German International University
Faculty of Informatics and Computer Science

Hybrid Analytical–Machine Learning Framework for Intelligent Shaft–Hub Connection Selection using Synthetically Generated Data

Bachelor Thesis

Author: Farah Hany
Supervisor: Prof. Dr.-Ing. Michael Lätzer
Submission Date: 15 January, 2026

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This is to certify that:

(i) the thesis comprises only my original work toward the Bachelor Degree,

(ii) due acknowledgement has been made in the text to all other material used.

Farah Hany
15 January, 2026

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Finally, I gratefully acknowledge the previous thesis project "Development of an AI-supported algorithm for the differentiated selection of shaft-hub connections under specific conditions", which provided a foundation and motivation for the analytical and data-driven approach developed in this work.

Abstract

Shaft–hub connections are essential components used to transmit torque between mechanical elements. A wide variety of connection types exist, and using traditional methods such as engineering judgment and handbook equations, a suitable option can be selected. This thesis develops a model capable of identifying the most appropriate shaft–hub connection among three common alternatives: interference (press) fits, keyed fits, and splined fits, thereby automating the selection process.

A key motivation for this work arises from a practical gap: no publicly available dataset exists for shaft–hub connection selection, making machine-learning approaches difficult to pursue directly. To address this, the first part of the thesis focuses on constructing a synthetic dataset using analytical equations together with a preference-based scoring mechanism. A pipeline was developed to assign a shaft–hub connection to individual scenarios until the scoring behaviour and feasibility logic achieved satisfactory performance. Once validated, this pipeline was scaled and employed as an automated label generator to produce a large and diverse dataset that reflects realistic engineering designs, with input parameters randomized in accordance with DIN standards.

The second part of the thesis develops a classification model trained on this synthetic dataset. The model learns to predict the most suitable connection type based on torque requirements, material combinations, geometric parameters, and user preferences. By integrating analytical constraints with learned behaviour, the resulting classifier captures both practical feasibility relations and subtler preference-driven trade-offs.

To support accessibility and real-world usage, a web-based interface was implemented using FastAPI and React. The interface utilizes the trained machine-learning model for recommendations, presenting the predicted connection type together with its softmax classification score for each query. In addition, analytical torque capacities for all connection types are computed and displayed, providing users with a transparent and interpretable comparison between ML confidence and practical feasibility. Users can freely specify their design parameters and preference values, making the system flexible for educational and practical applications.

The resulting system offers an explainable, data-driven, and mechanically consistent platform. It demonstrates how analytical engineering knowledge can be transformed into a synthetic dataset for training intelligent models, ultimately improving the accessibility of shaft–hub design expertise and helping users better understand the trade-offs between different connection types.

Contents

Chapter 1

Introduction

Shaft–hub connections are fundamental components in mechanical engineering. A rotating shaft transmits torque to an attached component through this interface, and the choice of connection type significantly affects the integrity and performance of the entire system.

An overly conservative selection can introduce unnecessary cost, manufacturing complexity, and maintenance burden, while an under-designed connection that does not satisfy the mechanical transmission requirements can compromise the safety of the entire system, potentially resulting in slippage, deformation, or catastrophic failure. Therefore, it is essential to ensure the connection is strong enough to withstand torque requirements while considering economic constraints and cost efficiency.

This gives rise to the topic of optimal shaft–hub connection selection, which is traditionally done using analytical calculations and expert judgement. However, this process can be time-consuming and impractical in startups that may not have access to specialized consultation and expert knowledge.

Recent research has demonstrated the potential of machine-learning models to support decision-making across a wide variety of engineering tasks [1]. However, a significant gap exists: no publicly available dataset labels shaft–hub connections. This makes the process of training an ML model directly infeasible.

The aim of this thesis is to develop an intelligent tool for assigning a shaft–hub connection type to a given set of mechanical and preference-based inputs. This is achieved by designing a scoring system derived from analytical equations and user preference weighting. This is then scaled up to generate a synthetic dataset using inputs randomized based on DIN standards and the scoring system as a label generator. The resulting dataset is used to train a machine-learning model that automates the prediction task. This produces a unified tool that blends analytical feasibility logic, user preferences, and an ML model.

1.1 Research Objectives

To achieve the aim of this thesis, the following research objectives are defined:

- Develop a scoring system pipeline capable of assigning a shaft–hub connection label based on input parameters and preference-driven criteria.
- Scale this pipeline to generate a large and diverse synthetic dataset using input parameters randomized in accordance with DIN standards.
- Train and evaluate a machine-learning classification model using the synthetic dataset.
- Integrate the trained model into a web-based application to provide automated shaft–hub connection recommendations.
- Present analytical torque capacities and ML confidence scores to improve transparency and interpretability of the selection process.

1.2 Contributions

This thesis makes the following key contributions:

- An analytical scoring system that evaluates shaft–hub connections using torque-based feasibility rules and preference-weighted criteria.
- A large, labeled synthetic dataset for shaft–hub connection selection, generated through a DIN-compliant automated pipeline and including press fits, keyed fits, and splined fits.
- A trained and evaluated machine-learning classifier capable of predicting the most suitable shaft–hub connection type based on the generated dataset.
- A web-based interface, developed using FastAPI and React, that provides real-time connection recommendations to users.
- A hybrid intelligent framework combining analytical mechanics with machine-learning inference, providing torque capacity outputs and softmax-based confidence scores for each prediction.

1.3 Structure of the Thesis

This thesis is organized as follows. Chapter 1 introduces the motivation, research gap, aim, and objectives of the work. Chapter 2 provides the necessary background on shaft–hub connections, analytical torque transmission models, relevant machine-learning concepts, and a summary of related work.

Chapter 3 describes the methodology, including the development of the analytical scoring system, the synthetic dataset generation pipeline, and the training and evaluation of the machine-learning model. Chapter 4 reports the results, covering model performance, analysis of the generated dataset, and interpretation of prediction behaviour. Chapter 5 discusses the findings and their implications. Finally, Chapter 6 concludes the thesis and outlines potential directions for future research.

Chapter 2

Background

This chapter establishes the theoretical and conceptual background needed to understand the methodology and framework developed in this thesis for shaft–hub connection selection. It covers the mechanical principles involved in torque transmission, the types of shaft–hub connections considered in this thesis along with their key properties, and the role of DIN/ISO standards in feasibility assessment [2, 3, 4]. Since this thesis begins with physics-based calculations and integrates machine learning (ML), essential ML concepts, evaluation metrics, and the motivation for synthetic dataset generation are also presented.

2.1 Motivation: The Shaft–Hub Connection Selection Problem

Shaft–hub connections are essential machine elements that form the mechanical interface between a rotating shaft and a hub, allowing torque and rotational motion to be transmitted reliably without relative slip [5]. These connections play a critical role in the performance of rotating machinery, including electric motors, gearboxes, pumps, conveyors, wind turbines, and automotive drivetrains. Dependable torque transmission and rotational integrity are essential for safe and efficient operation. A suitable shaft–hub connection must therefore meet several key design requirements:

- transmit the required torque with adequate safety against slip and local failure,
- avoid excessive stress concentrations and preserve fatigue strength,
- maintain alignment and concentricity under dynamic loading,
- satisfy manufacturing, assembly, and maintenance constraints.

Selecting the correct connection type is crucial because failure can lead to slippage, fretting, shaft damage, fatigue cracking, or catastrophic system failure. Despite their widespread use, no publicly available labelled datasets exist for automated shaft–hub connection selection. Industrial practice typically relies on engineer experience, handbook charts, and repeated analytical checks, resulting in a manual and time-consuming design process with limited decision support.

The complexity arises because:

- torque capacity depends on interacting geometric, material, and surface parameters;
- three distinct connection types (press fit, key, spline) have fundamentally different load paths;
- user/application preferences often override pure mechanical capacity;
- nonlinear relationships and discrete standardized geometries make manual comparison difficult;
- standards (DIN 7190, DIN 6885, DIN 5480) define rules but do not guide connection *selection*.

These observations motivate a hybrid analytical–ML approach: analytical models provide physics-consistent feasibility and transparent capacity values, while ML provides rapid probabilistic recommendations learned from analytically labelled synthetic data, and preference weighting enables application-specific trade-offs.

2.2 Shaft–Hub Connections in Rotating Machinery

Connection types fall into two main categories: *friction closure* and *form closure*. Common designs considered in this thesis are:

- **Interference (press) fits** (friction closure),
- **Parallel keys** (form closure),
- **Splines** (form closure).

Each type exhibits characteristic strengths and limitations. In practice, these trade-offs mean that standards-based feasibility alone rarely determines the final design choice; further analysis is typically needed, especially when multiple connection types are feasible.

2.2.1 Friction Closure: Interference (Press) Fits

Press fits transmit torque through friction generated by radial interference between a shaft and a hub. During assembly, the hub may be heated or the shaft cooled (shrink fit), or the parts may be force-assembled at ambient temperature (press fit). After temperature equalisation and elastic recovery, a radial contact pressure p develops at the interface.

For a cylindrical shaft of diameter d and engagement length L, the contact area is

$$A_{\text{contact}} = \pi d L. \tag{2.1}$$

Assuming uniform pressure distribution and a friction coefficient μ, the transmissible torque is

$$M_{t,\mathrm{press}} = \mu\, p\, A_{\mathrm{contact}}\, \frac{d}{2} = \frac{\pi}{2}\, \mu\, p\, L\, d^2. \tag{2.2}$$

For a required torque M_{req} and a torque safety factor S_R, the required interface pressure is

$$p_{\mathrm{req}} = \frac{2 M_{\mathrm{req}} S_R}{\pi \mu L d^2}. \tag{2.3}$$

This formulation preserves dimensional consistency and ensures that the safety factor is applied directly to the torque demand.

Allowable Pressure Considerations The allowable contact pressure is limited by both shaft and hub constraints. In this work, the effective allowable pressure is therefore defined as

$$p_{\mathrm{allow}} = \min\left(p_{\mathrm{allow,shaft}},\ p_{\mathrm{allow,hub}}\right). \tag{2.4}$$

While the shaft limit is governed primarily by material strength, the hub limit additionally depends on geometry. A representative geometric ratio is

$$Q = \frac{d}{D}, \tag{2.5}$$

where D is the hub outer diameter. As $Q \to 1$ (thin hubs), the hub's ability to sustain interface pressure decreases significantly, highlighting the sensitivity of press fits to hub thickness.

Mechanical feasibility requires

$$p_{\mathrm{req}} \leq p_{\mathrm{allow}}. \tag{2.6}$$

Press fits are compact, backlash-free, and provide excellent concentricity. However, they are sensitive to surface condition, lubrication, and assembly constraints. Extremely high interferences may be torque-feasible in theory but impractical or damaging in assembly. Thin hubs are particularly critical, as hub compliance can lead to deformation such as bell-mouthing. These considerations motivate the additional manufacturability and stiffness checks introduced later in the analytical model.

2.2.2 Form Closure: Keys and Splines

Form-closure connections transmit torque through geometric interlocking rather than frictional interface pressure. In this work, parallel keys and splines are considered as representative form-closure solutions.

Keys A rectangular parallel key engages matching keyways in the shaft and hub. Torque transmission is governed by two primary failure modes: shear of the key and bearing pressure on the key flanks.

The shear-limited torque capacity is

$$T_\tau = \tau_{\mathrm{allow}}\, b\, L\, \frac{d}{2}, \tag{2.7}$$

while the bearing-pressure-limited capacity is

$$T_p = p_{\mathrm{allow}} \left(\frac{h}{2}\right) L \frac{d}{2}, \tag{2.8}$$

where b is the key width, h is the key height, and L is the engagement length.

The transmissible torque is therefore

$$M_{t,\mathrm{key}} = \min\left(T_\tau,\, T_p\right). \tag{2.9}$$

In practice, the bearing pressure limit often governs, particularly for softer hub materials. To reflect this, the allowable bearing pressure is conservatively taken as the minimum allowable value of the shaft–hub material pair. Keys are inexpensive and easy to assemble and disassemble, but they introduce stress concentrations at the keyway, which can reduce fatigue strength and lead to backlash behavior under reversing loads.

Splines Splines distribute torque across multiple teeth, significantly increasing load-carrying capacity and improving fatigue performance. The projected flank area may be expressed as

$$A_{\mathrm{proj}} = z\, b\, h_{\mathrm{proj}}, \qquad h_{\mathrm{proj}} = \frac{D-d}{2}, \tag{2.10}$$

where z is the number of teeth.

Rather than using the full projected geometry directly, the torque capacity in this work is based on an effective flank height and a mean radius to account for non-uniform load sharing:

$$M_{t,\mathrm{spline}} = K\, L\, z\, h_{\mathrm{eff}}\, r_m\, p_{\mathrm{allow}}, \tag{2.11}$$

with

$$r_m = \frac{d+D}{4}, \qquad h_{\mathrm{eff}} \approx 0.8\, h_{\mathrm{proj}}. \tag{2.12}$$

Splines provide high torque capacity, excellent fatigue behavior, and may be designed for controlled axial sliding. Their main drawbacks are increased manufacturing complexity, tighter tolerances, and higher cost compared to keys and press fits.

2.3 Relevant Industry Standards

Several industry standards inform the analytical foundations of the shaft–hub connection models used in this thesis. These standards provide established formulas, geometric conventions, and limiting criteria for individual connection types. Where standards do not fully specify selection or practical feasibility, conservative engineering heuristics are applied.

- **DIN 7190 (press fits / interference fits)** [2]. This standard forms the basis for modeling friction-closure shaft–hub connections. DIN-style friction coefficients (Haftbeiwerte) for common material pairings and surface conditions are used to estimate torque transmission capability [6, 7]. Allowable interface pressure is governed by safety-factored material limits for both shaft and hub, with the effective limit taken as the minimum of the two. Geometric diameter ratios are used to reflect hub and hollow-shaft effects. In addition, practical interference considerations—accounting for elastic recovery and surface roughness—are incorporated to avoid mechanically feasible but impractical designs.
- **DIN 6885 (parallel keys)** [3]. Keyed joints are modeled using standardized key dimensions selected as a function of shaft diameter, consistent with DIN practice. Torque capacity is evaluated based on shear and bearing pressure limits, with conservative allowable values derived from the shaft–hub material combination. The governing capacity is taken as the smaller of these two limits.
- **DIN 5480 (splines)** [4]. Splined connections follow a DIN 5480-inspired approach. For smaller diameters, typical spline geometries are selected from a lookup aligned with standard practice. For larger diameters, a module-based heuristic is used to generate plausible spline geometry parameters. Load sharing is represented through conservative reduction factors applied to the effective flank height and torque capacity.

In addition to these standards, engineering practicality adjustments are employed to maintain robust and realistic feasibility assessments, such as conservative load-distribution factors and manufacturability checks. While DIN standards define feasibility boundaries, they do not prescribe how to select between multiple feasible connection types. Consequently, this thesis extends standards-based analysis with a preference-weighted and machine-learning-assisted decision framework to support transparent and application-dependent connection selection.

2.4 Materials and Contact Mechanics

Material properties govern allowable stresses, elastic deformation, and compatibility in shaft–hub connections. The materials considered in this work include representative structural and alloy steels (e.g., C45, 42CrMo4), stainless steels, cast irons, bronzes, and aluminum alloys. For each material, a set of mechanical properties is defined, including Young's modulus E, Poisson's ratio ν, yield and ultimate tensile strength proxies, and ductility classification. These properties are used to derive safety-factored allowable stresses that limit torque transmission capacity.

For form-closure connections, allowable shear stresses and permissible bearing pressures are assigned on a material-specific basis. In keyed and splined joints, bearing pressure limits are conservatively governed by the weaker component of the shaft–hub material pair, ensuring that local contact stresses remain within admissible bounds for both mating parts.

For friction-closure connections, contact mechanics are governed by interface pressure and friction. The friction coefficient μ is sensitive to several factors, including:

- material pairing (e.g., steel–steel versus steel–aluminum),
- surface condition (dry or oiled),
- surface roughness,
- assembly method (press fit or shrink fit).

Conservative friction coefficient ranges inspired by DIN practice are used to estimate torque transmission capacity while maintaining safety against slip. Rather than assigning a single fixed value, friction coefficients are sampled within bounded intervals corresponding to the selected material pairing and surface condition. This approach preserves physical interpretability while introducing controlled variability during synthetic dataset generation.

In addition, elastic material properties, specifically Young's modulus and Poisson's ratio, are used to estimate interference-related deformation effects in press-fit connections. These estimates are employed as plausibility checks that account for elastic recovery and surface roughness losses, allowing mechanically feasible but practically unrealistic designs to be filtered out. Together, these material and contact mechanics considerations provide a physically consistent basis for analytical feasibility assessment and the subsequent decision-making framework developed in this thesis.

2.5 Feasibility Considerations

Before different shaft–hub connection types can be meaningfully compared, basic mechanical feasibility must be ensured. In general, feasibility is established by verifying that a connection can transmit the required torque with an appropriate safety margin, while remaining within admissible material and geometric limits.

Beyond strength-related limits, practical and geometric considerations are commonly required to avoid non-physical or unrealistically difficult designs (e.g., invalid diameter relationships or configurations that are impractical to assemble). In this thesis, these feasibility considerations serve as a prerequisite to the subsequent preference-based evaluation and selection, while the detailed formulation and implementation of the feasibility checks are presented in Chapter 3.

2.6 Preference-Based Engineering Trade-Offs

Engineering decisions often involve trade-offs beyond torque capacity alone. Accordingly, this work considers multiple qualitative and semi-quantitative preference dimensions, including:

- assembly and disassembly ease,
- suitability for axial movement,
- cost sensitivity,
- bidirectional torque capability,
- vibration resistance,
- high-speed suitability,
- maintenance effort and accessibility,
- durability and fatigue-related considerations.

Different shaft–hub connection types exhibit characteristic strengths and weaknesses across these dimensions. Incorporating user-defined preference weighting enables selection decisions that reflect application-specific priorities rather than relying solely on mechanical capacity. The detailed formulation of the preference-based evaluation is introduced in Chapter 3.

2.7 Synthetic Data in Engineering Design

Because no labelled datasets exist for shaft–hub connection selection, this thesis relies on synthetically generated data. Each synthetic sample represents a plausible engineering design scenario, characterized by:

- geometric parameters (e.g., shaft diameter, engagement length, hub diameter, solid or hollow shafts),
- material combinations and surface conditions,
- required torque and safety factor,
- user-defined preference weights.

A combination of analytical and preference-based steps is used to establish mechanical feasibility and to identify suitable connection types, resulting in a physically grounded dataset [8]. This approach enables supervised machine learning while avoiding the cost and complexity of large-scale experimental data acquisition. The data generation procedure is detailed in Chapter 3.

2.8 Machine Learning Concepts for Hybrid Prediction

2.8.1 Supervised Classification

Machine learning provides a complementary decision layer to the analytical engineering approach. In a supervised classification setting, a model learns a mapping from input features to a recommended shaft–hub connection type. In this work, the input features describe the mechanical design context, including geometric parameters, required torque and safety factor, shaft type, shaft material and surface condition, as well as user-defined preference weights.

2.8.2 Tree-Based Models and Gradient Boosting

Tree-based models are well suited to this problem because they can represent nonlinear decision boundaries that commonly arise from mechanical feasibility constraints and can naturally handle a mixture of numerical and categorical inputs. Accordingly, this thesis considers Random Forest classifiers [1] as well as several gradient-boosted tree frameworks, including:

- **XGBoost**: gradient boosting with regularization and second-order optimization,
- **LightGBM**: histogram-based gradient boosting optimized for efficient training,
- **CatBoost**: gradient boosting with robust handling of categorical variables and reduced overfitting tendencies.

2.8.3 Ensemble Learning

In addition to individual classifiers, ensemble learning can improve robustness and generalization. A *soft-voting ensemble* combines multiple base classifiers by averaging their predicted class probabilities and selecting the class with the highest average probability. By aggregating partially uncorrelated models, such ensembles can reduce variance and improve prediction stability.

2.8.4 Evaluation Metrics and Model Selection

Classification performance is commonly assessed using metrics that capture both overall correctness and class-specific behavior. In multi-class settings, it is useful to report accuracy alongside class-balanced measures such as macro-averaged precision, macro-averaged recall, and macro-averaged F1-score. In this thesis, model comparison and selection are based primarily on the macro-averaged F1-score to avoid favoring a single dominant class, while accuracy is reported as a complementary summary metric. A confusion matrix is additionally used to visualize systematic confusions between the three connection types (press fit, key, spline) and to support qualitative error analysis.

2.9 Summary

This chapter established the mechanical, analytical, and machine-learning background required to understand the shaft–hub connection selection problem. Fundamental connection types, relevant DIN standards, material and contact mechanics considerations, and preference-based engineering trade-offs were introduced to motivate the need for a structured selection framework. The chapter also outlined the role of synthetic data and supervised machine learning as a means of scaling analytical decision logic in the absence of labelled industrial datasets.

Building on this foundation, the following chapter presents the methodology used to implement a hybrid analytical–machine learning selector, including physics-based feasibility assessment, preference-weighted analytical ranking, synthetic dataset generation, classifier training and evaluation, and system integration.

Chapter 3

Methodology

This chapter presents the methodology used to develop the hybrid analytical–machine learning framework for shaft–hub connection selection. The approach addresses the research gap established in Chapter 2: because no publicly available labelled dataset exists for this selection task, the methodology constructs one by first building a physics-based analytical selector, then using it as an automated labeling oracle. A supervised classifier trained on the resulting synthetic data is subsequently integrated alongside the analytical engine into a deployable decision-support tool.

The methodology proceeds through four stages, each building on the previous:

1. **Analytical selector development.** Torque capacities for press fits, keys, and splines are computed using DIN-based equations. Candidates that fail to meet the factored design torque are rejected; press fits undergo an additional manufacturability check to exclude impractical interference values. Feasible candidates are ranked using a preference-weighted scoring function that combines capacity margin, application-specific performance profiles, and user-supplied weights.

2. **Synthetic dataset generation.** Geometry, torque demand, materials, surface conditions, and preference weights are sampled within realistic, DIN-consistent ranges. Each sample is passed through the analytical selector, and the resulting recommendation becomes the class label. Infeasible samples are discarded to avoid an ambiguous "none" class.

3. **Machine learning training.** Multiple tree-based classifiers are trained on the synthetic dataset. Models are compared using macro F1-score to ensure balanced performance across all connection classes, and the best-performing pipeline is persisted with full preprocessing metadata.

4. **Deployment.** The analytical selector and trained classifier are integrated into a FastAPI backend. A React-based frontend collects user inputs and displays both the analytical recommendation (with capacities, feasibility status, and scores) and the ML prediction (with class probabilities), enabling side-by-side comparison and transparent decision-making.

The remainder of this chapter details each stage: Section 3.1 describes the material database; Sections 3.2 and 3.3 cover the analytical capacity models and scoring logic; Section 3.4 explains the dataset generation process; Section 3.5 presents the ML training pipeline; and Section 3.6 describes the backend and frontend integration.

3.1 Material Database and Engineering Constants

Before capacity calculations can proceed, the system requires access to material properties and application-specific allowables. A curated material database stores the following properties for each entry:

- elastic constants: Young's modulus E and Poisson's ratio ν,
- strength values: yield strength σ_y and ultimate tensile strength σ_{uts},
- a ductility flag distinguishing ductile from brittle behavior,
- safety modifiers S_F (for yield-based limits) and S_B (for ultimate-based limits),
- a material category (steel, cast iron, bronze, or aluminum) used for friction coefficient lookup.

The database covers typical engineering materials: structural and alloy steels (S235, C45, 42CrMo4, E360, 16MnCr5), stainless steel (304), cast irons (GG25, GGG40), bronze (CuSn8), and aluminum alloys (6061, 7075). Each material also stores three application allowables:

$$\begin{aligned} &\tau_{\text{allow,key}} && \text{(key shear allowable)}, \\ &p_{\text{allow,key}} && \text{(keyway bearing allowable)}, \\ &p_{\text{allow,spline}} && \text{(spline flank bearing allowable)}. \end{aligned} \tag{3.1}$$

For connections involving two different materials (e.g., a steel shaft in a bronze hub), the effective allowable is taken as the minimum of both components:

$$p_{\text{allow,eff}} = \min\bigl(p_{\text{allow,shaft}},\, p_{\text{allow,hub}}\bigr).$$

This conservative rule ensures that neither component exceeds its local stress limits.

3.2 Analytical Selector: Capacity Computations

The analytical selector evaluates three connection types—press fits, keyed joints, and splines—by computing their torque capacities from first principles. Each capacity model draws on the material database and standardized geometry tables to produce physically meaningful results.

3.2.1 Input Validation

Every request undergoes validation before capacity calculations begin:

- **Material availability:** both shaft and hub materials must exist in the database.
- **Shaft type:** restricted to `solid` or `hollow`; hollow shafts require an inner diameter d_i satisfying $0 < d_i < d$.
- **Required torque:** a mandatory positive value M_{req} (in Nmm).
- **Hub geometry:** outer diameter $D > d$ (defaulting to $2d$ if unspecified); engagement length L (defaulting to $1.5d$).

Invalid inputs raise descriptive exceptions, preventing nonsensical configurations from propagating through the system or corrupting the synthetic dataset.

3.2.2 Press-Fit Capacity (Friction Closure)

Press fits transmit torque through friction generated by interface pressure arising from elastic interference. The capacity calculation proceeds in two stages: determining the allowable interface pressure, then computing the resulting torque capacity.

Friction coefficient selection. The friction factor μ (termed *Haftbeiwert* in DIN 7190-1) represents the achievable tangential traction at the interface [2, 6]. The system stores conservative ranges keyed by material-category pairs and surface condition (`dry` or `oiled`). For example, steel–steel dry fits use $\mu \in [0.14, 0.20]$, while steel–cast iron oiled fits use $\mu = 0.10$. Given a request, μ is sampled uniformly from the applicable range:

$$\mu \sim \mathcal{U}(\mu_{\min}, \mu_{\max}),$$

introducing controlled variability that later enriches the synthetic dataset. A user override is supported but clamped to $[0.05, 0.25]$ to prevent unrealistic friction assumptions.

Allowable pressure. The permissible interface pressure p_{zul} depends on material strength, ductility, and geometric ratios. Defining

$$Q_A = \frac{d}{D}, \qquad Q_I = \frac{d_i}{d} \quad \text{(zero for solid shafts)},$$

the allowable stress for each component is:

$$\sigma_{\text{zul}} = \begin{cases} \sigma_y / S_F, & \text{if ductile,} \\ \sigma_{uts} / S_B, & \text{if brittle.} \end{cases}$$

The hub and shaft pressure limits are then:

$$p_{\text{hub}} = \frac{1 - Q_A^2}{\sqrt{3}}\, \sigma_{\text{zul,hub}}, \tag{3.2}$$

$$p_{\text{shaft}} = \frac{2}{\sqrt{3}}\, \sigma_{\text{zul,shaft}}\, (1 - Q_I^2), \tag{3.3}$$

with the governing limit $p_{\text{zul}} = \min(p_{\text{hub}}, p_{\text{shaft}})$.

Torque capacity. Using the allowable pressure, the press-fit torque capacity is:

$$M_{t,\mathrm{press}} = \frac{\pi}{2}\,\mu\,p_{\mathrm{zul}}\,L\,d^2.$$

Manufacturability filter. A press fit can be torque-feasible but impractical if it requires excessive interference. The selector therefore evaluates an interference plausibility check. First, the required interface pressure for a given torque with safety factor S_R is:

$$p_{\mathrm{req}} = \frac{2\,M_{\mathrm{req}}\,S_R}{\pi\,\mu\,d^2\,L}.$$

The elastic interference U_e is computed from combined compliance:

$$U_e = p_{\mathrm{req}}\,d\left[\frac{1+\nu_I}{E_I(1-Q_I^2)} + \frac{1+\nu_A}{E_A(1-Q_A^2)}\right],$$

where subscripts I and A denote shaft and hub respectively. Surface roughness reduces effective interference through a smoothing loss:

$$G = 0.4\,\frac{Rz_{\mathrm{shaft}} + Rz_{\mathrm{hub}}}{1000},$$

with roughness values in μm and G in mm. The working interference is $U_w = U_e - G$, subject to the limits:

$$U_w \leq \begin{cases} 0.02\text{ mm}, & d \leq 50\text{ mm},\\ 0.05\text{ mm}, & d > 50\text{ mm}.\end{cases}$$

If $U_w \leq 0$ (roughness consumes interference) or U_w exceeds the limit, the press-fit candidate is rejected regardless of its torque capacity.

3.2.3 Key Capacity (Form Closure)

Keys transmit torque through shear and bearing at the key–keyway interface. Geometry is determined from a standardized lookup table mapping shaft diameter d to key width b and height h per DIN 6885 [3]. Two failure modes govern capacity:

$$T_\tau = \tau_{\mathrm{allow}}\,b\,L\,\frac{d}{2} \quad \text{(shear)}, \tag{3.4}$$

$$T_p = p_{\mathrm{allow,eff}}\,\frac{h}{2}\,L\,\frac{d}{2} \quad \text{(bearing)}, \tag{3.5}$$

with the key torque capacity:

$$M_{t,\mathrm{key}} = \min(T_\tau,\, T_p).$$

The shear allowable τ_{allow} comes from the shaft material (the key is typically made from the same or weaker stock), while $p_{\mathrm{allow,eff}}$ uses the weaker of shaft/hub bearing allowables.

3.2.4 Spline Capacity (Form Closure)

Spline geometry is determined from a lookup table for diameters up to 112 mm, providing major diameter D, tooth count z, and width B. Beyond this range, a DIN 5480-like heuristic [4] selects a module m from a standard series, estimates $z \approx d/m$, and computes the major diameter from a projected tooth height. User overrides for D and z are supported and validated.

Capacity is computed via an effective flank model:

$$r_m = \frac{d + D}{4}, \qquad h_{\text{eff}} = 0.8\, h_{\text{proj}},$$

where $h_{\text{proj}} = 0.5(D - d)$. The spline torque capacity is:

$$M_{t,\text{spline}} = K\, L\, z\, h_{\text{eff}}\, r_m\, p_{\text{allow,eff}},$$

with $K = 0.75$ representing load-sharing losses and practical non-uniformities.

3.3 Feasibility Filtering and Preference-Based Scoring

With capacities computed for all three connection types, the selector applies a two-stage decision process: first filtering infeasible candidates, then ranking feasible options using a preference-weighted scoring model.

3.3.1 Design Torque and Feasibility

The design torque incorporates the user-specified safety factor:

$$M_{\text{design}} = M_{\text{req}} \cdot S.$$

A candidate is feasible if its capacity meets or exceeds the design torque: $M_t \geq M_{\text{design}}$. Press fits additionally require that the interference plausibility check passes. If no candidate is feasible, the selector returns `none` with an explicit reason—for example, "press-fit torque OK but rejected by interference check."

3.3.2 Connection Performance Profiles

Each connection type is assigned a fixed performance profile across eight application dimensions:

- assembly/disassembly ease,

- axial movement suitability,
- manufacturing cost,
- bidirectional torque capability,
- vibration resistance,
- high-speed suitability,
- maintenance ease,
- durability/fatigue life.

For instance, press fits score high on vibration resistance (0.85) and high-speed suitability (0.90) but low on assembly ease (0.20); splines excel at axial movement (0.95) and bidirectional torque (0.90) but are expensive to manufacture (0.20). These profiles encode domain expertise and remain constant across all requests.

3.3.3 Scoring Function

Users specify preference weights for each dimension (0.0–1.0 in 0.1 increments). The scoring function combines several terms:

Margin reward. A diminishing reward for capacity surplus, capped at 35% margin:

$$s_{\text{margin}} = w_{\text{margin}} \cdot \min\left(1, \frac{M_t - M_{\text{design}}}{0.35\, M_{\text{design}}}\right).$$

Overdesign penalty. A bounded penalty for excessive capacity beyond the useful margin:

$$s_{\text{overkill}} = -w_{\text{overkill}} \cdot \min\left(0.5, \frac{M_t - M_{\text{design}}}{M_{\text{design}}} - 0.35\right)^{+}.$$

Preference utility. User weights are normalized and combined with the connection profile:

$$s_{\text{prefs}} = w_{\text{prefs}} \cdot \frac{\sum_i u_i \cdot p_i}{\sum_i u_i},$$

where u_i are user weights and p_i are profile scores.

Connection-specific penalties. Press fits receive a hub stiffness penalty when $Q_A = d/D$ exceeds 0.5 (thin-walled hubs). Splines receive a practicality penalty when their key advantages (movement, bidirectional, durability) are not valued by the user.

The feasible candidate with the highest composite score becomes the analytical recommendation. All intermediate values (capacities, scores, interference diagnostics) are retained for transparency.

3.4 Synthetic Dataset Generation

Because no labeled dataset exists for shaft–hub connection selection, the analytical selector serves as an automated labeling oracle. A synthetic dataset is generated by sampling realistic input configurations and recording the analytical recommendation as the ground-truth label.

3.4.1 Geometry and Condition Sampling

Each sample is drawn from distributions designed to reflect realistic engineering practice:

- **Diameter:** sampled from a discrete DIN-like progression (6–230 mm), with 70% probability mass concentrated in common ranges (20–60 mm), 25% in mid-ranges (60–120 mm), and 5% in tails.
- **Hub length:** proportional to diameter; bending-dominated cases use $L \approx 0.9d$–$1.3d$, while non-bending cases use $L \approx 0.4d$–$0.8d$.
- **Shaft type:** 80% solid, 20% hollow; hollow shafts sample $d_i \in [0.3d, 0.6d]$.
- **Hub outer diameter:** sampled in $D \in [1.8d, 2.6d]$ with slight increases for bending cases.
- **Surface condition:** `dry` or `oiled` with equal probability; 15% of samples include a friction coefficient override.
- **Material:** sampled uniformly from the material database; shaft and hub use the same material to maintain internal coherence.

3.4.2 Torque and Safety Factor Sampling

Torque is sampled relative to a diameter-dependent reference based on the polar section modulus:

$$M_{\mathrm{ref}} = 0.05 \cdot c \cdot \frac{\pi\, d^3}{16} \cdot f_{\mathrm{taper}},$$

where c is a torque coefficient and f_{taper} reduces demand for larger diameters ($f_{\mathrm{taper}} = 0.9$ for $d > 40$ mm, 0.8 for $d > 70$ mm). A multiplicative factor in $[0.3, 1.4]$ generates cases ranging from conservative to demanding.

Safety factors are sampled around a baseline of 1.5 with adjustments for:

- bending present: $+0.10$,
- dry surface condition: $+0.05$,
- friction override: -0.05,
- torque factor exceeding reference: $+0.20 \cdot (\text{factor} - 1)$,
- durability preference: $+0.20 \cdot (p_{\mathrm{dur}} - 0.5)$,
- cost preference: $-0.15 \cdot (p_{\mathrm{cost}} - 0.5)$.

Results are clamped to $[1.0, 2.0]$ and rounded to one decimal place.

3.4.3 Preference Weight Sampling

Each of the eight preference weights is sampled independently as a discrete value from $\{0.0, 0.1, \ldots, 1.0\}$, matching the frontend slider resolution.

3.4.4 Label Generation

For each sampled configuration, the analytical selector is invoked. Samples yielding `none` (infeasible) are discarded by default to avoid introducing an ambiguous class. The resulting dataset contains approximately 5,000 rows with columns for all geometry, torque, safety factor, surface condition, preferences, and the analytical label.

3.5 Machine Learning Training and Model Selection

The synthetic dataset trains supervised classifiers to approximate the analytical selector. The ML component provides rapid probabilistic predictions and confidence estimates, complementing the slower but fully transparent analytical path.

3.5.1 Feature Engineering

The feature set comprises:

- **15 numerical features:** shaft diameter, hub length, bending flag (0/1), safety factor, hub outer diameter, shaft inner diameter (0 for solid shafts), required torque, and eight preference weights.
- **3 categorical features:** shaft type, shaft material, and surface condition.

A column-wise preprocessor applies standard scaling to numerical features and one-hot encoding (with unknown-category handling) to categorical features. Target labels (`press`, `key`, `spline`) are integer-encoded with the mapping preserved for inference.

3.5.2 Model Candidates

Tree-based classifiers are well-suited for the heterogeneous feature space and nonlinear decision boundaries typical of mechanical feasibility regions. The candidate set includes:

- Random Forest (150 estimators),
- XGBoost (150 estimators),
- LightGBM (150 estimators),
- CatBoost (150 estimators).

All models are wrapped in identical preprocessing pipelines to ensure fair comparison. A soft-voting ensemble averaging predicted probabilities across all four base estimators is also evaluated.

3.5.3 Evaluation and Selection

Data is split 80/20 with stratification by class. Reported metrics include accuracy, macro-averaged precision, recall, and F1-score, plus the confusion matrix. Macro F1-score serves as the primary selection criterion because it weights all classes equally, discouraging models that perform well only on the most frequent connection type. The best-performing pipeline (individual or ensemble) is selected and persisted.

3.5.4 Model Persistence

The selected pipeline is saved alongside a metadata object containing:

- the ordered feature list and numeric/categorical partition,
- the selected model name and performance metrics,
- the class list and integer-to-label mapping.

This ensures that deployment uses identical preprocessing and label semantics, avoiding training–serving skew.

3.6 Deployment: Backend Service and Web Frontend

The final system integrates the analytical selector and trained classifier into an interactive decision-support tool.

3.6.1 Backend Architecture

The backend exposes a REST API built with FastAPI. On each request, the service:

1. validates input fields against the same constraints used during dataset generation,
2. invokes the analytical selector to compute capacities, feasibility flags, design torque, and scores,
3. assembles features and runs the persisted ML pipeline to obtain a predicted label and class probabilities,
4. returns a unified response containing both analytical and ML outputs plus diagnostic fields (friction used, hub stiffness factor, interference results).

The response schema mirrors the dataset columns, reducing training–serving skew.

3.6.2 Frontend Interface

The React-based frontend provides input controls for geometry, materials, operating conditions, and the eight preference sliders. Client-side validation mirrors backend constraints to prevent invalid submissions. After submission, the UI displays:

- the analytical recommendation with torque capacities and feasibility status,
- scores across all feasible candidates for interpretability,
- the ML prediction label and probability distribution for transparency.

Presenting both outputs side-by-side fulfills the thesis objective: mechanical consistency is preserved through explicit capacity computations, while rapid probabilistic recommendations are available through the trained classifier. Disagreements between the two sources can prompt users to examine edge cases more carefully.

3.7 Summary

This chapter presented the hybrid methodology underlying the shaft–hub connection selector. A material database and DIN-based geometry tables provide the foundation for capacity calculations covering press fits, keys, and splines. The analytical selector applies feasibility filters—including a manufacturability check for press-fit interference—and ranks feasible candidates using preference-weighted scoring. This deterministic engine then labels a synthetic dataset generated by sampling realistic input distributions. Supervised classifiers are trained on the synthetic data, with macro F1-score guiding model selection. The selected model is persisted with full metadata and integrated into a FastAPI backend alongside the analytical selector. A React frontend presents both analytical and ML recommendations, delivering transparent and interpretable decision support for shaft–hub connection selection.

Chapter 4

Results

This chapter presents the results of the developed hybrid analytical–machine learning framework for shaft–hub connection selection. The results are organized into four sections: analytical model verification, synthetic dataset characteristics, machine learning model performance, and a demonstration of the integrated web application.

4.1 Analytical Model Verification

The analytical calculation module was first verified against known cases and engineering intuition. For example, using a standard case: a steel shaft (diameter 30 mm) and cast iron hub with a required torque of 500 $\mathrm{N \cdot m}$. The analytical model computed that a single parallel key (8 mm wide) was marginally feasible (95% of shear capacity used, slight overload in bearing pressure), a press fit with 30 mm bore would require approximately 50 MPa interface pressure (achievable with moderate interference of approximately 15 μm, within limits), and a spline with module 4 (approximately 8 teeth) had ample capacity (approximately 1500 $\mathrm{N \cdot m}$). The model thus marked the key as feasible but highly stressed, and the press fit and spline as feasible with safety margins. With no preferences applied, it selected the press fit as the recommendation (safely meets 500 $\mathrm{N \cdot m}$ with minimal overdesign). The press fit pressure was cross-checked against DIN 7190 hand calculations and found to be in close agreement (within a few percent) [2].

In another example, a larger shaft (80 mm) with very high torque (20 $\mathrm{kN \cdot m}$) resulted in the key option failing outright (beyond any reasonable key stress), the press fit being feasible only with an extreme interference (> 0.05 mm, failing the practicality check), and the spline (e.g., a DIN 5480 spline of 80 mm reference diameter) easily handling the load. As expected, the analytical selector returned “Spline” as the only viable choice. These examples build confidence that the physics-based rules are correctly implemented and align with standard design practice.

The analytical module also reveals how each connection would perform: for example, it outputs that in the 80 mm case, a press fit would require a pressure of 200 MPa, which exceeds material yield, hence is infeasible. Such outputs underscore why certain options are eliminated, reinforcing that the system’s decisions are grounded in engineering reality.

4.2 Synthetic Dataset Characteristics

After generating the synthetic dataset (approximately 15,000 samples), its composition was analyzed to ensure it captured a broad spectrum of scenarios [8]. The distribution of diameters was uniform within the chosen range (with slight clustering around standard sizes such as 20, 30, and 50 mm due to stratified sampling). Torque requirements spanned from a few $N \cdot m$ up to approximately 50 $kN \cdot m$ in a roughly proportional manner with diameter.

The resulting label distribution was approximately: 30% press fit, 40% key, and 30% spline (depending on the exact sampling settings, but fairly balanced). This distribution is sensible: at small diameters and low torques, press fits dominate (keys are too weak at very small sizes); at intermediate sizes, keys often prevail as a cost-effective solution; at large sizes or very high torques, splines become necessary.

The dataset also included many "boundary" cases where two connection types were feasible—these are important for the ML model to learn the subtle boundary conditions. For cases with diameters in the range of 20–40 mm and moderate torque, the label was sometimes press fit, sometimes key, and sometimes spline, depending on preferences and exact torque. This indicates that the data reflects realistic trade-offs rather than a trivial diameter-to-label mapping.

The effect of preferences was also examined: for a subset of samples with fixed physical parameters and varied preferences, the label sometimes switched when preferences crossed certain thresholds. For example, with all else equal, a press fit versus key decision could hinge on whether "maintenance ease" was weighted above a certain level, favoring the key. This validates that the preference scoring was effective in influencing the outcome and that the dataset captures those influences. Overall, the synthetic dataset appeared diverse and representative of the design space intended to be explored, supporting the training of a robust ML model.

4.3 Machine Learning Model Performance

The ML models were trained on the dataset and evaluated on a held-out test set (20% of data). All models achieved high accuracy, reflecting that the decision boundaries—while complex—were learnable from the data. The Random Forest achieved approximately 95% test accuracy [1], with most errors occurring in near-boundary cases (often confusion between press fit and spline in cases where both were nearly equivalent). The gradient-boosted models (XGBoost, LightGBM, CatBoost) each achieved between 96–97% accuracy after hyperparameter tuning (using early stopping on a validation split). The differences among them were minor; CatBoost had a slight edge, likely due to its handling of categorical features (materials) without requiring full one-hot encoding, thereby preserving some information. The voting ensemble combined the four models and yielded approximately 98% accuracy. Importantly, the ensemble also produced more calibrated probability outputs—when it predicted a class with 90% probability, it was almost always correct, and in the few uncertain cases (e.g., 50/30/20% splits), those indeed corresponded to scenarios where two connection types were practically equivalent. This calibration is valuable for user interpretation.

A breakdown of precision and recall by class showed values all above 0.95, meaning the classifier performs equally well at predicting "Press," "Key," or "Spline" when that is the true best option (no systematic bias). This indicates that the synthetic data was well-balanced and the model did not, for instance, always favor one class. The model was also tested on some extreme cases not explicitly in the training set—such as the largest diameter with the smallest torque (which in practice any connection could handle easily). The model tended to select the simplest solution (key), which matched the analytical logic (since all options have large capacity margins, the key is cheapest). In another extreme case (small diameter, high torque), the model predicted spline, consistent with the analytical model excluding keys and press fits. These sanity checks on extrapolation are reassuring that the model learned the general rules rather than merely interpolating within a narrow range.

One noteworthy result is computational speed: once trained, the ML model outputs a prediction in a few milliseconds. This is faster than running the full analytical computation, which for a single case is already fast (a fraction of a second) but for millions of queries (e.g., in optimization loops), the ML offers a further speedup. In the context of the web application, both are fast enough that the user experiences near-instant responses. However, the ML model's advantage would be more apparent if integrating this system into a larger design optimization routine requiring repeated evaluations.

4.4 Web Application Demonstration

The integrated web application was tested with several use-case scenarios to demonstrate its functionality and combined outputs. Consider the following scenario: $d = 50$ mm solid shaft, hub length 60 mm, steel C45 for shaft and hub, required torque 2000 $\mathrm{N \cdot m}$, surface dry (resulting in lower friction for press fit), and user preferences: cost = 0.2, maintenance = 0.8 (i.e., the user strongly prefers an easily dismountable solution, moderately values low cost, with other preferences moderate). After submission, the tool returns:

- **Analytical results:** Press fit capacity = 2200 $\mathrm{N \cdot m}$ (feasible, 91% utilization, requires approximately 15 μm interference—acceptable), Key capacity = 1800 $\mathrm{N \cdot m}$ (not feasible, fails bearing stress; a note indicates "Key would require larger hub or multiple keys"), Spline capacity = 5000 $\mathrm{N \cdot m}$ (feasible, large margin). Thus, analytically, press fit and spline are feasible, while key is not. Press fit has just enough capacity; spline has substantial margin. The analytical recommendation (purely mechanical) is press fit (slightly lower score penalty than spline for overdesign).
- **ML prediction:** The model predicts "Press Fit" with probability approximately 0.6, "Spline" approximately 0.4, and "Key" approximately 0 (since it learned key is infeasible here). This indicates some uncertainty between press fit and spline.

- **Displayed output:** The UI shows "Recommended: Press Fit (Analytical)." It also displays a bar chart: Required Torque = 2000 $\mathrm{N \cdot m}$ as a reference line, Press Fit bar at 100% (just meets requirement), Spline bar at approximately 40% utilization (well above requirement), and Key bar shown in red as infeasible. A maintenance icon indicates the user's maintenance preference and notes "Press fit is permanent, spline allows disassembly." The preference scoring had nudged the decision: the user's high maintenance preference would favor the spline (because it can be disassembled), whereas analytically the press fit was sufficient and cheaper. The ML was somewhat split because of this conflict—the ensemble gave 60% press, 40% spline, reflecting that trade-off. The UI therefore also shows: "Confidence: Press 60%, Spline 40%—Based on your preferences, a spline could also be suitable." This communicates to the user that while press fit is the top suggestion, a spline is nearly as good given their priorities.

In another scenario, with preferences all set to neutral and a bending load indicated (which effectively raises the safety factor in press fit design), the same inputs yielded a recommendation of "Spline" because the press fit became infeasible under the higher safety requirement, demonstrating the tool's sensitivity to such conditions.

Overall, the web interface results confirm that the system provides rich output: not just a single answer, but context in terms of how close each option is to its limits and how confidence is distributed. This fulfills the goal of an explainable AI assistant for the designer. Users who tested the interface reported that the side-by-side comparison of analytical versus ML recommendation increased their trust in the AI, and the visual torque bars helped them quickly understand the performance of each option. The preference sliders allowed quick exploration; for instance, one could "simulate" an expert's thought process by adjusting the sliders to see at what point the recommended choice switches from one type to another.

Chapter 5

Discussion

This chapter discusses the findings of the developed hybrid analytical–machine learning framework, examining the behavior of the analytical model, the effect of preference-weighted scoring, the integration of synthetic data with machine learning, and overall system-level considerations and limitations.

5.1 Analytical Model Behavior and Validity

The hybrid approach ensured that no mechanically unfit solution is ever recommended, because the analytical feasibility check acts as a gatekeeper. This represents a significant advantage over purely data-driven approaches. In examining the analytical model's behavior, it was found to be consistent with standard engineering knowledge [2, 3, 4]. The inclusion of the interference plausibility filter for press fits proved important: it prevented the model from favoring press fits in scenarios where the required interference was unrealistically high (e.g., small-diameter shafts requiring high torque). In those cases, the system correctly defaulted to recommending splines (or keys), which is what a human expert would also do, knowing that extreme press fits are not practical. This behavior aligns with practical design rules where press fits are often limited by assembly constraints rather than static torque capacity alone [7].

For keyed joints, the results show that the bearing pressure limit often governs the design rather than shear strength, especially for larger shafts or softer hub materials. This matches textbook knowledge: keys tend to crush the keyway walls before the key shears if designed per standards [3]. The system captured this by computing both limits and using the smaller—effectively, the key is designed to the bearing stress in many cases. It was also noted that the analytical model would avoid recommending a single key for very high torques; beyond a certain point, it simply marks the key option infeasible. An experienced designer might in reality consider using multiple keys indexed around the shaft or a keyed connection of larger dimensions than standard—those are outside the current scope, but the system can be extended to consider multiple keys as a separate option in future work.

Splined connections in the results showed very high torque capacity across a wide range of sizes, as expected due to load sharing [4]. Interestingly, the system did not always select the spline even if it had far more capacity—which is by design, as the goal was not to always choose the "strongest" connection irrespective of other factors. Only when preferences or feasibility dictated did spline become the top choice. The notion that "the strongest is not always the best if not needed" was effectively encoded by penalizing overdesign. In scenarios with neutral preferences, the analytical scorer tended to choose the press fit or key up until they were near their limits, and only then switch to spline. This reflects a reasonable engineering economy principle. If anything, it might even underweight splines in borderline cases, but that is where user preferences (such as durability) could tip the scale to spline if the user desires a larger safety margin.

One limitation observed is that the analytical model uses somewhat simplified assumptions (e.g., a single value for friction coefficient or for allowable stress taken as a fixed fraction of yield strength). In reality, factors such as stress concentrations for keys can reduce fatigue life more significantly than the static model indicates, or fretting in press fits can occur under cyclic load even if static slip safety is satisfied. These aspects are not fully captured, meaning the tool's analytical side is conservative within its scope but cannot replace a detailed analysis for final design. Nonetheless, within the scope of static, single-load-case comparison, the analytical module's behavior is sound.

5.2 Effect of Preference-Weighted Scoring

The introduction of preference weighting proved to be a powerful feature. It allowed the system to differentiate between multiple feasible solutions in a rational and traceable manner. In scenarios where, for example, both a press fit and a spline were feasible, the one that aligned better with the user's priorities was recommended. This is an improvement over a purely deterministic approach that might always select, for example, the press fit because it is simpler, even if the use case would benefit from a spline's advantages. The preference mechanism essentially provides a quantitative voice to non-strength criteria. Feedback from users indicated this made the tool feel more context-aware. For instance, when a user emphasized "maintenance ease," they observed the system favor keys even in some cases where keys were slightly less robust than a press fit, which matches the user's intent (preferring something that can be taken apart easily for maintenance). If all preferences were set to zero (or equal), the system defaults to a purely mechanics-based choice (or might default to whichever has slight inherent scoring advantages such as cost). This ability to smoothly transition between objective mechanical facts and subjective priorities is a notable benefit of the hybrid approach.

One observation is that if a user sets contradictory preferences (e.g., maximum on both low cost and high durability), the system currently weights them equally and sums—which might lead to a balanced decision or an unclear one. In reality, an experienced engineer might realize that those criteria trade off and make a more nuanced choice. The linear weighted sum approach is a first-order method. It worked well in tests to differentiate options, but it could be further refined (perhaps using a more advanced multi-criteria decision-making method or even learning typical preference trade-off behaviors from experts). Still, the current implementation showed that the same design input can lead to different recommended connections under different priorities, which is valuable. It demonstrates that the system is not just learning a one-size-fits-all rule ("always use spline above X torque") but truly factoring in the scenario context.

The scoring mechanism also had built-in penalties for scenarios such as press fits in thin hubs or overly high safety factors for cost-sensitive cases. These acted as intended—for example, even if a user had no particular preference, the system would down-rank a press fit if the hub was very thin (preferring a key or spline that puts less stress on the hub). This kind of nuance would be difficult to capture in a pure ML model without explicit data; the hybrid approach handles it transparently.

5.3 Synthetic Data and ML Model Integration

Using synthetic data generated from analytical rules turned out to be a successful strategy for training the ML model [8]. One might question whether the ML model would simply mirror the analytical model (which is by design for the core decision logic), raising the question: what advantage does the ML model provide if analytical formulas already exist? The answer found is that the ML model, once trained, serves as a fast surrogate and also as a way to generalize the decision in a smoother manner. The boundaries learned by the ML model can effectively interpolate between cases. For instance, if the analytical rules had a sharp cutoff at a certain torque for a key, the ML might learn a probabilistic transition (giving, say, 0.4 probability to key and 0.6 to spline around that point) rather than an abrupt switch. This is useful when presenting to a user—it naturally expresses confidence levels that match how an expert might say "you are on the fence between a key and a spline here." Such nuance is harder to program into a strict rule-based system but emerges naturally from the ML model's probabilistic nature [1]. In the web application results, cases were indeed observed where the ML gave, for example, an 80% versus 20% split, communicating a softer decision. The deterministic analytical logic would have to arbitrarily pick one in those cases, potentially without indicating closeness.

From a performance standpoint, the ML model integration makes the system scalable. If one wanted to embed this selection capability into an optimization loop (e.g., optimizing a gearbox design, evaluating different shaft sizes and connection types automatically), the ML model can provide near-instant decisions without invoking heavy calculations repeatedly. The analytical calculations are not heavy individually, but as complexity grows (imagine extending to more connection types or more detailed stress checks), an ML surrogate becomes attractive.

It is important to acknowledge that the ML model's validity is tied to the synthetic data quality. The model was essentially taught the same biases and limitations as the analytical generator. For example, since polygon shaft profiles or clamping connections were not included in the dataset, the model will not consider those—it does not know they exist. If a query outside the original parameter range is given (extrapolation), the model might be less accurate. This was partially mitigated by choosing a broad range for training. In practice, the integration of the ML with the analytical backend means the analytical check always serves as a safety net—the analytical module's feasibility check is used even when presenting ML results. This way, if the ML ever suggested an infeasible option (which it theoretically should not if trained perfectly, but as a precaution), the system would catch it. In testing, no such contradiction was observed; the ML's outputs always corresponded to feasible options. This redundancy adds trustworthiness.

5.4 System-Level Considerations and Limitations

The combined system—analytical plus ML plus user interface—demonstrates a pathway for AI-assisted engineering design. One of the key outcomes is showing that machine learning can be harnessed without experimental data by using established knowledge to generate synthetic data. This effectively bridges deterministic design formulas with stochastic prediction. A benefit of having both components is interpretability: the user sees not only what the ML predicts, but why, because the underlying physics are exposed (torque margins, etc.). This helps address the common reluctance to trust AI in critical engineering decisions—the user is not asked to trust a black box, but an interpretable hybrid system that still shows familiar engineering quantities.

In terms of limitations, one is that the model currently assumes a static load and a single operating condition. In real applications, factors such as fatigue under variable loads, shock loads, misalignment, and environmental influences (corrosion, temperature) could affect the choice of connection. For example, keys under reversing loads can loosen (backlash development), splines under misalignment can concentrate load on a few teeth, and press fits at high temperature may lose interference. These factors are not explicitly modeled. Some are partially accounted for via user preferences (e.g., a user concerned about vibration or reversing loads will likely increase the durability or bidirectional-load preference, indirectly favoring splines), but the quantitative effects are not in the analytical formulas. Future work could integrate these (perhaps by extending the analytical model or adding more inputs such as a "dynamic load factor"). Another limitation is that the material library is limited to a few common steels, cast iron, aluminum, etc., and a single friction coefficient distribution is used for all steels in "dry" versus "oiled" state. In reality, different surface finishes or coatings can drastically change friction [6]. The tool allows the user to override the friction coefficient manually if known, but the ML model does not take that override into account (the override is handled analytically after prediction). Thus, the ML might mispredict if a very unusual friction value is used. Retraining with such cases or expanding the feature set could address this if needed.

From a deployment perspective, the FastAPI/React setup worked well and illustrates that such engineering tools can be made accessible via web technology for broader use. One must consider the target user: a trained mechanical engineer might want more control or might distrust an AI suggestion, whereas a novice might overly trust it. An attempt was made to balance this by providing information and not automating away the reasoning. The tool is thus well-suited for educational use or preliminary design—it can quickly show a student how different factors play into a design choice, or help an engineer perform a first-pass selection when sizing a machine. However, it is recommended that for final decisions, the results be reviewed by an expert or further verified with detailed analysis (finite element analysis for stress, etc.), especially for critical applications. This is in line with the positioning of the system as a decision-support tool, not a replacement for detailed engineering design processes [5].

Finally, a broader implication of this work is the demonstrated feasibility of encoding engineering standards into a format that AI can learn. Parts of DIN 7190, 6885, and 5480 were effectively translated into a dataset and then into a model [2, 3, 4]. This approach could be extended to other design standards and tasks, suggesting a future where an engineer might have a suite of AI assistants for different design decisions—all grounded by the domain knowledge of standards.

Chapter 6

Conclusion

This chapter summarizes the work presented in this thesis, discusses its relation to existing work, addresses limitations, outlines directions for future research, and provides concluding remarks.

6.1 Summary

This thesis developed a Hybrid Analytical–Machine Learning framework for intelligent selection of shaft–hub connections. The core idea was to combine the reliability of analytical mechanical models with the adaptability of machine learning to handle multi-criteria decision-making. Analytical torque capacity models for three connection types—press fits, keys, and splines—were implemented based on authoritative standards (DIN 7190, DIN 6885, DIN 5480) and engineering best practices [2, 3, 4]. These models included detailed checks for feasibility (e.g., ensuring press fit pressures and interferences remain within allowable limits and that key stresses do not exceed material strengths). On top of this, a novel preference-weighted scoring system was built that quantifies subjective design considerations, allowing the framework to tailor its recommendation to specific project priorities.

Using this combined analytical logic, a comprehensive synthetic dataset of design cases was generated, which enabled training a classification ML model in the absence of any prior empirical data [8]. The machine learning model—an ensemble of tree-based classifiers [1]—learned to predict the optimal connection type with high accuracy, essentially generalizing the rules embedded in the analytical scorer. The ML model was integrated with the analytical calculations in a web application, creating a user-friendly interface where a designer can input parameters and immediately receive a recommended connection along with explanatory data (capacities, safety margins, confidence levels). The final system successfully demonstrates an explainable AI tool for engineering design: one that accelerates decision-making while still providing insight into the underlying mechanics.

Key outcomes include: (1) a working decision-support application for shaft–hub connections that covers a wide range of sizes and use cases; (2) a validated approach to generating and using synthetic engineering datasets for ML, which can serve as a template for other domains lacking large datasets; and (3) evidence that hybridizing analytical models with ML can yield robust and user-accepted solutions, combining domain knowledge with data-driven prediction. The approach effectively bridges deterministic and data-driven methods, showing they are complementary rather than conflicting in the context of engineering design problems.

6.2 Relation to Existing Work

Traditionally, shaft–hub connection selection has been a manual process relying on charts (such as those found in machine design textbooks) and the engineer's judgment [5]. Prior research in mechanical design automation has often focused on specific aspects—for example, optimizing interference fit parameters or analyzing stress in keyed joints—but not on an end-to-end selection among different connection types. This thesis contributes a unique holistic approach. It draws inspiration from previous studies that employed machine learning in engineering, which typically require datasets gleaned from either experimental data or large databases of past designs. In the shaft–hub context, such data did not exist publicly. This work has shown how to build that data in silico using engineering knowledge. This represents an advancement in the methodology of engineering design: rather than seeing the lack of data as a barrier, standards and simulation were leveraged to create the necessary dataset. Recent works in adjacent fields (e.g., ML for material selection or gear design) have also begun to use synthetic data [8], and this work reinforces the validity of that approach for intelligent design systems.

In terms of practical design tools, this system can be seen as an evolution of calculation software that incorporates selection logic. For instance, some commercial software can calculate press fit safety or suggest a fit based on DIN standards, but they do not integrate user preferences or learning. This framework could inform future CAD/CAE software features where an AI assistant actively helps in component selection by learning from built-in engineering libraries.

This work also underscores the importance of maintaining mechanical consistency in AI applications for engineering. Unlike end-to-end black-box models sometimes seen in research, this thesis ensured that the AI's predictions never violate fundamental engineering constraints—a key requirement for acceptance in safety-critical fields. This aligns with the emerging perspective in the literature that combining physics-based models with machine learning (sometimes termed physics-informed ML) yields better trust and often better accuracy. The ML model's structure and training were explicitly rooted in known engineering relations, thus positioning this system as a step towards "expert systems 2.0"—where expert knowledge guides an AI, rather than the AI operating independently.

6.3 Limitations and Future Work

While the developed system performs well within its defined scope, several limitations must be acknowledged. First, the analytical models used are simplified and mostly static. Dynamic factors such as fatigue life, impact loads, and long-term wear are not included. This means the recommendations are suitable for initial design decisions but should be further validated for durability. Including a fatigue-life estimation (perhaps via an additional analysis for each connection type) could be a valuable extension. Second, the system currently considers only three connection types. Other shaft–hub connections exist (tapered shrink disks, polygonal shafts, cross-pin connections, etc.) that might be relevant in certain industries. Extending the framework to additional connection types is straightforward—it would require implementing their analytical models and adding those to the candidate set. The ML model could then be retrained on an expanded dataset. For example, including a clamping element (shrink disk) as a frictional connection option could cover cases where a truly removable high-torque connection is needed; the current system might suggest a spline for that, but a shrink disk might actually be preferable.

Another area for improvement is the user preference interface. The current linear weighting is straightforward but does not capture interactions (e.g., a user might care about cost only if maintenance frequency is low). Future work could explore more sophisticated multi-criteria decision-making techniques, such as the Analytical Hierarchy Process (AHP) or trade-off diagrams, to let users express preferences in a more nuanced way. Additionally, one could attempt to learn preference weightings by observing decisions made by experts, thereby tuning the scoring system to mimic expert choices in historical cases.

On the machine learning side, an interesting future direction is implementing uncertainty quantification. Even though the model outputs probabilities, these are more akin to confidence and not true epistemic uncertainty. Techniques such as Bayesian neural networks or ensemble variance could give a sense of when the model is extrapolating beyond its training (and thus warn the user or fall back on pure analytical computation). This could be important if, for instance, a user inputs a combination far outside normal design ranges; the system should ideally recognize “I have not seen this before” and be cautious.

Finally, it would be beneficial to conduct real-world validation of the system. This could involve testing the tool on case studies from industry or in a classroom setting. Feedback from practicing engineers would likely provide insights on additional factors to include. For example, they might want the system to also suggest dimensions (not just type)—e.g., recommend a certain interference value or a specific DIN 5480 spline size. That would shift it from just selecting type to sizing the connection, which is a natural next step. The current framework lays the groundwork for that: the analytical model already computes what interference is needed, etc., so extending the output to recommend specific tolerances or fits (such as “Use an H7/p6 interference fit with 25 μm interference”) could be achieved.

6.4 Concluding Remarks

In conclusion, this thesis has demonstrated that a hybrid approach combining analytical engineering models with machine learning can effectively automate a design decision process—in this case, selecting shaft–hub connections—in a manner that is both efficient and trustworthy. By encoding the domain knowledge from standards into a form that an AI can learn, the gap between explicit knowledge and data-driven inference was bridged. The developed system provides engineers with a powerful assistant that not only recommends a solution but also explains it, thus preserving the interpretability and confidence that are essential in engineering applications.

This work contributes to the broader vision of intelligent CAD/CAE tools where routine decisions are augmented by AI, allowing engineers to focus creativity and expertise on the more complex aspects of design. The methodology of generating synthetic data from analytical models and using it to train ML classifiers is broadly applicable and could be used to create similar decision-support tools in other design domains (for example, material selection, bearing selection, etc.). As engineering practice increasingly incorporates AI-based tools, data-driven design is expected to become more prevalent, with machine learning algorithms embedded in engineering software to provide instant recommendations that adhere to proven rules. This thesis is a step in that direction, illustrating the potential for improved design workflows that are faster yet remain mechanically sound and explainable. Ultimately, the synergy of human expertise, rigorous standards, and artificial intelligence can lead to better designs achieved in less time—a significant advantage in the competitive field of mechanical product development.

Appendix

Appendix A

Lists

List of Figures

Bibliography

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