**DEVELOPMENT OF A PILOT MANUFACTURING CYBERINFRASTRUCTURE WITH AN
INFORMATION RICH MECHANICAL CAD 3D MODEL REPOSITORY**

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ABSTRACT

Data driven advanced manufacturing research is dependent on access to large datasets made available from across the product lifecycle – from the concept design phase all the way down to end use and disposal. Despite such data being generated at a rapid pace, most product design data is archived in inaccessible silos. This is particularly acute in academic research laboratories and with data generated during product design and manufacturing courses. This project seeks to create an infrastructure that allow users (academia and the general public) to easily upload project data and related meta-data. Current manufacturing research must shift from siloed repositories of product manufacturing data to a federated, decentralized, open and inter-operable approach. In this regard, we build ‘FabWave’ a cyber-infrastructure tool designed to capture manufacturing data. In its first pilot implementation, we focused our attention to gathering information rich 3D Mechanical CAD data and related meta-data associated with them, with the intent to make it easier for users to upload and access product design data. We describe workflows that we have initially tested out within the two academic universities and under two different course structures. We have also developed automated workflows to gather license appropriate CAD assemblies from commercial repositories. Our intent is to create the only known largest available CAD model set within academia for enabling research in data-driven computational research in digital design, fabrication and quality control.

Keywords: Manufacturing Cyber Infrastructure, Data Management, CAD Model Repository, Digital Thread, Machine Learning CAD.

INTRODUCTION

Advanced manufacturing research is dependent on access to large datasets of product models to enable product designers to learn from past errors, and to discover and develop new solutions. Similarly, data generated during manufacturing processes and

quality inspection also becomes valuable data for future research in advancing manufacturing research. However, such datasets are typically archived in inaccessible repositories and may be poorly described and difficult to use by others.

While the ‘Digital Thread’ in manufacturing has concentrated on the final end point data generated during a product lifecycle, there is much value in all forms of data generated during the product lifecycle, even if it is not directly associated with product manufacturing. Examples include, failed designs, or unstructured data generated during the product design, prototyping and manufacturing process. Such forms of data are hardly captured and may provide tremendous value for researchers in advancing data-driven forms of product design and manufacturing [1].

Data generated within industry are often times impossible to be shared outside of the enterprise. However data generated during research activities in manufacturing can be shared as evident in the US National Science Foundation and other Federal agency requirements on data management. Yet, manufacturing engineering researchers do not have an adequate workflow or any form of easy to use tool that allows data to be stored and made accessible to the community. The community of researchers simply rely on storage drives maintained at universities to store much of this data, with a small percentage of them made available through research datasets when the work is finally published. There is a much broader and possibly richer data-set generated within academia – be it within product design and manufacturing classes or through research activities conducted in manufacturing projects. These datasets if made accessible and usable by the community, can lower the barriers for other research groups to participate. For example, machine data generated during a biomedical manufacturing process, such as 3D bioprinting can be valuable to those who are interested in

quality control, provided the datasets are annotated, tagged, classified and/or categorized to ensure its usability.

This project during its initial phase focuses on 3D Model data related to product manufacturing. For any large data-driven project, the classical issue with large datasets is their classification, and product CAD data is no different. The classification of models using shape search has long been a topic of interest for researchers in the Computer Graphics and the Design/Manufacturing communities. Iyer et al. [2] classify research in 3D CAD Shape Search algorithms as follows: Global feature-based (Spherical Shape Harmonics (SPH) [3,4]), Graph-based [5], feature-based [6], Histogram-based Shape Distributions [7], Product information-based [8] and 3D Object Recognition based (Extended Gaussian Images [9], Geometric Hashing [10]). The effectiveness of Local Feature-oriented techniques such as Heat Kernel Signatures [11] and Wave-Kernel Signatures [12] are also well established.

With advances in computer vision techniques, there has been the rise in application of graphical techniques aligned with Machine Learning techniques for model recognition and classification. The use of Convolutional Neural Networks, applied to volumetric representations [13], octree representations [14], collections of 2D representations [15] and techniques using unsupervised image-capture [16] have shown high accuracies of 90% and above. [17]. While promising, these techniques depend on large amounts of classified and categorized data to help improve results. In product manufacturing context, such data is not easily accessible and/or even readily available. Repositories such as those in Autodesk Fusion and GrabCAD would require manual download to get any sizeable chunk of data. Moreover much of the data is not readily categorized to be useful to the community for conducting research activities.

LITERATURE SURVEY AND PREVIOUS WORK

Building comprehensive databases in a variety of domains has long been a topic of interest for researchers, especially in fields where large amounts of data are either easily generated, or where large datasets have great transformative potential and aid collaborative research. WordNet is one such online repository that provides a “large lexical dataset, where words are grouped into sets of cognitive synonyms that express distinct concepts”. [18] This structured grouping of words in WordNet has significantly influenced work in Natural-Language processing. In a similar vein, the ImageNet project [19] has built on the ‘synsets’ of WordNet to provide images that are annotated by the semantic classification of WordNet. The 3.2 million classified images on ImageNet provide Computer Vision researchers access to a large amount of data for use in further applications.

Another well-known large-scale research database infrastructure, the Global Biodiversity Information Facility (GBIF) [20], has successfully collated hundreds of millions of

species occurrence records through an international collaborative effort. Open access is provided to scientists and researchers to apply the data in peer-reviewed publications and policy papers. This data-driven approach to decision making has had far-reaching positive implications in biodiversity, climate change, human health and food security.

There have been multiple attempts to establish such a database for 3D shapes. The Princeton Shape Benchmark [21] is one of the well-established benchmarks that provides a standardized framework with 6,670 classified models for comparing experiments using different shape descriptors. 3-D mechanical CAD models require different classes as compared to regular 3-D models, since they are specific to the engineering discipline. The effort to construct a standard repository for 3-D mechanical CAD models [22] predates the Princeton Shape Benchmark; the National Design Repository (NDR) project by Regli et al. contains datasets classified on different bases such as Manufacturing (Machined, Cast-then-machined), Functional (Bracket, Gear, Housing, Linkage Arm, Nuts, Screws, Springs) Primitives (Cubes, Cylinders, Sphere, Torus), a Lego dataset etc. In all, there are around 600 CAD models classified on the previously mentioned bases. All the models were made available in ACIS-SAT, STEP and VRML formats. A smaller dataset of 40 models, with variable fidelities, and a dataset of 27 models with minor topological variation is also included, to test the sensitivity of the various search techniques [23]. The use of the NDR dataset was further expanded upon in [23], where 9 shape-based and solid-based graph techniques were performed on the dataset, in order to establish a benchmark on CAD shape search techniques. A performance evaluation using k-Nearest Neighbours classification showed the effectiveness of different techniques for each classification.

Jayanti and Ramani et al. established the Engineering Shape Benchmark (ESB) Dataset, by considering the Functional, Manufacturing, Lego model and real-world engineering parts from the NDR dataset (totaling 400 parts), and adding to this their own parts to bring up the total dataset to 867 models. [24] Instead of classifying the parts on the basis of function, the parts were classified on the basis of shape, giving due consideration to diversity of these 3D Models. These models were made available in STL and OBJ formats, along with the associated JPEG image. The higher level or ‘super-class’ categories were Flat-thin wall components, Rectangular Cubic Prisms and Solids of Revolution; sub-classes are further elaborated upon in [24]. 12 different techniques were tested on the ESB set, which can be classified into Feature Vector-Based, Histogram-Based and Graph-Based methods. A comparison between the NDR dataset and the ESB datasets was then performed, showing the superior performance of 2-D view methods such as 2.5D Spherical Harmonics [25] and 2D Shape Distributions [26].

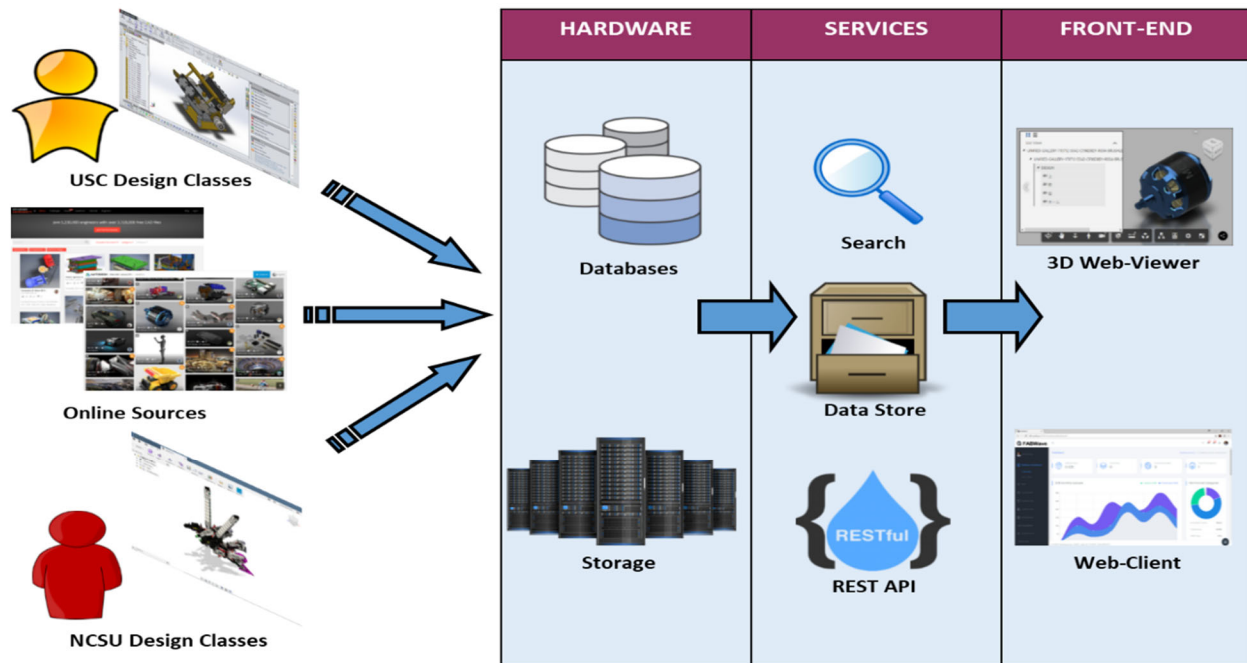


Fig. 1. A Pilot Manufacturing Cyberinfrastructure- 'FabWave'

Expanding on the concept of these existing benchmarks for 3D models, ModelNet [27], a 127,915-strong clean collection of 3D models of objects, has become a standard dataset for the testing of various shape-search algorithms. ModelNet classifies these objects into 662 categories, and provides a 40-class subset for validation of algorithms. More recently, ShapeNet has emerged as a larger, well annotated dataset of 220,000 models classified on the basis of WordNet synsets, with an overall size of 3,000,000 models [28]. ShapeNet's focus is on creating a large set of geometric data for object- and scene-recognition, and explicitly excludes "mechanical CAD parts, molecular structures and other such domain-specific objects" [28]. The dataset made available through ShapeNet is not directly relevant to product manufacturing science and research applications. Specifically, information such as the categories, feature level detail, material and tolerance specifications are lacking, which are critical to any data-driven product design engineering research.

FABWAVE (FW) – A CYBER-INFRASTRUCTURE (CI) FOR MANUFACTURING

The overall goal of this project is to design the initial building blocks for a nationwide manufacturing cyberinfrastructure to advance our nation's research and scholarly achievements in design and manufacturing (D&M) research. Current research must shift from siloed repositories of product manufacturing data to a platform that is federated, decentralized, open and inter-operable. This can be achieved through the transformation of techniques through which cyber-capability is embedded in every physical end-point, be it on a

desktop used by a product designer or within the control systems of a manufacturing machine. Advanced CI tools are rarely used in manufacturing science and research, primarily due to the lack of infrastructure to connect the diverse software tools and manufacturing machines used across the scientific community. Data generated during research are currently stored in siloed storage drives and hardly ever made accessible to the manufacturing community. Beyond availability of this data, making them usable for future research is critical to lowering the barriers for manufacturing researchers to use CI tools. This manufacturing cyberinfrastructure, which we call 'FabWave' (FW) aims to create the first of its kind foundational experimental infrastructure to eventually support research interaction between manufacturing science and computer science researchers.

In this work, we have focused on the ability to gather 3D CAD model data from a variety of sources generated within academic laboratories, teaching oriented classes and from publicly available open sourced data sources to create a comprehensive dataset of 3D mechanical CAD parts far beyond the amount of 3D models available today.

3.1. FabWave Infrastructure Use Cases

To aid the design the CI tool, the following use cases were considered to contextualize the design architecture of FabWave. While there are many more uses cases beyond the three listed below, the following have been chosen to be specific to the kind of data made available at present.

Use Case 1: A Design Aid for Novice Users: Ethan, an undergraduate student in mechanical engineering, is in the process of designing an L-bracket made out of aerospace grade titanium alloy. Ethan is not aware of the desired internal thread call-out for the holes in his bracket model, particularly because Titanium is a very hard to machine alloy and has strict design for manufacturability rules. He connects his 3D model of the bracket to FW's plugin within his design software, FabWave analyzes his design and then recommends thread call-outs on the bracket. FabWave is able to do so, because it has analyzed hundreds and thousands of previous designs available in its repository and has made an informed decision on the recommended callout based on similar designs that exist in its repository.

Use Case 2: Enabling Manufacturing Researchers: Rachel, a manufacturing science academic researcher is building a deep layer convolutional neural network algorithm to identify if a 3D product model is similar to a repository of digital product models existing in an organization's database. However, Rachel has no easy way of training her model and stress testing her algorithm against several thousands of product model categories. Manual methods would simply be time consuming and impossible. If FabWave existed, she could use API tools available through FabWave, to link her algorithm and test it against thousands of product digital models, while using the available cloud and university's resources to conduct the study.

Use Case 3: Artificial Intelligence in Product Design: Sid, an artificial intelligence researcher is studying how humans design products. He writes code to access FabWave's repository of product model data to crawl through the individual product design features built into products, and searches through the meta-data surrounding the design of those products, which include design specifications, meeting minutes, audio, 2D sketches and design versions. He is now able to generate the next generation of contextual adaptation algorithms, which will allow computers to learn how to generate new products. The repository of heterogeneous data surrounding the design and making of a product within FabWave enriches and hastens the speed of his algorithm development.

FabWave is intended to be a cyber-infrastructure to enable science and engineering research in manufacturing. In this first component, FabWave's structure is designed to capture 3D CAD model data. However the underlying infrastructure can accommodate other forms of manufacturing data generated from a diversity of sources. Fig. 1 shows the overall stacked layer software architecture of FabWave. The goal is to create a detailed, continuously developing and eventually decentralized and inter-operable database of digital data (example CAD models), for use in design and manufacturing applications. Researchers will be able to access the entire dataset contained in the repository through the use of API tools, and therefore to build applications and enable their own research. Students have plug-

ins to record all the data automatically with limited human input, thereby easing the path to storing rich content in the repository and removing barriers to sharing data. To facilitate the entry of 3D CAD model data, add-ins were developed at the design software level for both SolidWorks and Autodesk Fusion 360 design software using their API features, to enable users to upload their data to the repository with ease.



Fig. 2. FabWave Web User Interface 1

3.2 Description and Structure

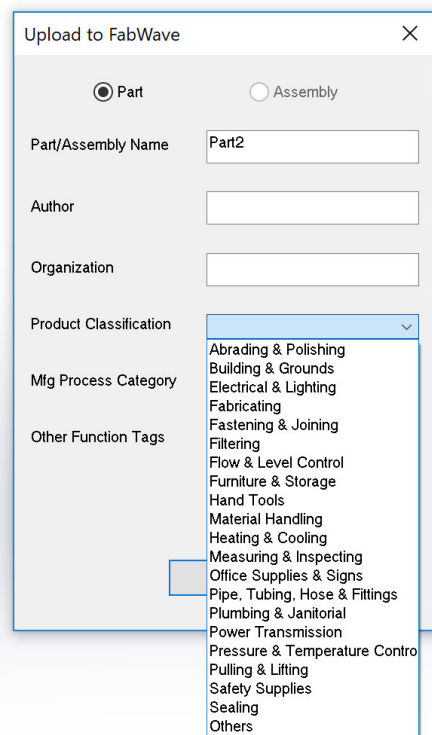


Fig. 3. SolidWorks Publisher Plugin

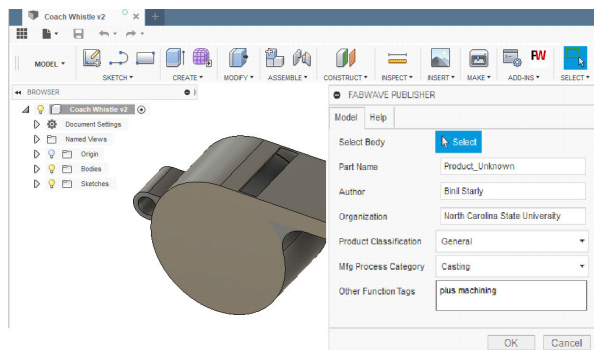


Fig. 4. Autodesk Fusion 360 Publisher Plugin

The front-end web interface for accessing FabWave (Fig. 2) is currently being built, using a Python based Django web framework; a basic user management system will be integrated into the Web UI. A Data Store integrated with ElasticStack, for uploading and visualizing the data is also under development. This front-end will connect to a storage repository containing the parts and related metadata for each of these parts. The remainder of the paper describes the workflow of capturing 3D model data of assemblies and associated parts, types of models captured and its organization.

3.3 Data Collection and Add-Ins

The repository for FabWave was initially built from the following sources: Student data from design oriented classes at

NCSU and USC, other parametrically generated CAD models in academic projects, and data available freely for non-commercial purposes from CAD-sharing platforms such as Autodesk Gallery and GrabCAD.

Data Source 1: Academic Sources of 3D Model Data

To enable capturing student generated content, plugins were built for SolidWorks and Autodesk Fusion, two CAD software platforms heavily utilized in academic engineering curriculums. The plugins were created to make it easier for students/teaching assistants to upload content to the FW repository. Plugins created within SolidWorks and Fusion are shown in Fig. 3 and Fig. 4 respectively. Data generated by the student exercises or projects are routed to the Google Drive currently maintained by NC State University. Authentication level grant access was built-in to allow data from USC to flow through into the Google Drive Account setup within NCSU (Fig. 5). In future, we would set individual storage accounts and then data made available through federated access across distributed repositories.

Data Source 2: CAD Model Repositories

Web-scraping and automation tools were utilized to download assemblies from sources such as Autodesk Fusion Gallery and GrabCAD. The workflow was adjusted to only download models that had the appropriate shareable license to allow the model to be used for research and other re-use purposes. Each model assembly came with a limited set of meta-data properties that

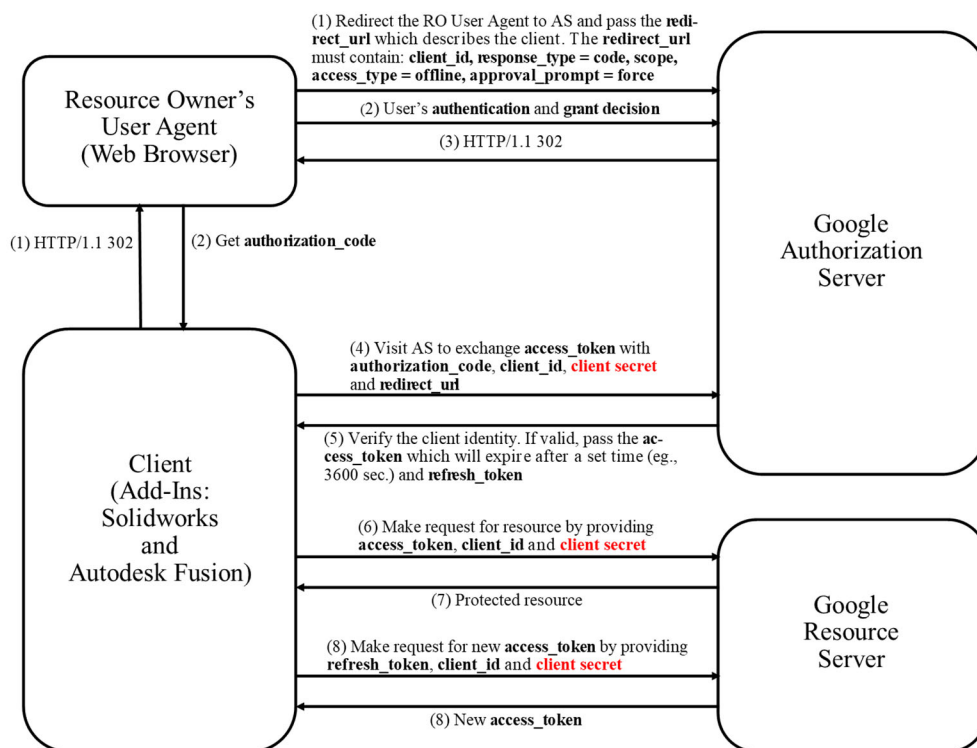


Fig 5. Workflow of data transfer from CAD Plugin to FW Repository on Google Drive

was available on each webpage of the model. The author of the assembly model, model categories and other description was also saved as part of the download process. While such data is limited with regards to characteristics of the assembly model, future workflow can include further categorization and classification of parts. Due credit to the website and the author of the file was recorded in the form of the author name and download URL.

```
descriptor [2]
  0 : Assembly
  1 : GrabCAD
num_extrude_feat : 0
volume : 21991083.16272338
num_vertices : 27147
download_url : https://grabcad.com/library/2017-pwnage-offseason-775pro-gearbox-1
download_filename : 2017 OFFSEASON 775PRO GEARBOX.STEP
display_name : 2017 PWNAGE OFFSEASON 775PRO GEARBOX
x_dim : 719.1974542236329
num_chamfer_feat : 0
location_author : Unknown
name_author : Pwnage Robotics
publish_date : LookForURL
area : 9915882.5747231
ind_categ_tags : STEP / IGESgearboxshifterballball-shifter32dp775pro
num_hole_feat : 0
num_edges : 39109
num_faces : 14820
num_revolve_feat : 0
z_dim : 816.7501538638401
num_fillet_feat : 0
y_dim : 2393.1313895613885
UUID_assembly : 0beed84e-fcae-46c9-9bfff-afe07b56cf38
va_ratio : 2.217763572430917
```

Fig. 6. Assembly Level JSON Document

The file downloads were restricted to the .STEP or .F3D formats; .STEP is an industry standard for CAD data, whereas F3D is a format specific to Autodesk Fusion software. Other popular formats such as .STL and .OBJ were not preferred, as they do not contain enough initial information about the part dimensions and other associated metadata. As of the date of writing this paper, 4700 CAD files of assemblies have been downloaded from these sources.

3.4 Post-Processing of the CAD Data

The models obtained from the Design classes at NCSU and USC were mostly individual parts. These parts were classified into various categories before uploading them to the repository. The categories were based on a combination of function and shape, derived from the listings on McMaster-Carr's website [29]. These categories are listed in Table 1. However, the majority of the parts obtained from the web-sources were in the form of assemblies.

Since part model data could be generated from any source near simultaneously from any end-point, models were assigned a Universally Unique Identifier (UUID). Using Autodesk Fusion 360 CAD/CAM software, basic meta-data about the models were collected. This included, Bounding-Box dimensions, Volume and Surface Area of the files were extracted. These details, along with those extracted from the URL that the file was downloaded from, were added to a JSON file. The JSON format was chosen because of its compatibility with the NoSQL database schema, which allows flexibility in adding data without conforming to a rigid structure. This accounts for different sources of data having varying formats and representations, with the added possibility of selectively adding further metadata in the future. Each of these assemblies were then exported in .STEP, .F3D and .STL, along with a screenshot of each model and the .JSON document containing the metadata as shown in Fig. 6. It was essential to



Fig. 7. Miscellaneous sample parts from the FabWave 3D Part Model Repository (As of Nov 2018: >125,000 3D Model Parts)

split the assemblies that were obtained, in order to isolate individual parts; these add far more value to the manufacturing applications that FabWave is oriented towards. Fig. 7 shows some of the parts that were obtained after splitting the assemblies.

For models that have an assembly structure, each assembly was scanned and all parts were extracted from within the assembly structure. A UUID was assigned to them and a thorough acquisition of properties associated with these parts was made. In addition to the previously mentioned Area, Volume and Bounding Box dimensions, various other associated metadata such as edges, vertices and the position of the part in the assembly tree structure were obtained; the complete details are shown in Fig. 8. Each of the Part JSON documents also refers back to the Assembly JSON documents and its position in the BRep tree. The parts were exported in the same formats as previously mentioned for the assemblies.

```
num_revolve_feat : 0
num_hole_feat : 0
y_dim : 50.366402284304286
UUID_assembly : 0beed84e-fcae-46c9-9bff-afe07b56cf38.f3d
area : 4561.532142135055
x_dim : 50.32416894555183
num_faces : 162
num_fillet_feat : 0
UUID_part : a71b5626-56c0-4644-b3db-128e90182cc3
num_extrude_feat : 0
num_edges : 472
va_ratio : 1.8198423203458303
body_name_STEP [2]
  0 : Body1
  1 : 0beed84e-fcae-46c9-9bff-afe07b56cf38
num_chamfer_feat : 0
volume : 8301.269237875145
z_dim : 11.391734815623309
num_vertices : 316
descriptor [2]
  0 : Part
  1 : GrabCAD
```

Fig. 8. Part level JSON Document

In total, we have compiled together more than 125,000 individual parts with full .STEP model information and as much meta-data possible about the part as possible. These models are available as a public resource for research purposes at <http://www.dimelab.org/fabwave>. Models generated from academic sources are mostly standard parts which can be useful to train machine learning models for classification type problems. When a model exercise was given to student group in a particular class, the workflow allows us to capture multiple ways in which

students have generated the same final end-result. Such datasets become extremely valuable to train machine learning algorithms to learn how humans create models. The limitation is that such workflow in-advertently also captures amateur product models, especially the work of students. Nevertheless, it does represent a starting point to gather data from start point of the design to the fabrication of it, rather than just collect the final end-point of any design process.

CONCLUSION

The intersection of manufacturing sciences and data sciences are reinforced with the digital integration across the product lifecycle. Machine learning algorithms require access to copious amounts of classified and categorized data to help advance manufacturing systems and process research. However access to such data has hampered the broader use of machine learning and artificial intelligence research across the manufacturing domain. This pilot project which we have termed 'FabWave' is designed to collect data across academic and research grade projects with the intent to create datasets for academia to use and study. In this first phase, we have implemented the collection of 3D product design data from student led projects and crawled the web to collect sources of 3D mechanical CAD assemblies and individual parts. As of this writing, the project has collected more than 125,000 individual CAD part files in various parts for the intent to making the data accessible for research to the community. Part meta-data was also captured to make it easier to search and find parts. In the future, we intend to integrate across many other forms of manufacturing data. In addition, a community led effort must be undertaken to classify and categorize the data to create a comprehensive and accessible dataset.

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