

Predictive Engineering CAD Design: An Effective Approach to Rapid Design and Reuse

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Content

- My research work
- Predictive Engineering CAD Design
 - Discovery of common design structures in a design CAD database
 - Rank shape similarity between design components
 - Identify substitutable design features in a component design

Engineering Design and Manufacturing



Efficient System

Innovation

Sustainability

Predictive CAD

Patent Informatics





Crowdsourcing Design and Manufacturing Processes

Development of Responsive Manufacturing System



Product-Service Systems Design

Through-Life Engineering Services

Modelling and Management of Engineering Processes

Collaborative Design Support System



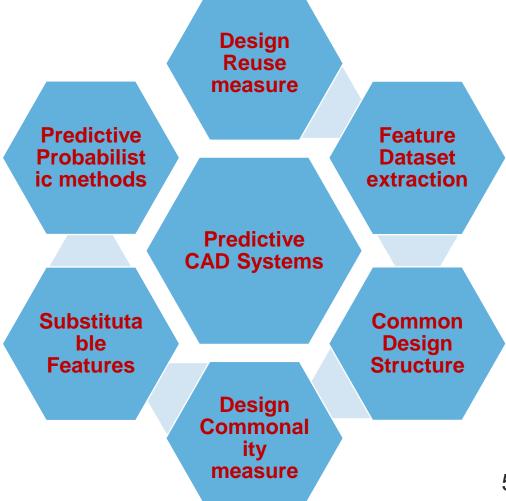
Information and Knowledge Management

3

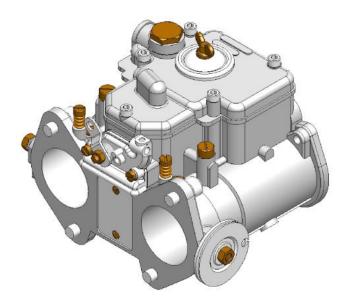
Video link: https://youtu.be/ZnbixQowRzc



Predictive CAD Systems









Issue:

- More than 75% of design activity comprises reuse of previously existing knowledge.
- Product development groups within manufacturing enterprises frequently "reinventing the wheel" rather than using known solutions.

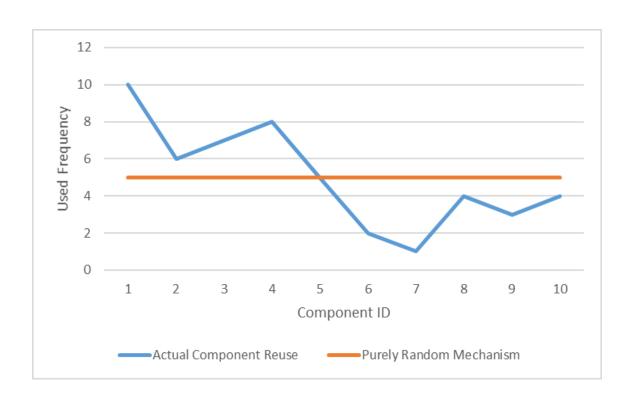
Research Gap:

- Existing approaches to quantifying the amount of design reuse within a company's product range are laborious and often provide only aggregated reuse value.
- The lack of a benchmark dataset to reference results against. The relative scale 0 1 provides a benchmark against an ideal scenario, but this may not provide sufficient insights for increasing commonality measures.



- Proposed Solution:
 - A novel approach to objectively quantifying levels of reuse by comparing actual probability distributions of component use with virtual ones, where every component is used with equal preference.
- Validation:
 - A Flat-pack furniture and Valve companies CAD data.
- Impact:
 - Assist to create a number of product variations from a limited range of components, or sub-assemblies.
 - Companies who can effectively reuse elements of existing designs when creating new products will be more productive and profitable.





Effectively comparing the difference between two probability distributions.



 The Kullbeck-Leibler divergence measure provides a means to measure the difference between distributions

$$D_i = \sum_{j=1}^{n_i} \hat{p}_{ij} \ln \left(\frac{\hat{p}_{ij}}{p_{ij}^{PRDM}} \right)$$

$$= \frac{x_{ij}}{\sum_{j=1}^{n_i} x_{ij}} \qquad p_{ij}^{PRDM} = \frac{1}{n_i}$$

If $\hat{p}_{ij} = p_{ij}^{PRDM}$ for all options 'j' then $D_i = 0$ and as the difference grows so does D_i .

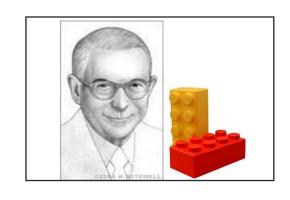
Divergence between distributions Edinburgh Napier provide a measure of the level reuse UNIVERSITY



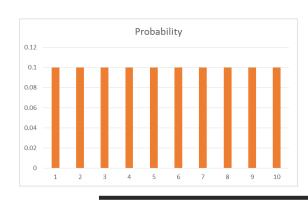
Poor Designer

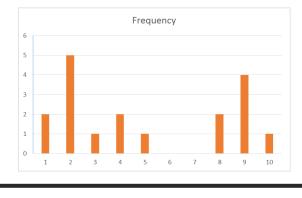


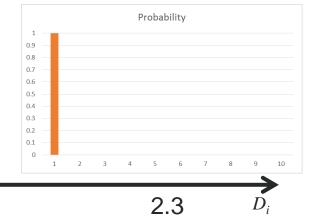
Average Designer



Excellent Designer





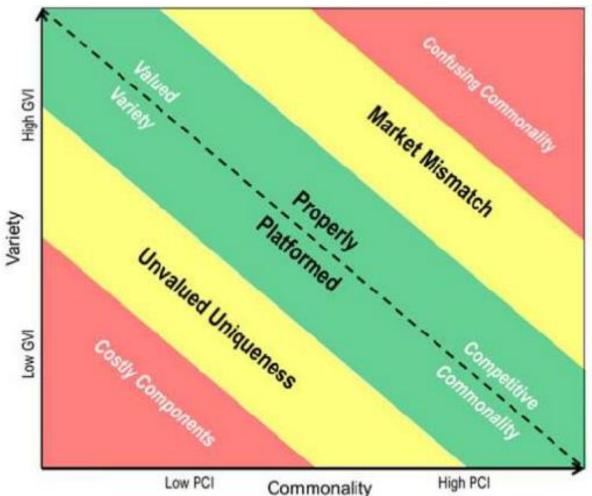


Measure of the Divergence between the purely random and actual distribution

0.40

The "ideal" amount of feature, or component, Reuse is determined by a product's market

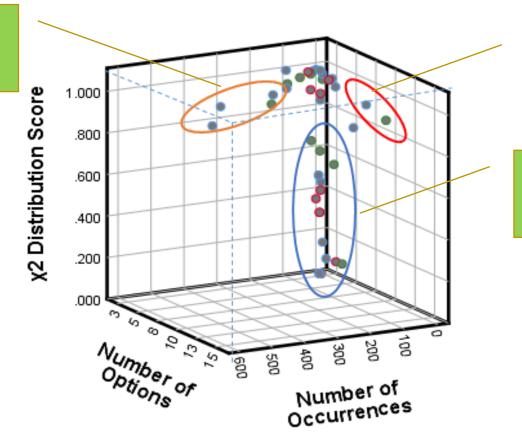




There is a trade-off between the **variety** of a product range and the level of **common** design (i.e. features or components) [T. Simpson]2017]



Components with high occurrences



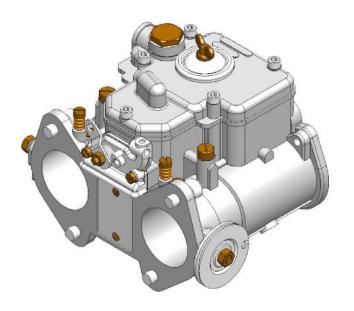
Components with high options

Low reuse components

3D scatter plot of χ^2 distribution value, number of options and total occurrences for each component family

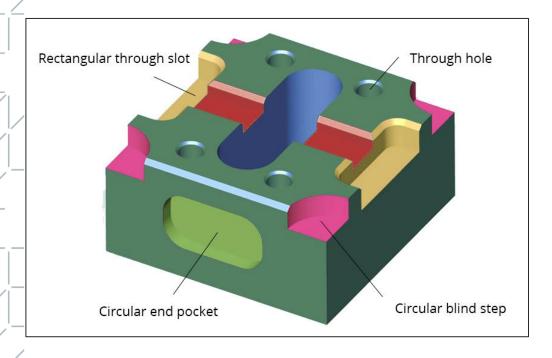


Common Design Structure





What is Common Design Structure?

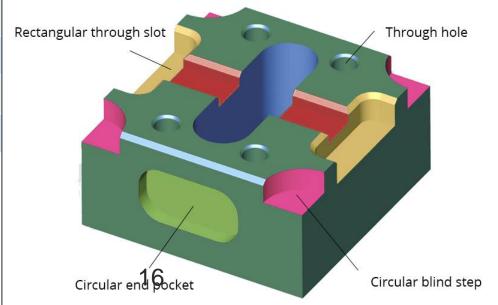


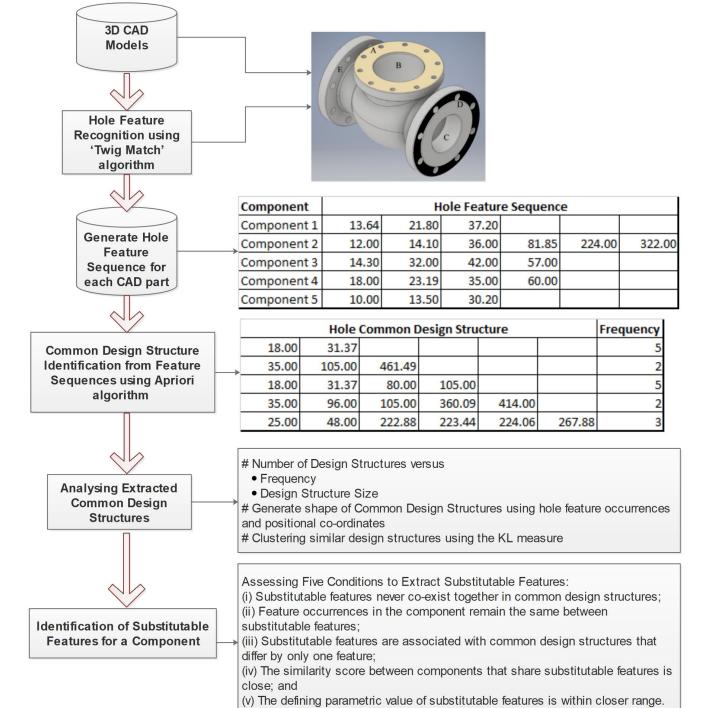
- A CDS is composed of a set of features that frequently occur in a CAD database. More formally a CDS is defined as a problem of frequent substructure discovery that appears above a given frequency threshold value in a set of 3D models.
- A CDS as collections of frequently occurring features (e.g. holes) with common parametric values (e.g. diameters) in a CAD database (irrespective of their locations or spatial connectivity between other features on a component).



Characteristics of Common Design Structures

Characteristics			
Repetition	Reusability		
Cohesive (Dependant, intersection and adjacent)			
Decoupled	Compatibility		
Complexity	Scalability		
Rich information	Maintainability		
Function	Portability		
Substitutable	Comprehensibility		





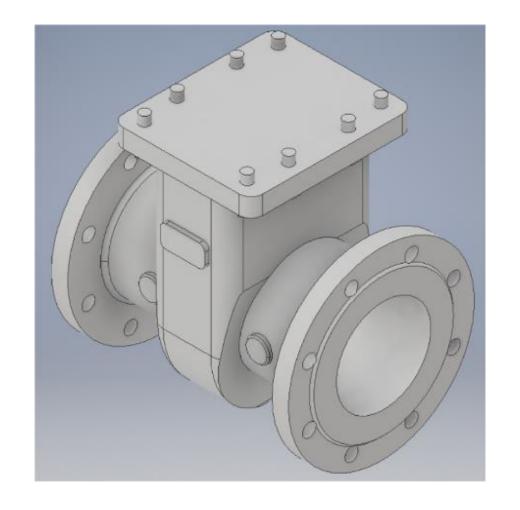


Steps to extract Common Design Structures and Substitutable Features



Dataset

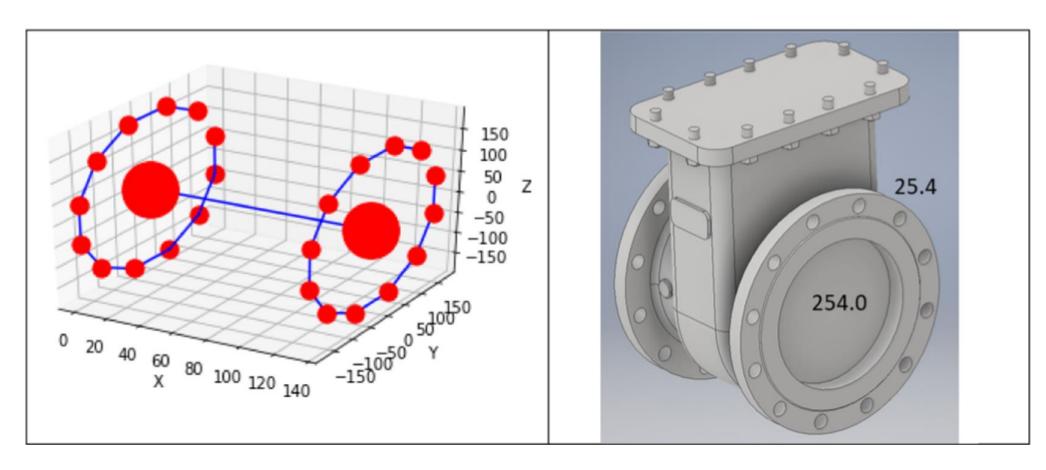
- A valve design dataset was created from an online catalog of industrial components.
- In total 1851 3D models of the industrial valve were downloaded from several manufacturers.





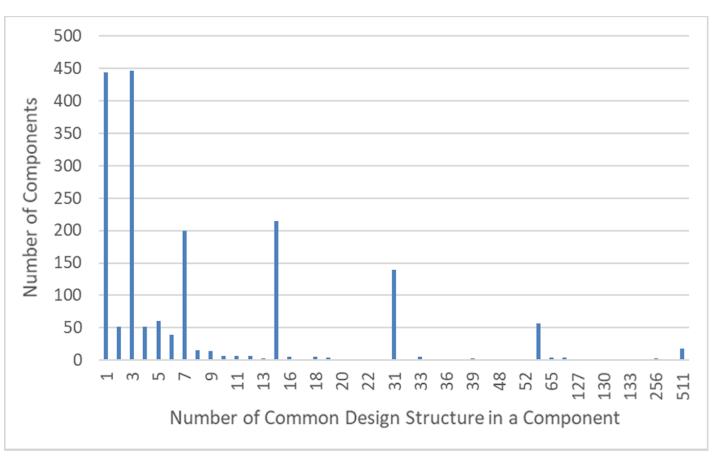
Common Design Structure Illustration

Common Design Structure for {25.4, 254}





Common Design Structure

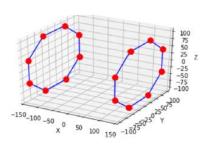


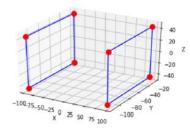
- e Each component could generate a maximum number of CDSs of 2ⁿ 1, where n is the number of different hole diameters.
- However, 51% of the components contain less than four CDSs.

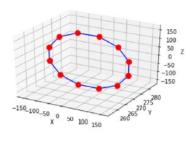
Shapes of a common design structure for 18 mm hole diameter

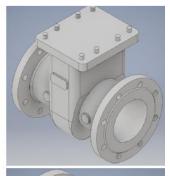


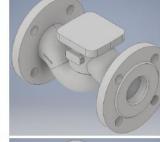
Variation of Structures across flanges for 18 mm hole

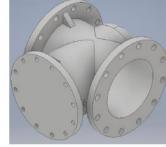


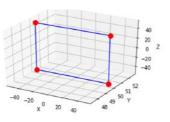


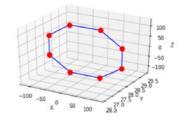


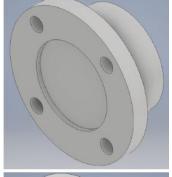










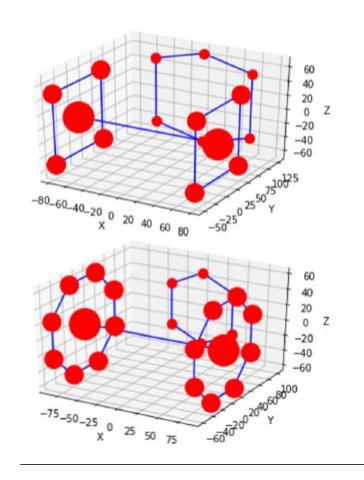


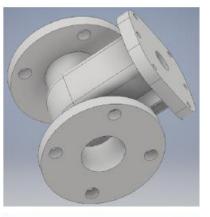


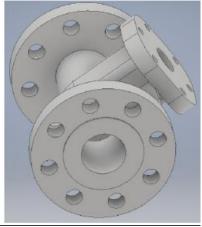
Shapes of a common design structure for {10.0, 19.05, 32}.



Variation of Structures across flanges for {10.0, 19.05, 32} hole diameters









Component Similarity Measure

■ Used the Kullback—Leibler Divergence Measure to calculate similarity score between two parts using feature positional co-ordinates.

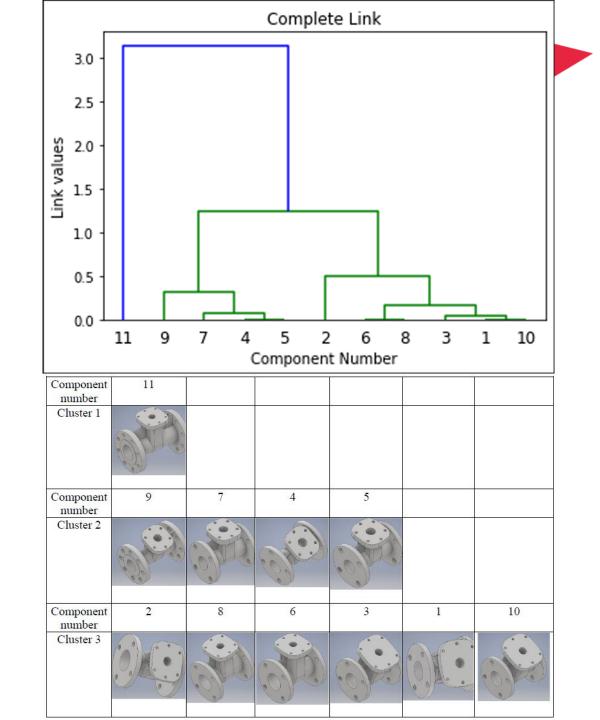
$$D_{KL}(P||Q) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[\frac{\sum_{i=1}^{n_p} \phi\left(\frac{x-x_i}{\sigma}\right) \phi\left(\frac{y-y_i}{\sigma}\right) \phi\left(\frac{z-z_i}{\sigma}\right)}{n_p} \right] ln \left(\frac{\frac{\sum_{i=1}^{n_p} \phi\left(\frac{x-x_i}{\sigma}\right) \phi\left(\frac{y-y_i}{\sigma}\right) \phi\left(\frac{z-z_i}{\sigma}\right)}{\sum_{j=1}^{n_q} \phi\left(\frac{x-x_j}{\sigma}\right) \phi\left(\frac{y-y_j}{\sigma}\right) \phi\left(\frac{z-z_j}{\sigma}\right)}}{\frac{\sum_{j=1}^{n_q} \phi\left(\frac{x-x_j}{\sigma}\right) \phi\left(\frac{y-y_j}{\sigma}\right) \phi\left(\frac{z-z_j}{\sigma}\right)}{n_q}} \right) dx dy dz$$

- The K.L. divergence score of 0 indicates that the hole positional coordinates between two components are identical and the higher the measure implies higher variation between the two components.
- The K.L. is a measure of divergence, not distance and as such $D_{KL}(P||Q) \neq D_{KL}(Q||P)$



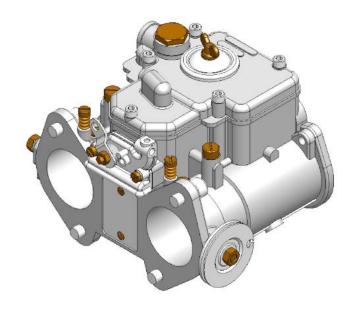
Component Similarity Measure

- A common design structure (10.0, 19.05, 32) was shared across 11 components.
- These 11 components were used to illustrate the clustering process using the K.L. measure.
- The Hierarchical clustering process was used to create the similarity clusters.





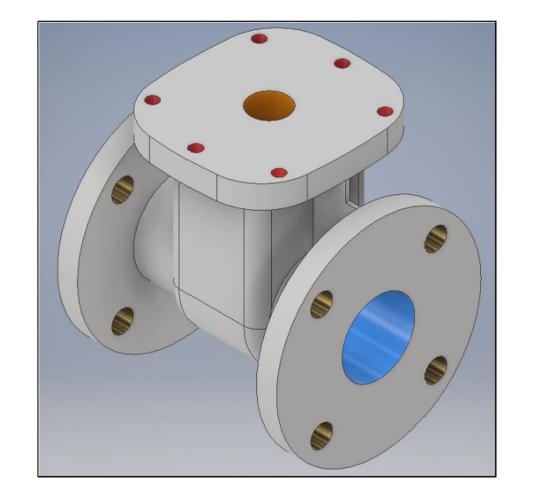
Finding Substitutable Features





Approaches for Finding the Substitutable Features

- In the first approach, the engineer can choose a component and look for a possible substitutable feature within the component.
- In the second approach, the engineer can browse through all the substitutable features from a knowledgebased system.

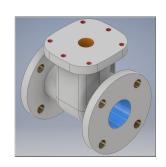




Conditions for Identifying Substitutable **Features**

_	Conditions for substitutable features	Rationale		
	Substitutable features never co-exist together in common design structures.	Substitutable words never co-occur in a sentence. The same analogy is applied to CAD models.		
	Feature occurrences in the component remain the same between substitutable features.	The same number of times substitutable features occur in components will ensure the significance of the structural appearance.		
	Two common design structures have a one-hole feature difference between them.	Triadic closure defines a common component that shares features with two separate components. This one-feature difference between CDSs has the potential substitutable opportunity.		
	The similarity score between components that share substitutable features is close.	Restricting the difference in the similarity score will ensure the substitutable features belong to the same component type.		
- _	The defining parametric value of substitutable features is within close range.	The substitutable features will be within a close range of parametri √alues.		

Identifying Substitutable Features for 63.5 mm



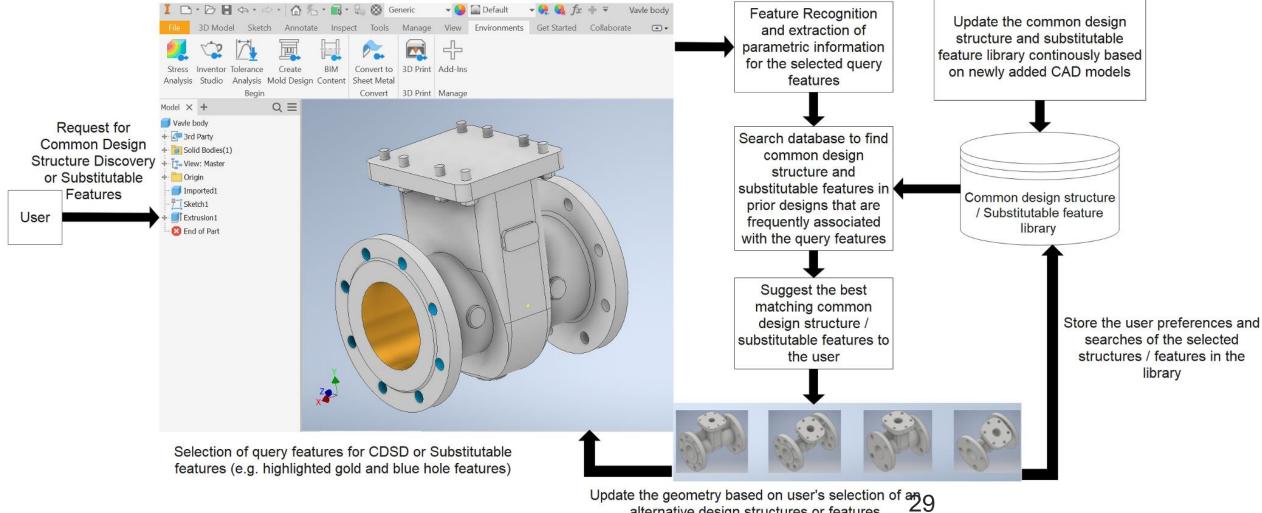
- Eight out of 13 possible substitutable hole diameters were found to be useful.
- Eight identified substitutable hole diameters are valid as all these diameters represent bore diameter in the valve body and share a similar topological structure.
- The K.L. score above of four represents the largest variation with reference to the selected component, and is adopted as a cut-off score to eliminate the substitutable hole diameters.







Implementation Architecture

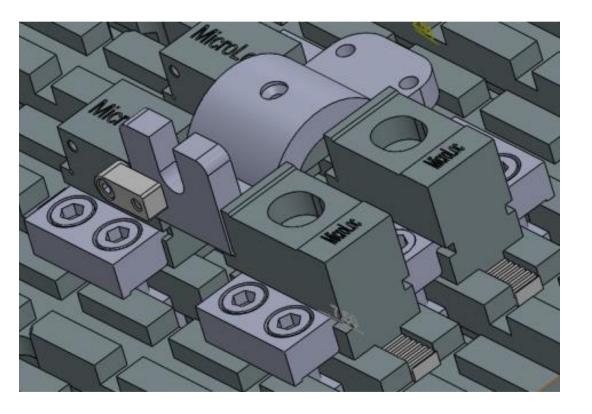


alternative design structures or features



Current Work

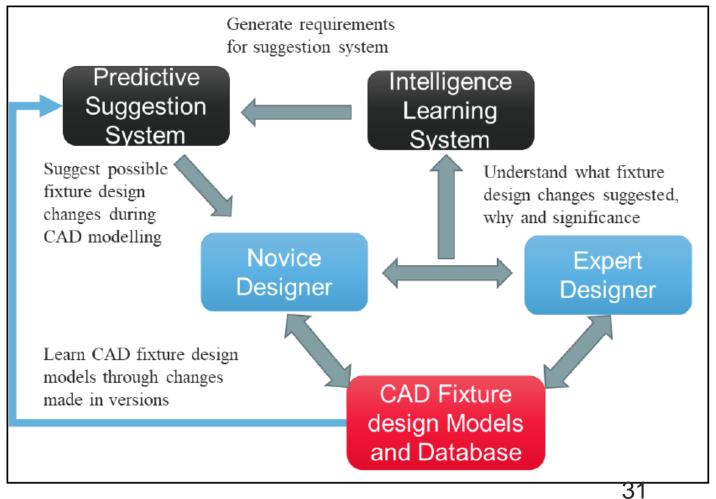
 Predictive Design to support CNC Fixture
 Design in Collaboration with The National Manufacturing Institute Scotland (NMIS).



Modular fixture



Future Development





Published work

- Vasantha, G., Purves, D., Quigley, J., Corney, J., Sherlock, A., & Randika, G. (2021).
 Common design structures and substitutable feature discovery in CAD databases. Advanced Engineering Informatics, 48, 101261.
- Vasantha, G. V., Purves, D., Quigley, J., Corney, J., Sherlock, A., & Randika, G. (2022).
 Assessment of predictive probability models for effective mechanical design feature reuse. AI EDAM-Artificial Intelligence for Engineering Design, Analysis and Manufacturing.
- Quigley, J., Vasantha, G., Corney, J., Purves, D., & Sherlock, A. (2022). Design as a marked point process. Journal of Mechanical Design, 144(2).
- Vasantha, G., Corney, J., Stuart, S., Sherlock, A., Quigley, J., & Purves, D. (2020). A probabilistic design reuse index for engineering designs. Journal of Mechanical Design, 142(10), 101401.