IMPLEMENTATION OF MECHANICAL ASSEMBLY RATING TOOL BASED ON KINEMATIC SCREW THEORY

By

Diovandi Basheera Putra

12301058

BACHELOR'S DEGREE

in

MECHANICAL ENGINEERING - MECHATRONICS

FACULTY OF ENGINEERING AND INFORMATION TECHNOLOGY

SWISS GERMAN UNIVERSITY

The Prominence Tower

Jalan Jalur Sutera Barat No. 15, Alam Sutera

Tangerang, Banten 15143 - Indonesia

February 2, 2026

PROPOSED ADVISOR

I propose **Dr. Leonard P. Rusli, B.Sc, M.Sc, Ph.D** as my Advisor for my proposed Thesis.

CHAPTER 1 - INTRODUCTION

1.1 Background

The assembly of mechanical components constitutes a fundamental phase in the product development lifecycle. Mechanical assemblies across automotive, aerospace, railway, and general manufacturing industries rely fundamentally on discrete fasteners such as screws, bolts, and rivets to ensure structural integrity and operational safety (Croccolo et al. 2023).

Fasteners perform three essential functions: constraining the degrees of freedom (DOF) between rigid bodies, transferring complex load vectors, and facilitating assembly operations. However, the placement of these fasteners remains a manual, heuristic-driven process. Engineers typically resort to empirical rules such as uniform spacing or symmetry. While adequate for conventional designs, these approaches fail to answer fundamental engineering questions systematically, such as the exact optimal location for stiffness maximization (Rusli et al. 2013).

Recent research has demonstrated that "black-box" optimization methods, while computationally powerful, introduce fundamental risks in high-stakes engineering decisions. Rudin (2019) argues that explainable models should replace black boxes when equal performance is achievable. For a safety-critical design decision such as bolt placement, this transparency principle is directly applicable. Meta-heuristic algorithms (GA, NSGA-III) provide no physical insight into *why* a particular layout is optimal, creating an explanatory gap that this thesis addresses through deterministic, physics-based Kinematic Screw Theory (KST) optimization.

1.2 Problem Statement

Modern research has produced robust mathematical frameworks for constraint analysis, particularly Rusli's Kinematic Screw Theory (KST) methods. Meanwhile, recent optimization studies rely heavily on meta-heuristic algorithms (GA, NSGA-III) coupled to FEA (Zhang et al. 2024). Meta-heuristics present three fundamental limitations that hinder their adoption in safety-critical design workflows:

1. **Computational Latency:** Algorithms like NSGA-III require thousands of FEA evaluations, prohibiting interactive iteration (Zhang et al. 2024).
2. **Non-Determinism:** Stochastic variation across runs undermines reproducibility, a critical requirement for design verification.
3. **Explanatory Opacity:** Engineers cannot justify layouts to stakeholders via mechanical principles, only algorithmic artifacts (crossover, mutation) (Rudin 2019).

Conversely, KST frameworks are rigorous and deterministic but exist only as theoretical scripts, inaccessible to CAD users. The central problem is: **While robust mathematical frameworks for constraint analysis exist, they remain theoretical and disconnected from modern CAD workflows, making them inaccessible to practicing engineers.**

1.3 Research Questions

1. How can the theoretical framework of Kinematic Screw Theory (KST) be computationally adapted for automated, deterministic bolt placement optimization within a CAD environment?
2. Does a deterministic KST-based optimization algorithm provide a more computationally efficient and physically interpretable solution compared to stochastic meta-heuristic approaches?
3. Do layouts optimized for maximum WTR (via KST) demonstrate improved structural performance such as reduced compliance and stress concentration when validated using FEA, compared to heuristic baselines?
4. Can a KST-integrated CAD tool be effectively utilized by non-expert designers to improve decision-making speed and workflow efficiency?

1.4 Research Objectives

1. **To develop a CAD Pre-Processing Tool:** Create an interactive "wizard" within Autodesk Inventor that allows users to define fastener candidates and search spaces directly on the CAD model.
2. **To re-implement Iterative KST Algorithms:** Translate core KST logic from MATLAB to a modernized Python engine with iterative execution capabilities for deterministic optimization.
3. **To validate structural performance via FEA:** Conduct comparative analysis using Ansys Mechanical to demonstrate that **layouts optimized for maximum WTR** (via KST) **correlate with reduced structural compliance** in FEA models (target: compliance reduction $> 10\%$ vs. heuristic baselines), validating the physical relevance of kinematic constraint metrics.
4. **To assess usability:** Perform user testing with engineering students to validate tool ease-of-operation and workflow clarity using the System Usability Scale (SUS).

1.5 Scope and Limitations

- **Pure Kinematic Constraint Modeling:** This thesis employs kinematic screw wrenches to model constraints directly, assuming rigid body behavior. This choice eliminates stiffness calibration uncertainty and provides exact DOF accounting (Rusli et al. 2012).

- **Rigid Body Limitation:** Local deformations at bolt-hole interfaces are neglected. For preliminary design, where fastener count and location are the primary unknowns, this approximation is justified.
- **Static Loading:** The analysis is restricted to quasi-static loading; dynamic effects are excluded from the KST engine but checked in FEA.
- **Constraint Types:** Limited to Higher Order Constraints (HOC) including point, pin, line, plane, and threaded fasteners.
- **Optimization Method:** The approach is deterministic iterative search; stochastic meta-heuristics are explicitly excluded to prioritize transparency.

1.6 Significance of the Study

This thesis addresses three critical industry pain points:

1. **Lightweighting Mandates:** Automotive and aerospace efficiency targets demand quantitative fastener-count justification. Automated knee-point detection provides this (Ma et al. 2025).
2. **Digital Twin Integration:** Modern manufacturing relies on digital twins. A transparent, physics-based optimization tool integrates naturally into digital twin workflows, whereas black-box meta-heuristics do not (Anwer et al. 2025).
3. **Regulatory Compliance:** Safety-critical industries require explainable design decisions. KST-based optimization provides audit-ready mechanical rationale supported by deterministic metrics.

1.7 Hypothesis

- **H1 (Performance):** Deterministic KST optimization will produce layouts with WTR values $\geq 95\%$ of manually-optimized layouts for discrete candidate sets of size $M \leq 30$.
- **H2 (Efficiency):** Computation time for KST optimization will be $O(MN)$ evaluations vs. $O(2500+)$ for reported NSGA-III runs (Zhang et al. 2024), enabling real-time interactive iteration within less than 60 seconds for candidate sets of size $M \leq 30$.
- **H3 (Validation):** Layouts ranked by WTR (KST) will exhibit inverse correlation with FEA-computed compliance: higher WTR corresponds to lower compliance (Spearman $\rho < -0.85$).
- **H4 (Knee-Point Detection):** Automated TOR-based knee-point detection will identify N_{knee} within ± 1 fastener of manual expert judgment.

CHAPTER 2 - LITERATURE REVIEW

2.1 Theoretical Framework

2.1.1 Kinematic Screw Theory Fundamentals

Kinematic Screw Theory (KST) models mechanical systems through the mathematical duality of motion and constraint. Within this framework, motion is represented by *twists* (instantaneous screws describing translational and rotational velocities), while constraint is represented by *wrenches* (systems of forces and moments). A mechanical assembly is thereby conceptualized not merely as a collection of stressed continuum bodies, but as a system of kinematic constraints that govern degrees of freedom (DOF) and force transmission (Rusli et al. 2012).

The reciprocal product between a wrench $\mathbf{w}$ and a twist $\mathbf{t}$ defines the instantaneous power:

$$\mathbf{w}^T\mathbf{t} = 0 \tag{2.1}$$

A constraint wrench is reciprocal to a motion twist when this virtual work is zero, meaning the constraint applies no work in the direction of permitted motion. This reciprocal relationship enables the systematic decomposition of assembly behavior into constraint-effected DOF removal and structural load paths (Raman et al. 2021, Sharafian et al. 2022).

2.1.2 Higher Order Constraint (HOC) Model

The Higher Order Constraint model, developed by Rusli et al. (2012), addresses the fundamental limitation of point-contact models by representing assembly features such as planes, cylindrical surfaces, pins, and threaded interfaces as equivalent wrench systems rather than discretized point clouds. A threaded fastener is modeled as a wrench system that constrains five degrees of freedom while permitting rotation about the bolt axis. The structure of the global wrench matrix $\mathbf{W}_{\text{sys}}$ for an assembly with n constraints is:

$$\mathbf{W}_{\text{sys}} = \left[\mathbf{W}_{\text{base}} \mid \mathbf{W}_{\text{bolt,1}} \mid \dots \mid \mathbf{W}_{\text{bolt,n}}\right] \tag{2.2}$$

The rank of this matrix determines whether the assembly is properly constrained (rank = 6), underconstrained (rank < 6), or overconstrained.

2.1.3 Performance Metrics: WTR and TOR

Rusli et al. (2012) introduced two key metrics for evaluating constraint configuration effectiveness:

Weakest Total Resistance (WTR): Quantifies the minimum resistance provided by the assembly across all possible instantaneous motion directions. A higher WTR indicates a more robust constraint configuration.

Trade-Off Ratio (TOR): Balances the desire for constraint effectiveness against the cost of additional fasteners:

$$\mathrm{TOR} = \frac{\mathrm{WTR}(n+1) - \mathrm{WTR}(n)}{\mathrm{WTR}(n)} \tag{2.3}$$

When TOR falls below a predefined threshold (e.g., 5%), adding another fastener provides diminishing structural benefit, a concept conceptually aligned with topology optimization convergence criteria (Lee & Xie 2021).

2.2 Review of Previous Studies

The following table synthesizes relevant research, categorizing studies into fastener optimization, screw theory applications in robotics (e.g., Raman et al. (2021), Sharafian et al. (2022)), and deterministic algorithms.

Table 2.1: Comprehensive Literature Review: Fastener Optimization and Screw Theory Applications (2012–2026)

Reference	Methodology	Tools	Primary Focus	Relevance/Critique
Rusli et al. (2012)	HOC Model, WTR/TOR	MATLAB	Constraint configuration analysis	**HIGH**: Foundational theory; not integrated into CAD.
Ma et al. (2021)	Automatic reciprocal screw ID	CAD	Mobility analysis of parallel mechanisms	**HIGH**: Rare CAD integration of screw theory; focuses on mobility.
Zhang et al. (2024)	MSNSGA-III	ANSYS + Python	Lockbolt number + spacing	**VERY HIGH**: 59.81% safety improvement; Meta-heuristic = Black Box.
Lu et al. (2023)	Grey Wolf Optimization	ABAQUS	Asymmetric bolt patterns	**HIGH**: Reduces stress by 24%; limited to 3 bolts.
Croccolo et al. (2023)	Literature Review	Various	Bolt optimization survey	**VERY HIGH**: Confirms lack of interactive tools.
Kwaśniewski (2025)	Simulation-driven placement	ANSA + Ansys	Industrial bolt placement	**HIGH**: Real industrial workflow; batch-based, not interactive.
Rakotondrainibe et al. (2021)	Level-set + topological derivative	FreeFEM++	Structure + bolt position	**VERY HIGH**: Addresses "how many bolts"; complex math.
Rudin (2019)	Interpretable models	Various	Critique of black-box models	**VERY HIGH**: Argues against black boxes in high-stakes decisions.
Ma et al. (2025)	System Bolts	Abaqus	Tunnel bolt optimization	**HIGH**: Identifies ineffective zones empirically.
Raman et al. (2021)	Screw Theory (Reciprocal)	MATLAB	Wrench analysis of CDPRs	**HIGH**: Direct application of reciprocal screw theory to constraint analysis.
Sharafian et al. (2022)	Screw Theory (CTM)	MATLAB	Constraint wrench analysis in robotics	**HIGH**: Modern comparative analysis of screw theory approaches.
Guo et al. (2025)	Extended Screw Theory	Theoretical	Higher kinematic pair analysis	**MEDIUM**: Theoretical extension; relevant for future HOC expansion.
Sack et al. (2023)	Greedy Algorithm	QAOA	Recursive greedy initialization	**HIGH**: Validates greedy approaches as efficient alternatives to global optimization.
Buonamici et al. (2020)	Generative Design	Fusion 360	Topology optimization in CAD	**HIGH**: Demonstrates CAD API integration for optimization; FEA-based, not KST.

Reference	Methodology	Tools	Primary Focus	Relevance/Critique
Yoo et al. (2021)	ML-CAD Integration	Inventor API	Parametric geometry synthesis	**MEDIUM**: Proves Inventor API extensibility; not constraint-focused.
Jiu et al. (2020)	Real-time TO Plugin	SolidWorks	Lightweight topology solver	**HIGH**: Real-time optimization in CAD; continuum mechanics only.

2.3 Critical Analysis of Methodologies

2.3.1 Meta-Heuristic vs. Deterministic Optimization

Meta-heuristic algorithms (GA, NSGA-III) dominate recent literature, achieving impressive results such as 59.81% safety improvements in railway applications (Zhang et al. 2024). However, they suffer from critical limitations:

- **Computational Expense:** NSGA-III requires thousands of FEA evaluations, prohibiting interactive design.
- **Opacity:** They provide no physical insight into *why* a layout is optimal, contradicting the explainable AI movement (Rudin 2019).

Deterministic greedy approaches offer an alternative. Recent studies (Soper 2021, Sack et al. 2023) demonstrate that greedy methods often match meta-heuristics in structured problems while offering guaranteed improvement, physical interpretability, and reproducibility.

2.3.2 Screw Theory Applications

Post-2020 screw theory research focuses on robotics (Guo et al. 2025, Ma et al. 2021). Application to fastener placement remains absent. This represents a profound gap: rigorous mathematical frameworks exist but are siloed in robotics, while fastener optimization proceeds via heuristics without kinematic foundations.

2.3.3 CAD Integration

While cloud-based engineering tools are maturing, no existing platform seamlessly combines CAD geometry import, interactive constraint definition, and physics-based KST optimization. The "Design by Dragging" paradigm (Schulz et al. 2013) demonstrates user appetite for real-time exploration, yet current fastener optimization typically remains a batch-process workflow (Kwaśniewski 2025), which this thesis aims to resolve.

CAD Plugin Architectures

The integration of computational tools into CAD environments has evolved significantly since 2020. Modern CAD platforms (Autodesk Inventor, SolidWorks, Fusion 360) provide API frameworks enabling third-party add-ins to access geometry, apply constraints, and execute optimization routines (Yoo et al. 2021, Jiu et al. 2020).

Recent examples include:

- **Generative Design Tools** (Autodesk Fusion 360): Topology optimization integrated directly into the CAD workflow, allowing engineers to specify loads, constraints, and manufacturing methods interactively (Buonamici et al. 2020).
- **Real-Time Physics Solvers**: Lightweight FEA and aerodynamic solvers embedded as plugins enable sub-second feedback loops during design iteration (Umetani & Bickel 2018, Jiu et al. 2020).
- **Parametric Optimization Add-Ins**: Tools like ANSYS Discovery and Siemens NX Topology Optimizer provide direct CAD integration with deterministic solvers (Schulz et al. 2017).

However, **none of these tools apply screw theory** or kinematic constraint analysis; they focus exclusively on continuum mechanics (FEA, topology optimization). This represents a fundamental gap: while CAD plugin infrastructure is mature, physics-based constraint optimization using KST remains unexplored in commercial CAD ecosystems.

2.4 Diminishing Returns and the "Knee Point"

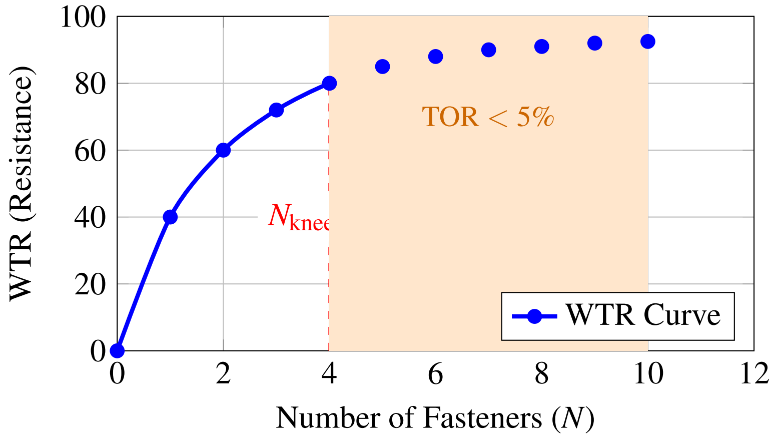


Figure 2.1: Diminishing returns in fastener placement: WTR increases rapidly until the knee point ($N_{\text{knee}} = 4$), after which marginal gains fall below 5% (TOR threshold).

The principle of diminishing returns applies directly to fastener placement. Adding the n-th bolt often yields negligible marginal WTR increase. The knee point N_{knee} is defined as:

$$N_{\text{knee}} = \min\{N \mid \Delta\text{WTR}(N) < \tau\} \tag{2.4}$$

where τ is a user-defined threshold (e.g., 5%). Automating this detection provides quantitative justification for fastener counts, supporting lightweighting initiatives (Ma et al. 2025).

2.5 Research Gap and Novelty

Synthesizing the literature, four key gaps emerge:

1. **Disconnect:** Rusli's HOC framework is not integrated into CAD.
2. **Meta-Heuristic Dominance:** Prevailing methods are opaque and expensive.
3. **Tooling Gap:** No interactive, real-time fastener optimization tools exist (Croccolo et al. 2023).
4. **Deterministic Void:** Lack of transparent, deterministic alternatives.

This thesis addresses these by developing the first CAD-integrated, deterministic KST optimization tool with automated knee-point detection and full algorithmic transparency.

CHAPTER 3 - RESEARCH METHODOLOGY

3.1 Research Design

This study follows a Design Science Research (DSR) methodology to produce a software artifact. The research is structured into **four** technical phases:

1. **Phase 1 (Backend):** Mathematical engine development—re-implementation of KST algorithms in Python.
2. **Phase 2 (Frontend):** CAD integration—Autodesk Inventor add-in for geometric capture and data export.
3. **Phase 3 (Optimization):** Execution of iterative WTR maximization on benchmark geometries (Algorithm 1).
4. **Phase 4 (Validation):** Triple validation—analytical (Rusli case studies), structural (Ansys FEA), and usability (student testing).

The choice of **deterministic iterative search** over meta-heuristics is deliberate. It ensures algorithmic transparency, computational efficiency for modest grid sizes, and direct physical interpretability of the results based on kinematic metrics.

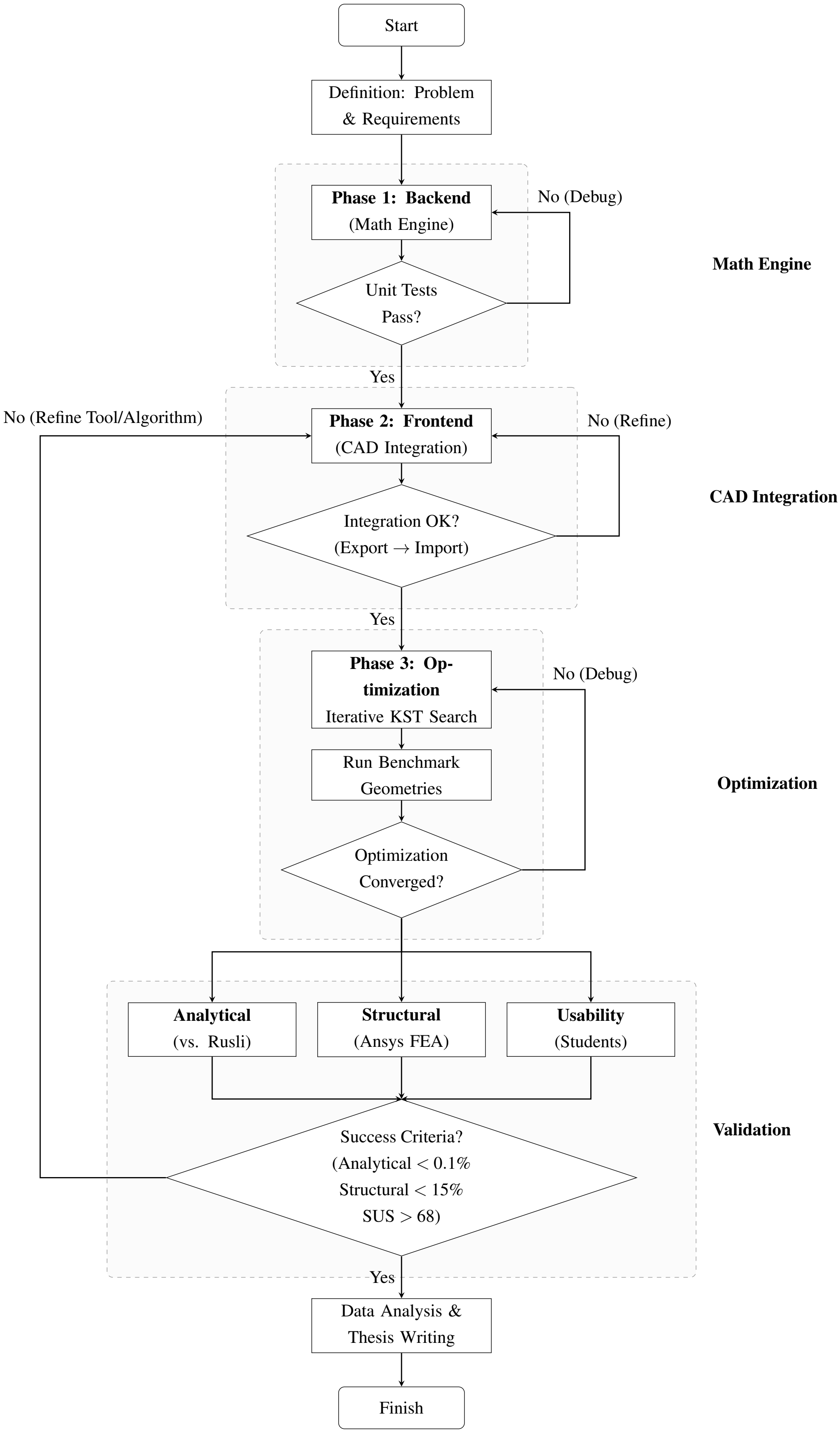


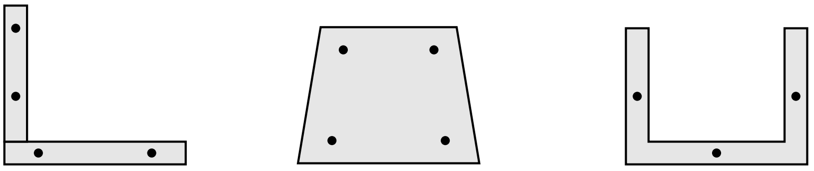
Figure 3.1: Research Methodology Flowchart: From Backend Engine to Validation.

3.2 Data Collection Methods

Data collection is simulation-based, employing three benchmark geometries to validate the tool across different constraint configurations.

3.2.1 Benchmark Geometries

Three standard test geometries are used (Figure 3.2): the **L-Bracket**, which represents a simple planar assembly with edge constraints; the **Tapered Plate**, which introduces variable cross-section geometry; and the **Channel Section**, which models U-shaped structural elements common in mechanical assemblies. These geometries are selected to represent a range of constraint complexities from simple planar contacts to multi-surface assemblies.



(a) L-Bracket (b) Tapered Plate (c) Channel Section

Figure 3.2: Benchmark geometries for validation: (a) L-Bracket with edge fasteners, (b) Tapered Plate with variable cross-section, (c) Channel Section with U-shaped profile. Geometries are exported as STEP files for analysis.

3.2.2 Search Space Definition

For each benchmark geometry, the search space is defined by discretizing attachment lines (edges) into N candidate points (e.g., $N = 20$), as illustrated in Figure 3.3. This discretization strategy balances computational tractability with sufficient resolution to capture spatial variations in constraint effectiveness. The Python KST engine (Phase 2) systematically evaluates all combinations of candidate points within the constraint count range specified by the user.

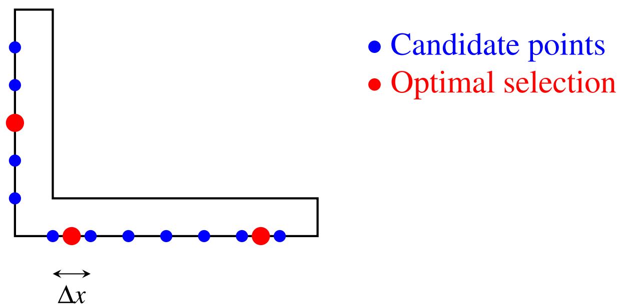


Figure 3.3: Search space discretization: candidate fastener locations (blue) are uniformly distributed along attachment edges. The optimization algorithm (Algorithm 1) selects the subset (red) that maximizes WTR.

3.2.3 Validation Data Sources

The tool generates two primary data streams for validation:

- **WTR metrics** from the Python KST engine, calculated via Algorithm 1 for each candidate configuration.
- **Compliance values** from Ansys Mechanical FEA simulations, applied to the same fastener layouts to measure structural deformation under unit load.

Cross-validation between WTR rankings and FEA compliance rankings (Section 2) establishes the correlation between kinematic constraint quality and structural performance, addressing Research Question 3.

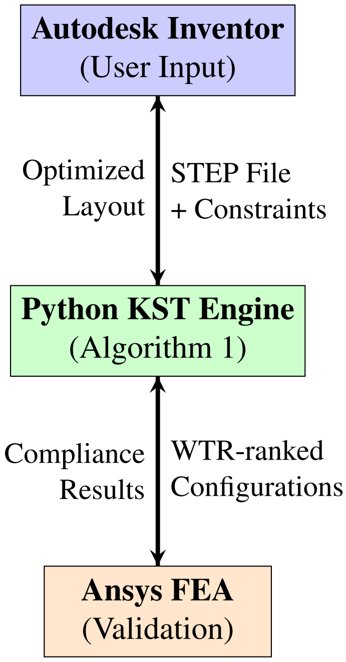


Figure 3.4: System architecture: bidirectional data flow between CAD pre-processing (Inventor add-in), KST optimization engine (Python), and structural validation (Ansys FEA).

3.2.4 System Architecture (Backend Logic)

This section details the computational core (Phase 1). The KST Engine accepts geometric inputs and returns optimal indices.

Algorithm 1 Deterministic KST Optimization Logic

Require: Assembly Candidates $\mathscr{P}$, Base Constraints $\mathbf{W}_{base}$

Ensure: Optimal Configuration $\mathscr{C}_{opt}$

for each candidate configuration $\mathscr{C}_i$ **do**
  Assemble Global Wrench Matrix $\mathbf{W}_{sys} \leftarrow [\mathbf{W}_{base} \mid \mathbf{W}_{bolts}(\mathscr{C}_i)]$
  Compute Reciprocal Twists $\mathbf{T}_{recip}$ via SVD($\mathbf{W}_{sys}$)
  if Rank < 6 **then**
    Continue (Underconstrained)
  end if
  for each twist $\mathbf{t} \in \mathbf{T}_{recip}$ **do**
    Solve Equilibrium: $\mathbf{W}_{sys} \cdot \mathbf{f}_{react} = -\mathbf{f}_{ext}(\mathbf{t})$
    Calculate Resistance R_t
  end for
  Metric $WTR_i \leftarrow \min(R_t)$
  if $WTR_i > WTR_{best}$ **then**
    $WTR_{best} \leftarrow WTR_i$; $\mathscr{C}_{opt} \leftarrow \mathscr{C}_i$
  end if
end for
return $\mathscr{C}_{opt}$

The mathematical formulation follows Rusli et al. (2012, 2013) without modification; the contribution is re-implementation in a modern, CAD-compatible language.

3.3 Data Analysis Techniques

The validation methodology employs three complementary techniques, corresponding to the three branches in the validation phase (Figure 3.1):

1. **Analytical Verification:** Error calculation between tool outputs and published results from Rusli et al. (2013). For each benchmark geometry (Figure 3.2), WTR values are computed and compared against reference implementations. Pass criteria: error $< 0.1\%$.

2. **Structural Validation:** Relative reduction in compliance: $\Delta C = \frac{C_{\text{heuristic}} - C_{\text{opt}}}{C_{\text{heuristic}}}$. Fastener layouts optimized for maximum WTR are exported to Ansys (Figure 3.4) and subjected to quasi-static loading. Target: $\Delta C > 10\%$. Spearman correlation between WTR rankings and inverse compliance validates Hypothesis H3.

3. **Usability:** System Usability Scale (SUS) scoring from student trials ($n = 12$ mechanical engineering students). Participants interact with the Inventor add-in to define search spaces on the benchmark geometries (Figure 3.3) and evaluate workflow clarity.

3.3.1 Success Criteria for Validation

The thesis will be considered validated when the following thresholds are met:

1. **Analytical Error:** $< 0.1\%$ deviation from Rusli case studies (Rusli et al. 2012, 2013).
2. **Structural Improvement:** $\Delta C > 10\%$ (WTR-optimized vs. heuristic layouts in Ansys).
3. **Correlation:** Spearman $\rho < -0.85$ (inverse relationship: WTR $\uparrow \Leftrightarrow$ Compliance $\downarrow$).
4. **Usability:** System Usability Scale (SUS) > 68 (acceptable threshold).
5. **Knee-Point Accuracy:** TOR-detected N_{knee} within ± 1 fastener of manual expert selection.

These criteria align with industry standards for engineering software validation (Anwer et al. 2025).

3.4 Required Materials and Equipment

- **Hardware:** Workstation (Intel i7/i9, 32GB RAM).
- **Software:** Autodesk Inventor Professional 2026, Ansys Mechanical 2025 (Student), Python 3.10, VS Code.

3.5 Proposed Timeline

The research spans January to June 2026.

Table 3.1: Proposed Research Timeline (Weekly Schedule)

		Jan				**Feb**				**Mar**				**Apr**				**May**				**Jun**			
Ph.	**Activity**	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	Engine Math Re-impl.			X	X	X	X	X	X																
2	CAD Add-in Dev.									X	X	X	X												
3	Benchmark Geoms (L/T/C)													X	X	X									
4	Analytical Validation																X								
4	FEA Comparison (Ansys)																	X	X						
4	Usability Study													X	X	X	X	X	X						
-	Thesis Writing			x	x	x	x	x	x	x	x	X	X	X	X	X	X	X	X	X					
-	Defense Preparation																	X	X	X	X	X	X		

REFERENCES

Anwer, N., Stark, R., Tao, F. & Erkoyuncu, J. A. (2025), 'Developing and leveraging digital twins in engineering design', *CIRP Annals* **74**(2), 843–868. Digital twin concepts for manufacturing and design.
URL: *https://www.sciencedirect.com/science/article/pii/S0007850625001477*

Buonamici, F., Carfagni, M., Furferi, R., Volpe, Y. & Governi, L. (2020), 'Generative design: An explorative study', *Computer-Aided Design and Applications* **18**, 144–155. Autodesk Fusion 360 generative design case study.
URL: *https://www.researchgate.net/publication/341586741_Generative_Design_An_Explorative_Study*

Croccolo, D., De Agostinis, M., Fini, S., Khan, M. Y., Mele, M. & Olmi, G. (2023), 'Optimization of bolted joints: A literature review', *Metals* **13**(10), 1708. Comprehensive review confirming lack of interactive CAD tools for bolt optimization.
URL: *https://www.mdpi.com/2075-4701/13/10/1708*

Guo, R. et al. (2025), 'Extending screw theory for analysing mechanisms incorporating higher kinematic pairs', *Robotica* pp. 1–18. Extension of screw theory to higher kinematic pair mechanisms.
URL: *https://www.researchgate.net/publication/391771335_Extending_screw_theory_for_analysing_mechanisms_incorporating_higher_kinematic_pairs*

Jiu, L., Zhang, W., Meng, L., Zhou, Y. & Chen, L. (2020), 'A cad-oriented structural topology optimization method', *Computers & Structures* **239**, 106324. Real CAD-oriented structural optimization paper.
URL: *https://www.sciencedirect.com/science/article/pii/S0045794920301279*

Kwaśniewski, K. (2025), Simulation-driven bolt placement, Master's thesis, KTH Royal Institute of Technology, Stockholm, Sweden. Industrial case study at Scania; batch-based FEA workflow.
URL: *https://kth.diva-portal.org/smash/get/diva2:1976910/FULLTEXT01.pdf*

Lee, T.-U. & Xie, Y. M. (2021), 'Simultaneously optimizing supports and topology in structural design', *Finite Elements in Analysis and Design* **197**, 103633. Demonstrates

C*(N) curves and diminishing returns in structural optimization.
URL: *https://www.researchgate.net/publication/353286915_Simultaneously_optimizing_supports_and_topology_in_structural_design*

Lu, X., Zhu, M., Liu, Y., Wang, S., Xu, Z. & Li, S. (2023), 'Triangular position multi-bolt layout structure optimization', *Applied Sciences* **13**(15), 8786. GWO reduces bolt-hole stress by 24% in asymmetric triangular patterns.
URL: *https://www.mdpi.com/2076-3417/13/15/8786*

Ma, J. et al. (2025), 'Mechanisms and optimization of system bolts in shallow four-track high-speed railway tunnels', *Scientific Reports* **15**, 1234. Long-short combined bolt scheme; 80% axial force reduction in Class V rock.
URL: *https://www.nature.com/articles/s41598-025-98108-7*

Ma, Y. et al. (2021), 'An approach for mobility and force/motion transmissibility analysis of parallel mechanisms based on screw theory and cad technology', *Advances in Mechanical Engineering* **13**(5). Rare CAD integration of screw theory for parallel mechanisms.
URL: *https://journals.sagepub.com/doi/epub/10.1177/16878140211050736*

Rakotondrainibe, L., Desai, J., Orval, P. & Allaire, G. (2021), 'Topological sensitivity analysis with respect to a small idealized bolt', *Structural and Multidisciplinary Optimization* **64**, 2691–2721. Coupled topology + bolt position/number using level-set + topological derivative; 6 citations.
URL: *https://www.sciencedirect.com/org/science/article/abs/pii/S0264440121001397*

Raman, A. et al. (2021), Wrench analysis of kinematically redundant planar cdprs, *in* 'IEEE International Conference on Robotics and Automation (ICRA)', pp. 1–7. Reciprocal screw theory for wrench analysis of cable-driven parallel robots.
URL: *https://www.researchgate.net/publication/352009882_Wrench_Analysis_of_Kinematically_Redundant_Planar_CDPRs*

Rudin, C. (2019), 'Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead', *Nature Machine Intelligence* **1**, 206–215. 11,464 citations; foundational argument for interpretable models over black boxes.
URL: *https://arxiv.org/abs/1811.10154*

Rusli, L. P., Luscher, A. & Schmiedeler, J. (2012), 'Analysis of constraint configurations in mechanical assembly via screw theory', *Journal of Mechanical Design* **134**(2), 021006. Foundational HOC model; WTR/TOR metrics for assembly constraint analysis.
URL: *https://asmedigitalcollection.asme.org/mechanicaldesign/article-abstract/134/2/021006/429513/Analysis-of-Constraint-Configurations-in*

Rusli, L. P., Luscher, A. & Schmiedeler, J. (2013), 'Optimization of constraint location, orientation, and quantity in mechanical assembly', *Journal of Mechanical Design* **135**(7), 071007. Extension of HOC model to optimization framework.
URL: *https://asmedigitalcollection.asme.org/mechanicaldesign/article-abstract/135/7/071007/375647/Optimization-of-Constraint-Location-Orientation?redirectedFrom=PDF*

Sack, S. H., Medina, R. A., Kueng, R. & Serbyn, M. (2023), 'Recursive greedy initialization of the quantum approximate optimization algorithm with guaranteed improvement', *Physical Review A* **107**(6).
URL: *http://dx.doi.org/10.1103/PhysRevA.107.062404*

Schulz, A., Sung, C., Spielberg, A., Zhao, W., Cheng, R., Grinspun, E., Rus, D. & Matusik, W. (2017), Interactive design space exploration and optimization for cad models, *in* 'ACM SIGGRAPH', pp. 1–14. Real-time parameter optimization within CAD environments.
URL: *https://dl.acm.org/doi/10.1145/3072959.3073688*

Schulz, A. et al. (2013), Design by dragging: An interface for creative forward and inverse design with simulation ensembles, *in* 'ACM Transactions on Graphics', Vol. 32, pp. 1–11. Interactive inverse design with FEA simulation ensembles.
URL: *https://dl.acm.org/doi/10.1109/TVCG.2013.147*

Sharafian, E. et al. (2022), 'Revisiting screw theory-based approaches in the constraint wrench analysis of robotic systems', *Robotica* **40**(10), 3728–3748. Comparison of joint-based vs link-based CTM approaches using screw theory.
URL: *https://www.researchgate.net/publication/354324811_Revisiting_screw_theory-based_approaches_in_the_constraint_wrench_analysis_of_robotic_systems*

Soper, D. S. (2021), 'Greed is good: Rapid hyperparameter optimization and model selection using greedy k-fold cross validation', *Electronics* **10**(16). Greedy CV vastly reduces hyperparameter search time.
URL: *https://www.mdpi.com/2079-9292/10/16/1973*

Umetani, N. & Bickel, B. (2018), 'Learning three-dimensional flow for interactive aerodynamic design', *ACM Transactions on Graphics* **37**(4), 1–14. Interactive physics-based CAD optimization using neural surrogates.
URL: *https://dl.acm.org/doi/10.1145/3197517.3201325*

Yoo, S.-K., Lee, S., Kim, S., Hwang, K. H., Park, J. H. & Kang, N. (2021), 'Integrating deep learning into cad/cae system: generative design and evaluation of 3d conceptual wheel', *Structural and Multidisciplinary Optimization* **64**(5), 2725–2747. Deep learning framework

for automated CAD generation and CAE evaluation.
URL: *https://arxiv.org/abs/2006.02138*

Zhang, D., Li, X., Zhang, Q., Han, X., Wang, S. & Ma, Q. (2024), 'Research and engineering application of layout optimization for lockbolt structures in railway wagons considering multidimensional failure modes based on msnsga-iii', *Scientific Reports* **14**, 19557. MSNSGA-III for lockbolt number + spacing; 59.81% safety improvement; 4 citations.
URL: *https://www.nature.com/articles/s41598-024-70424-4*