Czech Technical University in Prague

Faculty of Mechanical Engineering

Project SGS24/126/OHK2/3T/12

1- Summary

This report details an approach to quality control in Fused Deposition Modeling (FDM) 3D printing, combining a real-time, vision-based fault detection system with a kinematically optimized 5-DOF robotic manipulator. The fault detection system, built with multiple YOLO (You Only Look Once) Convolutional Neural Network (CNN) models, identifies and classifies defects in real-time. The robotic manipulator addresses a key limitation of fixed cameras—blind spots—by dynamically positioning a camera to capture previously inaccessible areas of the print in process. This integrated solution enhances the reliability, precision, and efficiency of additive manufacturing.

2- Project Objectives

1. **Develop a Real-Time Fault Detection System**: Enable automated identification of common FDM defects such as blobs, cracks, and under-extrusion.
2. **Introduce a Robotic Manipulator to Mitigate Blind Spots**: Use a 5-DOF robotic arm to dynamically adjust camera angles, improving coverage and monitoring precision.
3. **Optimize CNN Model Integration for Real-Time Performance**: Employ YOLOv4 Tiny, YOLOv5, YOLOv8, and YOLOv10 for a balanced solution that combines detection accuracy with processing speed.
4. **Implement Adaptive Learning for Enhanced Accuracy**: Continuously refine the defect detection models based on real-time data.

3- Background and Rationale

3.1 Industry Context

As industries increasingly turn to 3D printing for custom, high-precision components, quality control has become essential. FDM 3D printing is a cost-effective manufacturing technique but can suffer from quality issues, with defects compromising structural integrity and increasing waste. Traditional quality control methods, such as manual inspections, often lack the speed and consistency needed for real-time defect monitoring.

3.2 Technology Overview

This project addresses these challenges by combining:

- **CNN-Based Fault Detection**: A YOLO-based fault detection system monitors the FDM printing process in real time, identifying defects that could impact the quality of the printed part.

- **Robotic Manipulator for Dynamic Camera Positioning**: A 5-DOF robotic manipulator enables flexible camera movement to eliminate blind spots in the fault detection system, ensuring comprehensive monitoring of the entire printing process.

4- Proposed Solution Overview

4.1 Fault Detection System

The fault detection system uses a set of CNN models to identify defects during the printing process:

- **3D Printer and High-Resolution Camera Setup**: The camera captures live video feeds of the print in progress.
- **Computing Unit**: Processes video frames with YOLO models (YOLOv4 Tiny, YOLOv5, YOLOv8, YOLOv10) to detect and classify defects.
- **Real-Time Monitoring and Logging Interface**: Detected faults are displayed and logged in real time, providing valuable data for immediate intervention or post-analysis.

4.2 Robotic Manipulator Integration

The 5-DOF robotic manipulator, with its precise control over camera positioning, addresses the limitation of blind spots in fixed camera systems. By adjusting the camera's position and orientation, it enables full 360-degree coverage of the printing process:

Figure 1: 3D model of the 5-DOF robotic manipulator integrated with the camera

4.3 Adaptive Learning Module

An adaptive learning module refines model performance over time by incorporating real-time data, enhancing defect detection for newly observed types of defects or changing printing conditions.

5- System Architecture and Methodology

5.1 Fault Detection Workflow

1. **Video Stream Quality Assessment**: Frames are checked for quality parameters such as brightness, focus, and contrast, filtering out suboptimal frames.
2. **Defect Detection**: YOLO models analyze frames, classifying defects, with each model tailored to specific types of faults.
3. **Data Logging and Analysis**: Detected defects are logged with information on type, location, and timestamp, creating a record for quality control analysis

Figure 2: Example of Acceptable vs. Unacceptable Frame.

5.2 Robotic Manipulator Kinematic Model

The 5-DOF robotic manipulator's kinematic model, based on Denavit-Hartenberg (DH) parameters, enables controlled, precise positioning of the camera:

- **Forward and Inverse Kinematics**: FK calculates end-effector positions, while IK determines joint angles for desired camera orientations.

- **Jacobian Analysis**: The Jacobian matrix is used for velocity control and singularity avoidance, ensuring smooth, uninterrupted monitoring.

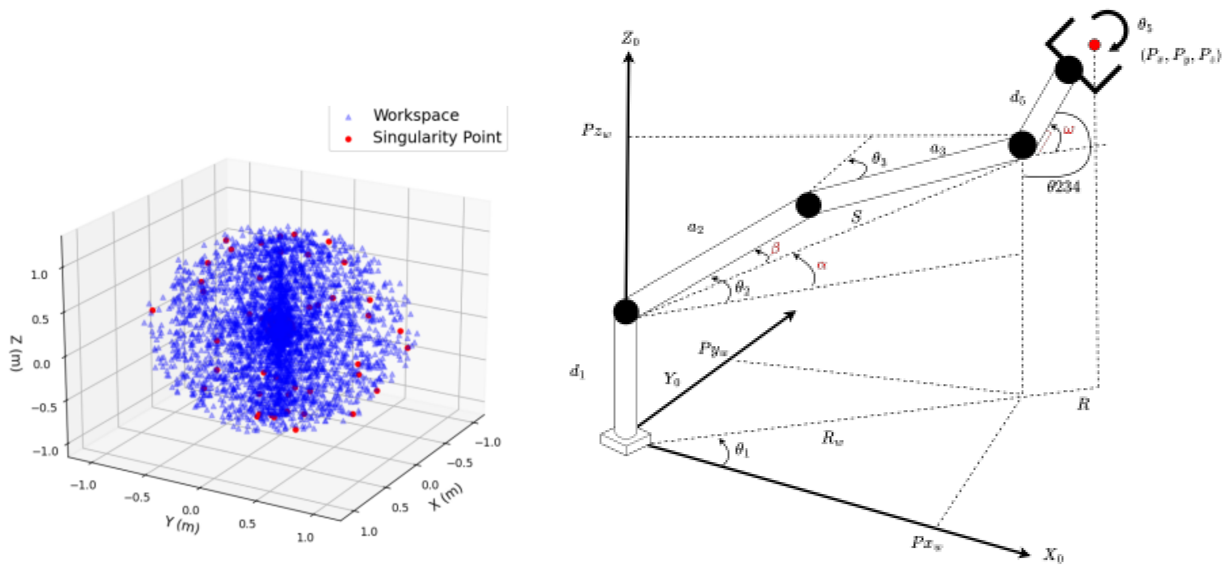

Figure 3: Robotic Arm Frame Assignment and Singularity Map.

5.3 Integration of Adaptive Learning

To ensure continuous accuracy improvement, an adaptive learning system updates the detection models with new defect data, refining their response to changing conditions

5.4 Model Selection and Integration

Four YOLO models—YOLOv4 Tiny, YOLOv5, YOLOv8, and YOLOv10—were selected for their unique strengths in terms of speed, accuracy, and computational efficiency. The combined use of these models allows the system to adapt to different defect types and operating conditions.

YOLOv4 Tiny

- **Speed**: Fast (60 ms), **Accuracy**: Moderate, **Resources**: Low
- **Best for**: Basic, low-resource setups
- **Limit**: Limited for complex defects

YOLOv5

- **Speed**: Moderate (18.6 ms), **Accuracy**: High, **Resources**: Moderate
- **Best for**: Balanced performance

- **Limit**: Higher resource demand

YOLOv8

- **Speed**: Fastest (15.6 ms), **Accuracy**: Very High, **Resources**: High
- **Best for**: Real-time, high-accuracy detection
- **Limit**: High computational load

YOLOv10

- **Speed**: Moderate (20.3 ms), **Accuracy**: High, **Resources**: Moderate-High
- **Best for**: Advanced feature detection
- **Limit**: Needs tuning

6- Data Collection and Model Training

6.1 Dataset Preparation

The dataset includes 2,221 images annotated for six common FDM printing defects: blobs, cracks, spaghetti, stringing, under-extrusion, and warping. Images were sourced from open repositories and augmented to improve model robustness.

Defect Type	Images	Description
Blob	646	Accumulation of excess material forming round deformities.
Crack	821	Linear separations or breaks due to cooling stresses.
Spaghetti	683	Disorganized extrusion resembling noodles from adhesion failures.
Stringing	790	Thin plastic strands between parts caused by nozzle oozing.
Under-extrusion	743	Insufficient material delivery leading to gaps or missing layers.
Warping	562	Print parts distort and lift from the bed due to uneven cooling.

Table 1: Defect Types and Dataset Distribution.

6.2 Training and Testing

YOLO models were trained using the Darknet framework on an NVIDIA GPU-enabled computing unit. Model performance was validated against a reserved subset of data to evaluate accuracy, precision, and inference speed.

7- System Implementation

7.1 Hardware and Software Requirements

- **Hardware**: 1080p minimum cameras, NVIDIA RTX 3060 GPU, Ryzen 5000 CPU, 32GB RAM.
- **Software**: Anaconda with Darknet, Python 3.8, OpenCV 4.5.5 with CUDA, and Roboflow for dataset management.

7.2 Real-Time Fault Detection and Logging

Faults detected by the YOLO models are highlighted in real-time, with defect data such as type, coordinates, and timestamps logged for further analysis.

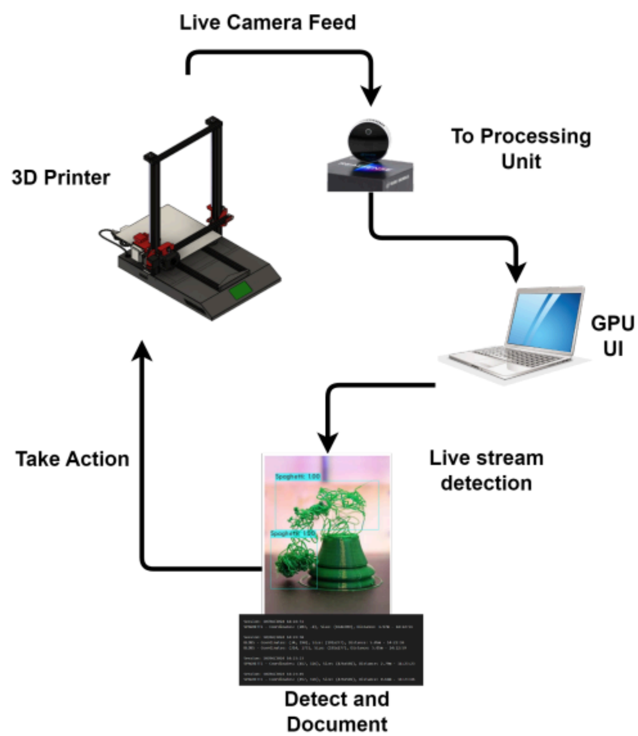

Figure 4: Real-Time Fault Detection in FDM Printers.

7.3 Integration with FDM 3D Printer

The system interfaces with the Creality CR-10S Pro V2 printer, using USB serial communication and G-code commands for control, allowing immediate intervention upon defect detection.

7.4 Robotic Manipulator for Comprehensive Coverage

The robotic manipulator’s flexibility enables dynamic repositioning of the camera, covering hard-to-reach areas and blind spots on large or complex 3D prints.

8- Results and Evaluation

8.1 Fault Detection System Performance

Each YOLO model was assessed for detection accuracy, speed, and computational efficiency. YOLOv8 demonstrated the best balance for real-time monitoring:

Metric	YOLOv4 Tiny	YOLOv5	YOLOv8	YOLOv10
Mean Average Precision (mAP@0.50)	81.4%	87.5%	89.3%	86.0%
mAP@0.50:0.95 (%)	58.4%	62.3%	71.4%	64.9%
Precision (%)	77.0%	91.4%	90.3%	88.1%
Recall (%)	81.0%	84.0%	86.7%	80.2%
F1-Score	0.79	0.80	0.87	0.84
Inference Time (ms)	60	18.6	15.6	20.3

Table 2: Performance Metrics of YOLO Models.

8.2 Kinematic Simulation and Validation

The 5-DOF manipulator’s FK and IK models were validated against target positions, ensuring accurate and reliable camera placement throughout the print:

Point	Target Position (X, Y, Z)	FK Result (X, Y, Z)	Error (Distance)
1	(0.50, 0.30, 0.50)	(0.50, 0.30, 0.49)	0.01
2	(0.40, 0.30, 0.45)	(0.41, 0.30, 0.45)	0.01
3	(0.30, 0.30, 0.40)	(0.30, 0.30, 0.41)	0.01
4	(0.20, 0.30, 0.35)	(0.20, 0.31, 0.35)	0.01
5	(0.10, 0.30, 0.30)	(0.10, 0.30, 0.30)	0.00
6	(0.00, 0.30, 0.25)	(0.00, 0.30, 0.26)	0.01

Table 3: Kinematic Validation of Target vs. Actual Positions.

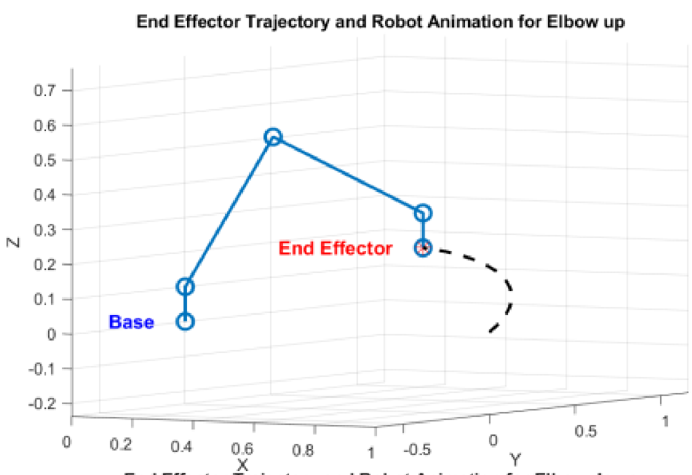

Figure 5: End-Effector Path and Joint Angles for Target Trajectories.

8.3 Adaptive Learning Impact on Detection Accuracy

The adaptive learning component improved detection accuracy by 4.1% over six months, significantly reducing the false positive and negative rates.

Metric	Initial (%)	3 Months (%)	6 Months (%)
mAP@0.50 (%)	89.3	91.7	93.4
Precision (%)	90.3	92.1	94.2
Recall (%)	86.7	88.9	91.5

Table 4: Impact of Adaptive Learning on Model Performance.

8.4 Torque Dynamics and Robotic Stability

Torque and energy analyses were performed to ensure the robotic manipulator operates within safe mechanical limits, maintaining stability during dynamic camera adjustments:

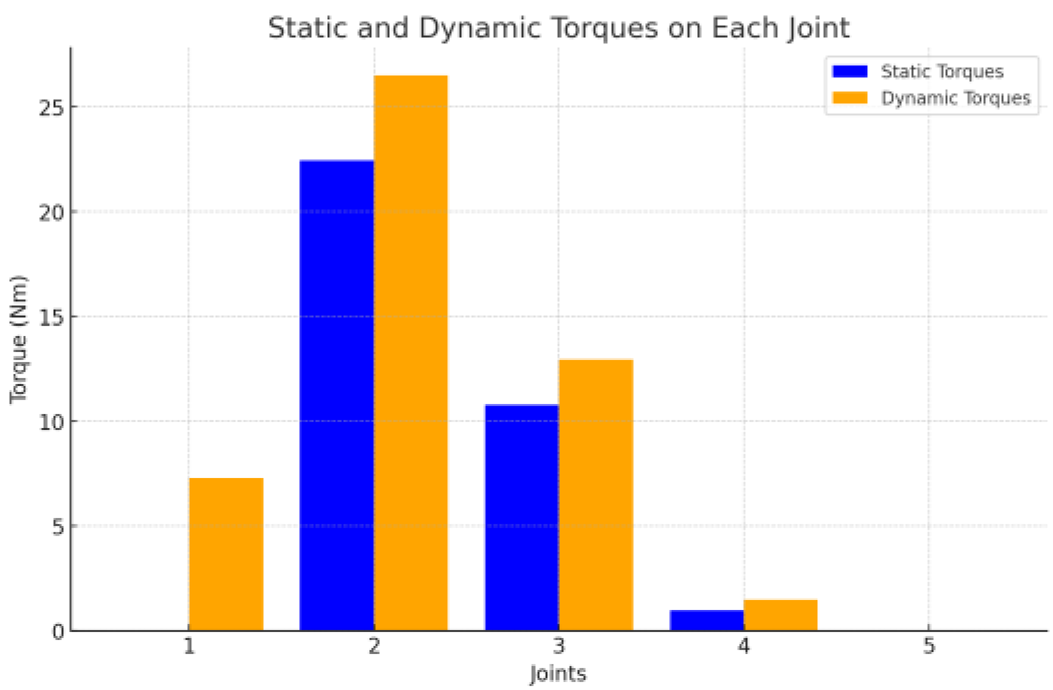

Figure 6: Torque Distribution across Robotic Joints.

8.5 Error Analysis and Mitigation

Misclassifications between similar defect types, such as 'Cracks' and 'Stringing,' were identified and addressed through data augmentation and model fine-tuning. Further improvements were achieved by using ensemble methods to combine model predictions.

Metric	Before (%)	After (%)
Precision (Cracks)	81	89
Recall (Stringing)	86	93
mAP@0.50	89.3	93.4

Table 6: Performance after/Before Mitigation

8.6 System Scalability and Long-Term Impact

Over a three-month testing period, the system achieved a 30% reduction in print errors, saving approximately 58.5 kg of filament. The adaptive learning mechanism enabled continued accuracy improvements, contributing to material savings and operational efficiency.

Metric	v4 Tiny	v5	v8	v10	Overall
Errors Avoided (%)	30.4	35.2	38.1	33.7	-
Filament Saved (kg)	12.5	14.8	17.2	14.0	**58.5**
Total Filament (kg)	50.0	55.0	60.0	55.0	220.0
Filament Saved (%)	25.0	26.9	28.7	25.5	26.6
Time Saved (hrs)	32	42	52	40	**166**

Table 7: Long-Term Performance Metrics

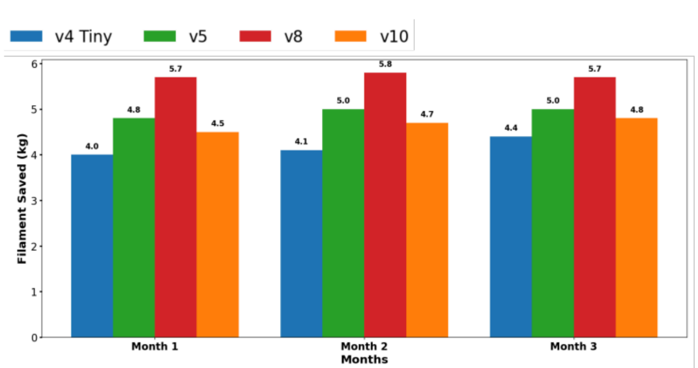

Figure 7: Monthly Filament Savings

9- Discussion

9.1 Eliminating Blind Spots with Robotic Manipulation

The addition of the 5-DOF robotic manipulator effectively addresses the limitations of a fixed camera setup, providing full 360-degree monitoring coverage and enabling detailed, uninterrupted observation of complex prints. The robotic arm's kinematic configuration allows it to reposition the camera dynamically, eliminating blind spots and ensuring high-resolution capture of the entire print surface.

9.2 Impact of Adaptive Learning on Detection System

Adaptive learning has proven effective in enhancing detection accuracy, allowing the system to adapt to variations in print conditions and new defect types over time. This capability is especially valuable in ensuring long-term operational reliability.

10. Conclusion and Recommendations

10.1 Summary of Achievements

This project successfully developed a real-time fault detection system that integrates YOLO-based defect classification with a 5-DOF robotic manipulator for enhanced monitoring flexibility. Key contributions include:

- **Improved Defect Detection**: Achieved through YOLO models and adaptive learning.
- **Elimination of Blind Spots**: Enabled by dynamic camera positioning with a 5-DOF robotic manipulator.
- **Enhanced Accuracy and Efficiency**: Through adaptive learning and kinematic analysis.

10.2 Future Work

Future enhancements could focus on:

- **Real-Time Fault Correction**: Directly linking the detection system to the printer's control to automatically correct print parameters.
- **Predictive Maintenance with Machine Learning**: Preemptively identifying potential issues based on historical defect data.

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1- Summary

This project focuses on advancing the 3D printing of electric machine components through innovative design and material applications. It encompasses the creation and optimization of various motor types, including an DC brushless motor developed from open-source designs. The core objective is to enhance the performance and functionality of these motors by exploring novel design approaches and utilizing advanced materials like iron-embedded PLA for stator cores and steel-embedded PLA for structural components such as casings, rods, and bolts.

By incorporating the advanced fault detection system detailed in the broader project, this work aims to ensure the production of defect-free, high-quality 3D printed motor components. This integration is critical to achieving consistent performance and reliability, laying the foundation for the development of superior electric machines. This approach leverages the capabilities of additive manufacturing, driving innovation in motor design and optimizing efficiency and precision across various motor types.

2- Project Objectives

1. **Develop and Customize 3D-Printed Electric Machine Designs:** Start by using and modifying open-source motor models, embedding advanced materials such as iron-embedded PLA. Progressively move toward creating unique, tailored designs optimized for specific electric machine applications.
2. **Analyze and Evaluate Motor Performance:** Conduct thorough performance testing and analysis of the initial printed motors, focusing on efficiency, durability, magnetic properties, and structural integrity. Use this data to guide iterative improvements.
3. **Integrate Advanced Materials for Enhanced Functionality:** Experiment with and incorporate materials such as iron-embedded PLA for stator cores and steel-embedded PLA for other components, like casings, rods, and bolts, to optimize both mechanical and electrical performance.
4. **Incorporate Fault Detection for Quality Assurance:** Use the fault detection system from the broader project to monitor and eliminate defects in real-time during the 3D printing process, ensuring high-quality, defect-free parts for electric machine components.

5. **Iteratively Refine Motor Designs and Performance:** Based on performance analysis and material testing, create and model original 3D designs, print these unique models, and iteratively refine both the designs and printing parameters to achieve the highest levels of performance, reliability, and efficiency

3- Background and Rationale

3.1 Importance of 3D Printing for Electric Machines

Additive manufacturing, particularly Fused Deposition Modeling (FDM), has revolutionized the production of custom electric machine components. Its ability to create complex geometries, integrate multifunctional materials, and reduce manufacturing costs makes it a powerful tool for innovation in the field of electric machines. 3D printing enables the rapid prototyping of motors and other components, offering unprecedented flexibility in design and material application.

3.2 Challenges in 3D Printing for Electric Machines

Despite its potential, the 3D printing of electric machine components presents several challenges:

- Ensuring precise material deposition for magnetic and structural components.
- Managing defects such as under-extrusion, warping, or delamination that can compromise the functionality of the components.
- Thermal management, especially for materials like iron-embedded PLA, which may exhibit thermal sensitivity during operation.
- Achieving consistent quality and performance in components with unique material properties like magnetic PLA.

4- Proposed Solution Overview

4.1 Material Advancements

This project focuses on testing a variety of PLA filaments with embedded magnetic and metallic properties to determine their suitability for 3D-printed electric machine components. The materials being evaluated include iron-embedded PLA for stator cores and steel-embedded PLA for structural components like casings, rods, and bolts. Key material properties such as magnetic permeability, mechanical strength, thermal stability, and electrical conductivity are analyzed to assess their performance under real-world operating conditions. Comparative testing will focus on how these materials influence the overall efficiency, durability, and functional performance of the electric machines.

4.2 AI Driven Design Optimization

The project incorporates AI-driven tools to refine and enhance the design of 3D-printed electric machine components. Based on the results of material testing and performance analysis, design errors will be systematically evaluated to identify areas for improvement. Using insights from these evaluations, a unique and optimized design will be developed with the assistance of AI tools. These tools enable predictive modeling, defect mitigation, and iterative refinement of geometries to address material-specific challenges such as layer bonding, magnetic flux distribution, and structural integrity. The goal is to create an innovative design that not only eliminates 3D printing defects but also maximizes the performance and reliability of the electric machines, leveraging the synergy of advanced materials and AI-driven design processes.

4.3 Thermal Management

Thermal issues in 3D-printed electric machines will be addressed by utilizing thermal imaging cameras to identify areas of excessive heat generation in the printed motors. These investigations will guide targeted design improvements, such as adding cooling channels or optimizing material distribution in problematic areas. AI tools will assist in analyzing thermal patterns and suggesting design modifications to enhance heat dissipation, ensuring optimal performance and reliability.

4.4 Precision and Quality Control

Precision and quality control in the 3D printing process will be overseen by integrating the fault detection system developed in the broader project. This advanced system will monitor the printing process in real-time, identifying and addressing defects such as layer misalignment, under-extrusion, and surface irregularities. By leveraging this system, the project ensures the production of high-quality, defect-free components, enhancing both the reliability and performance of the electric machine parts.

5- Methodology

In this phase of the project, a fully functional 3D-printed DC brushless motor has been successfully constructed using parts and designs sourced from open-source repositories. This motor serves as a proof of concept for the integration of advanced materials and optimized designs. Additionally, work has begun on a second motor, designed specifically for underwater operation. This underwater motor, also based on parts and designs found in open-source repositories, is currently a work in progress and highlights the project's aim to explore innovative and versatile applications of 3D-printed electric machines.

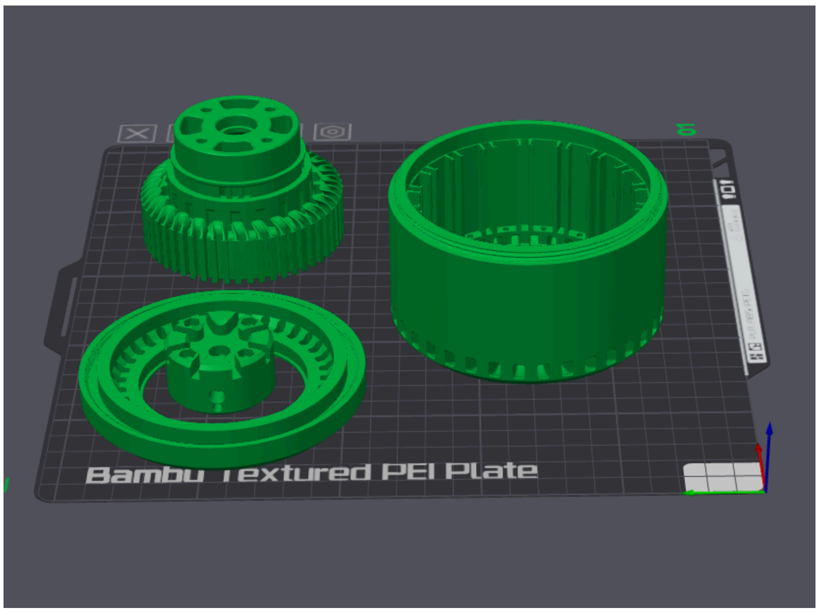


Figure 1: CAD Design of the main open-source model constructed using 3D printing

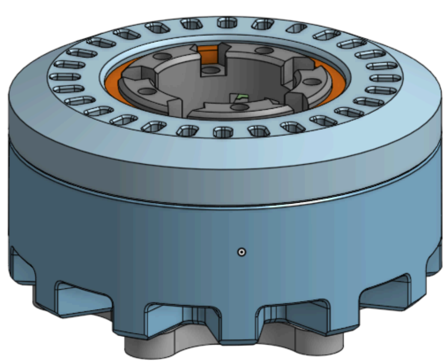


Figure 2: CAD Design of the secondary open-source model constructed using 3D printing (design for underwater applications)

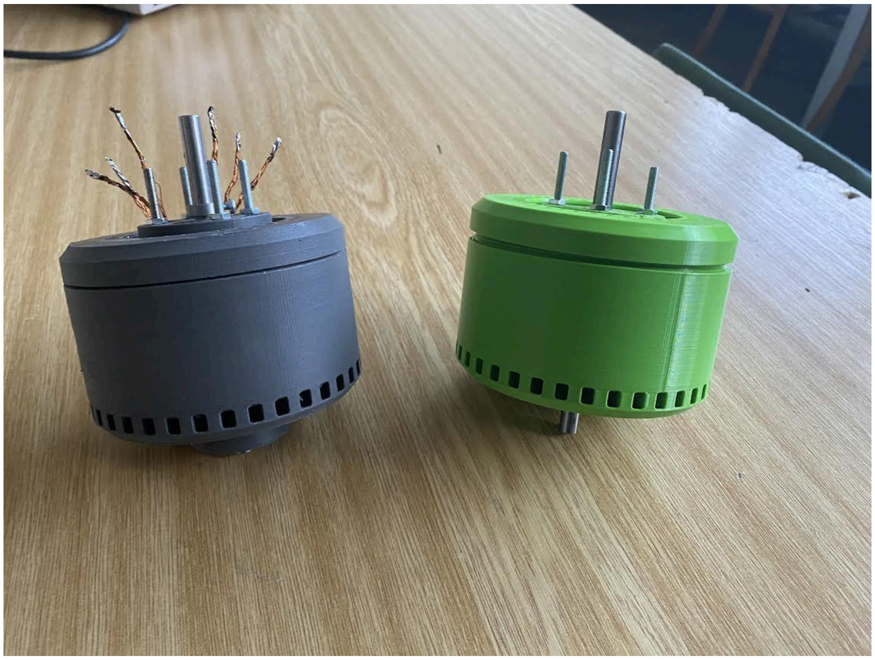


Figure 3: Two variations of the main open-source motor model constructed using 3D printing: the left model is made entirely of iron-embedded PLA, while the right model uses iron-embedded PLA only for the core

6- Results and Evaluation

The virtual motor was modeled in **JMAG-Express Online** based on the exact dimensions and specifications of the 3D-printed motor created during the project. This simulation replicates the physical attributes of the printed motor to evaluate its expected performance and identify potential areas for improvement.

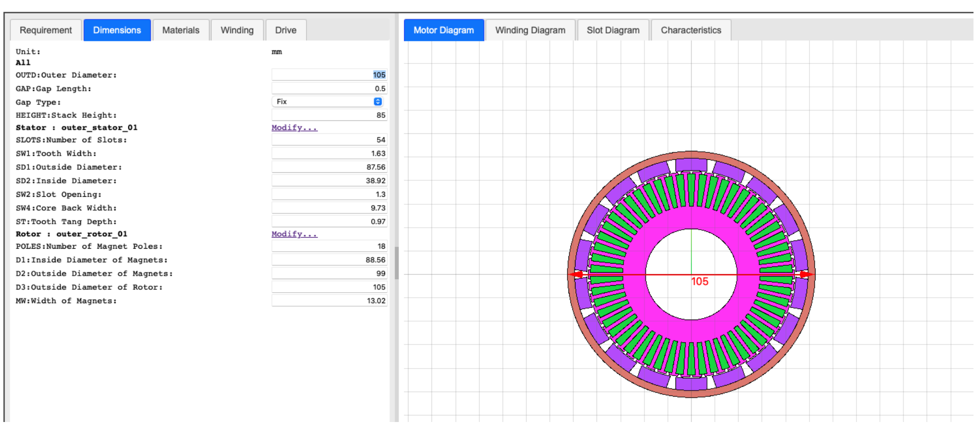
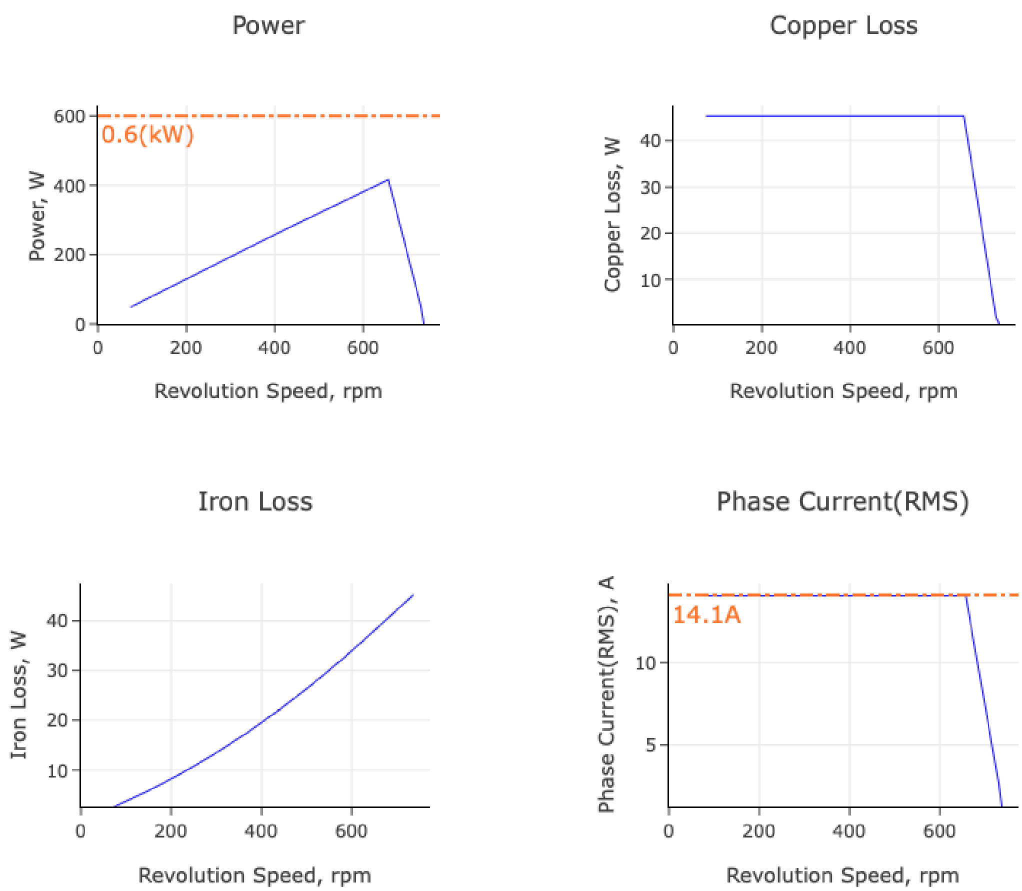


Figure 4: Virtual construction of the main model to anticipate the results

The following tables present the expected results for the motor, simulated using **JMAG-Express Online**. This tool was utilized as a practical alternative due to the current lack of access to more advanced simulation tools such as ANSYS Maxwell. However, if further research or detailed analysis is required, integrating ANSYS or other comprehensive tools into the project workflow will be considered.



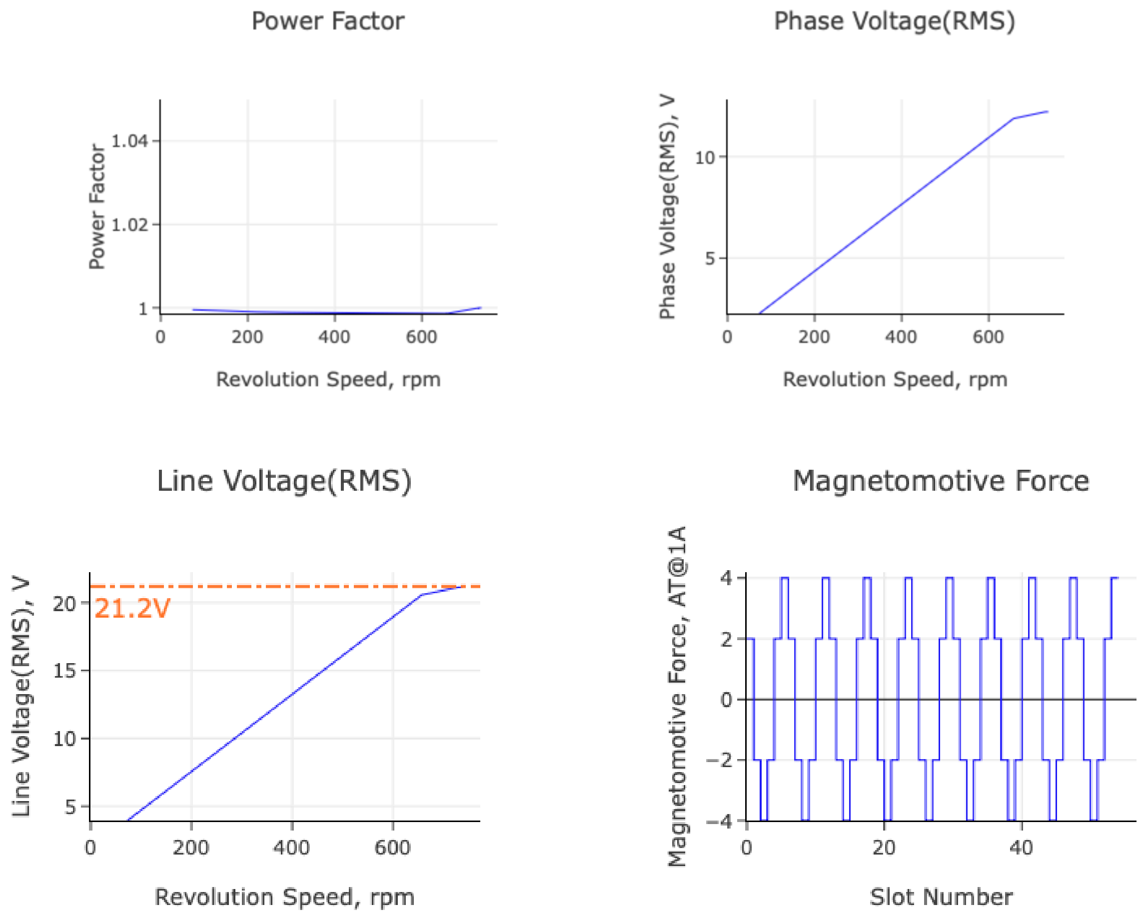


Figure : Simulation results of the virtual construction of the main model in JMAG-Express Online, presented across eight graphs

9- Discussion

These results will be used as a baseline for comparison with:

1. A motor constructed using fully iron-embedded PLA.
2. A motor with iron-embedded PLA limited to the core.
3. A commercially available motor with similar dimensions and specifications.

This comparative analysis aims to evaluate the impact of material choices on performance metrics such as torque, efficiency, and thermal behavior. By benchmarking against a market-available motor, the project will also assess the feasibility and potential of 3D-printed motors in practical applications.

It is anticipated that there will be only a small difference between the two constructed motors—one made with fully iron-embedded PLA and the other with iron-embedded PLA limited to the core. The expected superiority of the fully iron-embedded PLA motor is attributed to its enhanced magnetic properties; however, this remains a hypothesis until validated through physical testing.
Neither of the 3D-printed motors is expected to achieve performance parity with the commercially available motor. Nevertheless, the primary objective of this project is to innovate and refine 3D-printed motor designs to progressively achieve a performance level comparable to that of market-standard motors, thereby exploring the feasibility of additive manufacturing in high-quality electric motor production.

10- Conclusion and Recommendations

10.1 Summary of Achievements

As part of the project, two 3D-printed motors with distinct configurations have been successfully developed. The first motor uses iron-embedded PLA exclusively for the stator core, while the second motor incorporates iron-embedded PLA in all components except for bolts and rods. These motors will undergo comprehensive testing to evaluate their magnetic properties and overall performance. Additionally, the printing process for an underwater motor has been initiated, marking significant progress in exploring diverse applications of 3D-printed electric machines. This systematic approach aims to provide valuable insights into the capabilities and limitations of various materials and designs.

10.2 Future Work

The project is currently focused on the “Analyze and Evaluate Motor Performance” and “Integrate Advanced Materials for Enhanced Functionality” stages. These tasks are being conducted simultaneously to accelerate progress and ensure a cohesive development process. By testing the performance of initial motor designs and experimenting with advanced materials such as iron-embedded and steel-embedded PLA, the project aims to gather critical insights for refining designs and enhancing functionality.

Future efforts will build on these findings, transitioning to iterative design refinement and the development of unique motor models tailored for superior performance. Additionally, incorporating insights from thermal management and quality control will further optimize the production process and ensure the reliability and efficiency of the final electric machine components.