A Neural-Fuzzy System for Predicting the Areal Surface Metrology Parameters

Ronak Sharma

Computer Systems Engineering

The University of Sheffield

Supervisor: Mahdi Mahfouf

Content

- Motivation
- Aims and Objectives
- Experimental Setup
- Artificial Intelligence (AI) Based Model
- Reverse Engineering
- Graphical User Interface(GUI)
- Conclusion and Future Work

Motivation – Industry 4.0

Rise of Industry 4.0

- Increasing demand for faster manufacturing has given birth to Industry 4.0
- Despite the rise of Industry 4.0, the physical inspection of end products like measuring surface roughness is still a challenge
  - Costly and Time Consuming

Motivation - Surface Metrology

Surface Metrology

- Measuring small scale characteristics such as vibration and force
- These are highly correlated to a product’s physical properties like surface roughness

A typical 3D surface plot for the surface metrology measurement

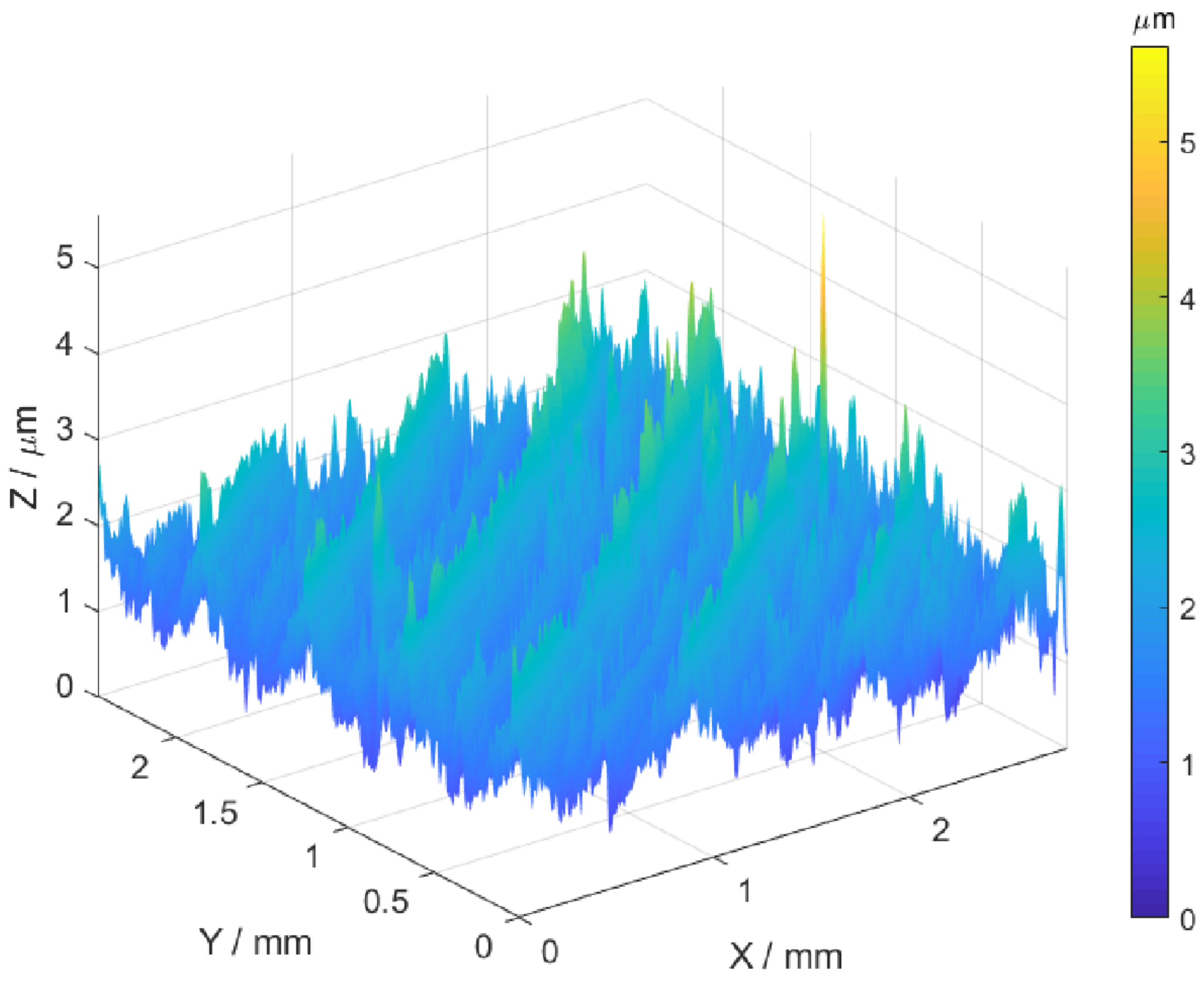


Fig 1: *Typical surface metrology measurement of a part. This includes a 3mm x 2.5mm surface patch with a sampling density along the two axes equals to 100 samples per mm; the sampling interval being 10 microns [1]*

Motivation - Surface Metrology

Aim

- Develop a framework to predict the optimal surface metrology parameters, required to achieve the desired surface roughness

- Substitute the physical inspection of end products with this “digital twin” thus achieving quicker production cycles, lower costs and better customer satisfaction

Research Aims and Objectives

1. Design an AI model to predict the surface roughness of an end product, using surface metrology data such as force and vibration

2. For right-first time production, reverse-engineer the above designed model to determine the optimal surface metrology parameters

3. Develop a GUI to embed the modelling and the reverse-engineered framework for use by industries

Experimental Setup

- Seventeen Steel (EN24) Blocks underwent machining processes i.e. milling and turning at Advanced Research Manufacturing Centre (AMRC), UK
- Vibration, Force and Temperature were recorded using digital measurement systems
- Physical property of the end product i.e. surface roughness was measured at The University of Huddersfield

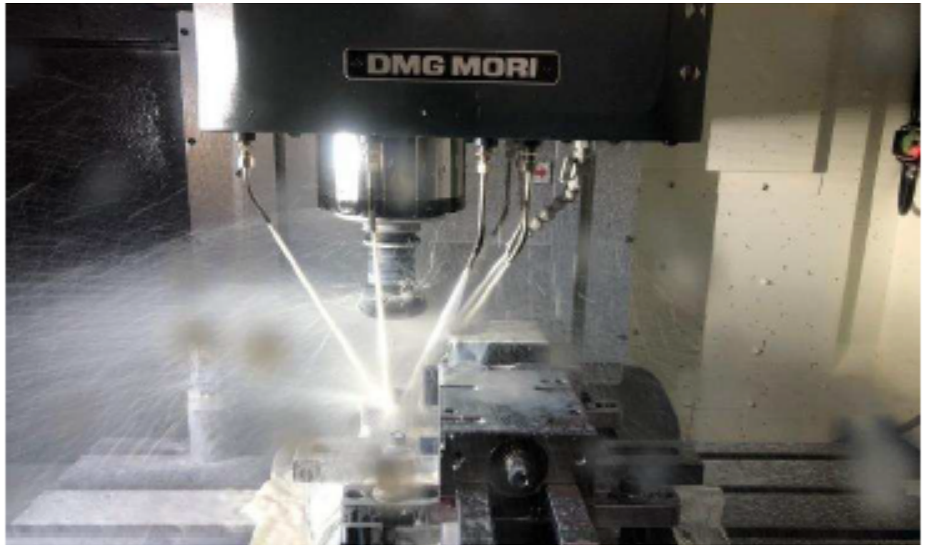


Fig 2: *Shows machining of the block [1]*

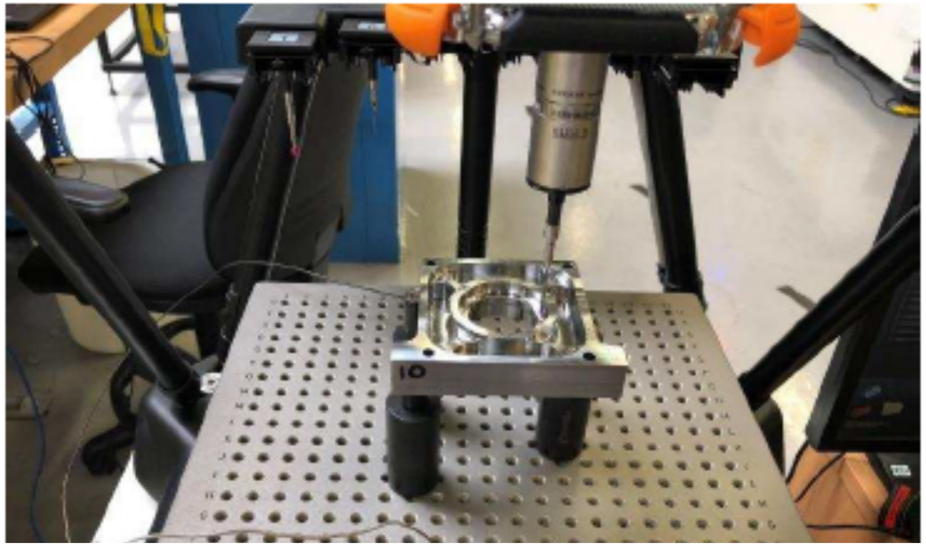


Fig 3: *Shows the surface roughness being measured[1]*

Stage 1
Model Design

Preliminary Model Design

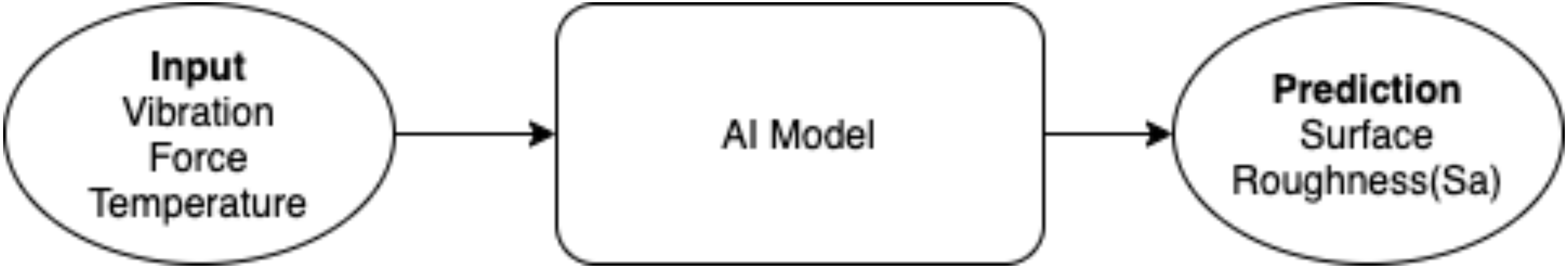


Fig 4: Shows the high-level AI model design for predicting the surface roughness

Feature Extraction

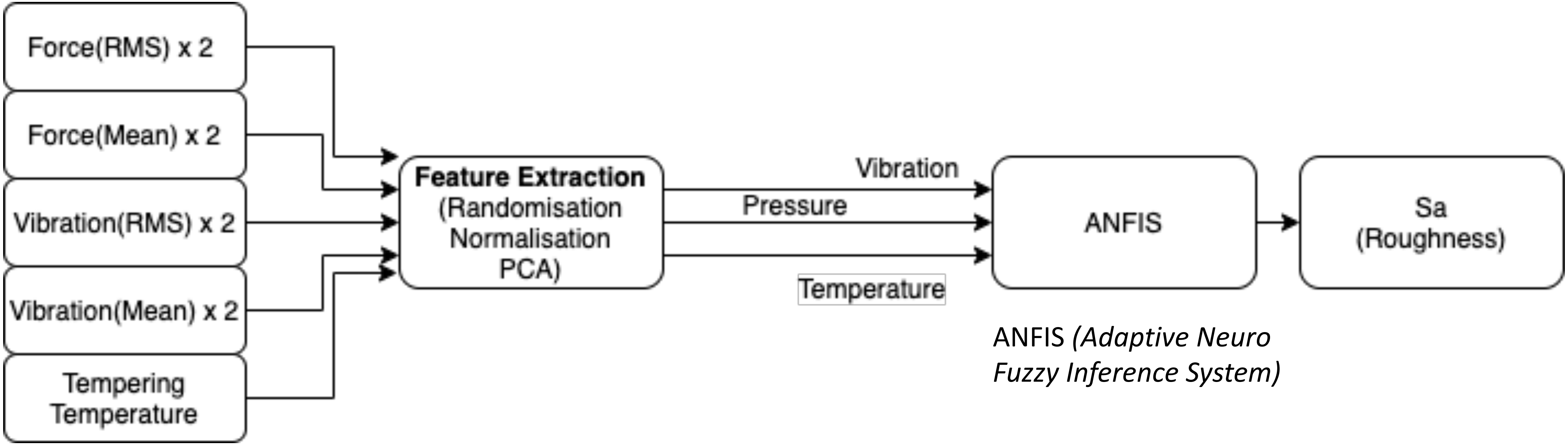
Using the statistical features of the Force and Vibration dataset rather than the actual values

- Root Mean Square (RMS)
- Mean

Milling				**Turning**				
Force		**Vibration**		**Force**		**Vibration**		**Temperature**
RMS	Mean	RMS	Mean	RMS	Mean	RMS	Mean	Discrete Value

Table 1: Shows the structure of dataset used for training the model

ANFIS Model Architecture



ANFIS *(Adaptive Neuro Fuzzy Inference System)*

Fig 5: Shows the Nine Input Single Output architecture designed for predicting surface roughness

Verification and Results

Verification

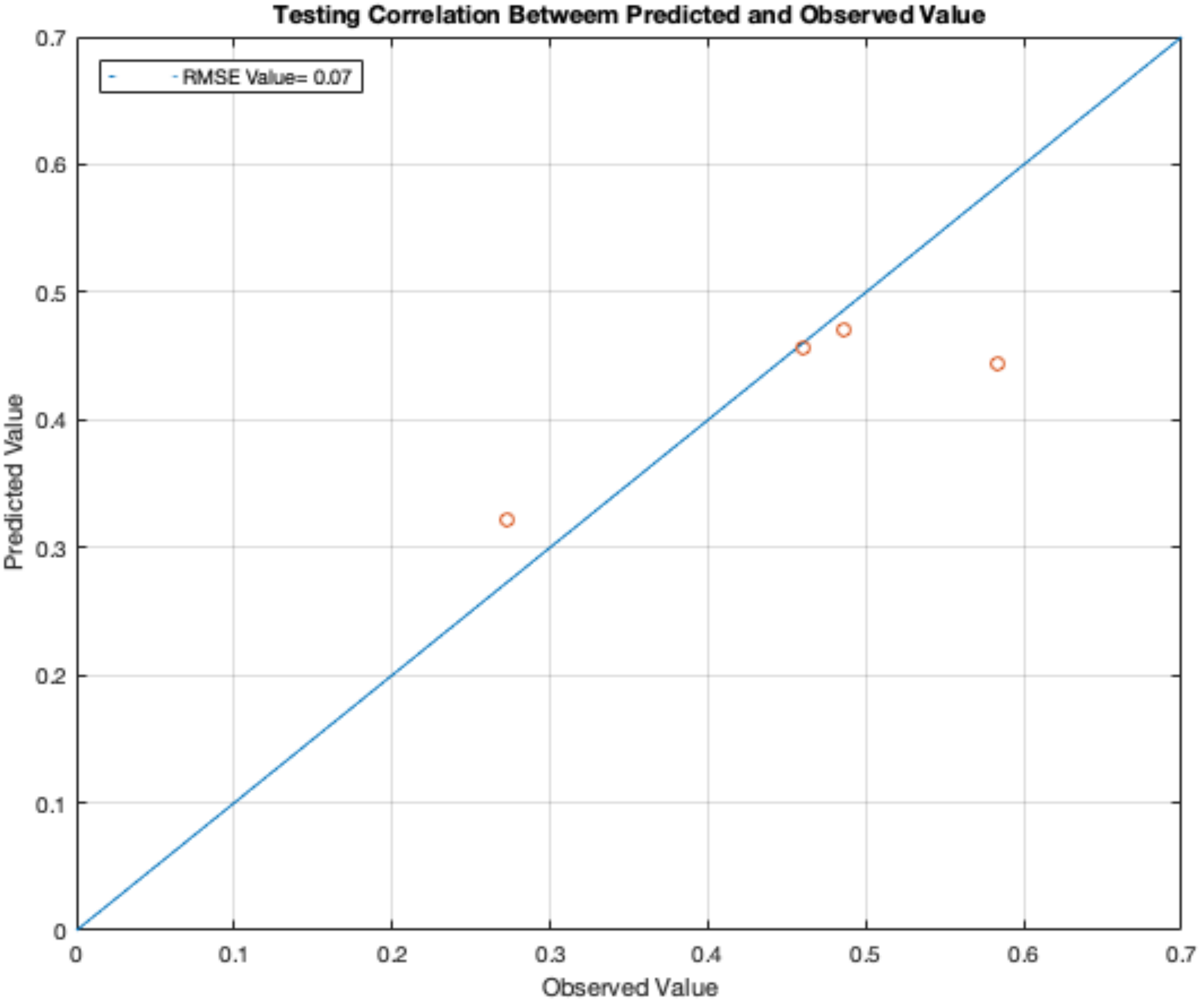
- 10 runs with randomising the input to the model
- 4 Fold Cross Validation performed due low data availability

Results

- Comparing the ANFIS predicted and target surface roughness value
  - Average over 10 runs: High Correlation Coefficient **i.e.** ***Corr=0.89***
  - Average over 10 runs: Low RMSE Values *i.e.* ***RMSE=0.07***

Correlation Plot

Fig 6: Shows the correlation between predicted and observed surface roughness values



ANFIS 3D Surface Plots

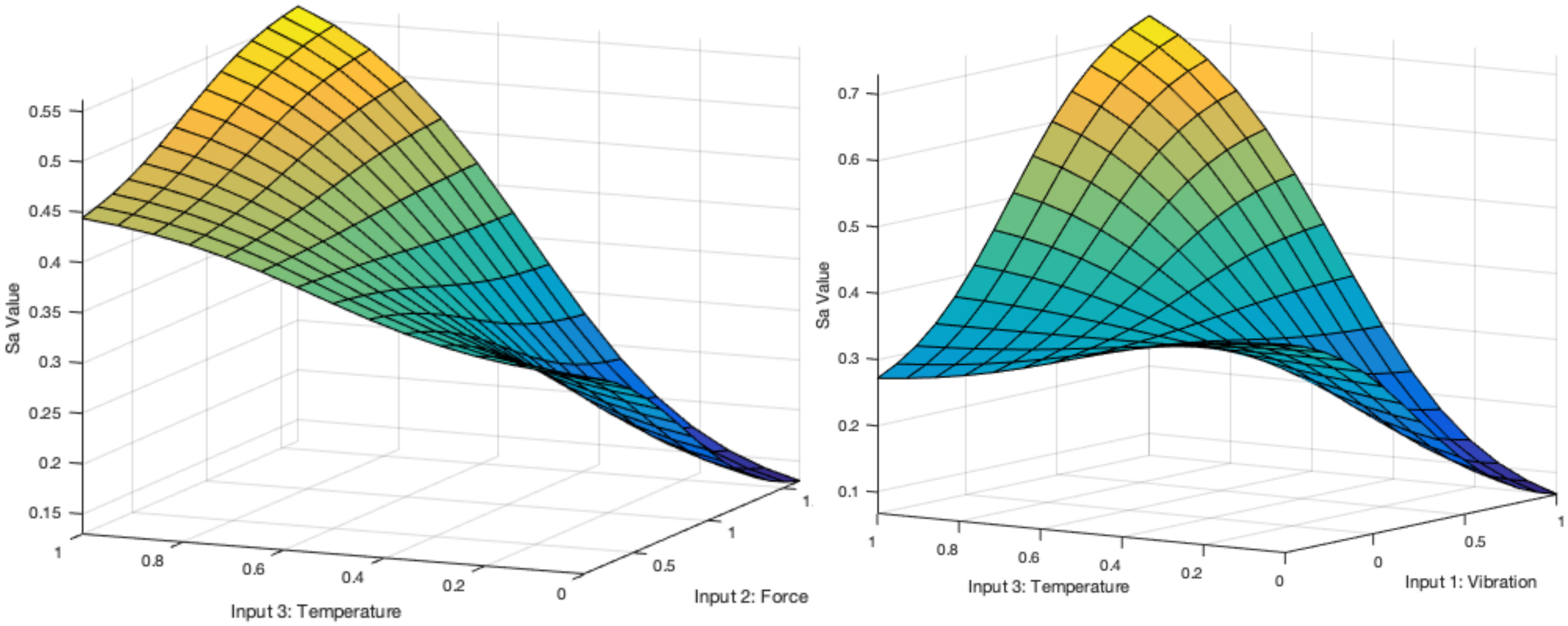


Fig 7: Shows the 3D surface plots between the Surface roughness and two inputs

Stage 2
Reverse Engineering ANFIS Model

Reverse Engineering Framework

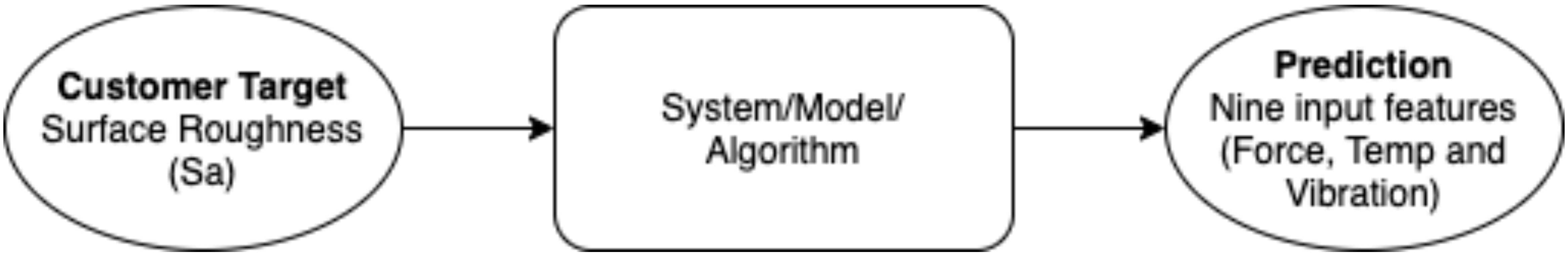


Fig 8: Shows the high-level reverse engineering architecture

Reverse Engineering Methodology

- The developed ANFIS model was non-linear and hence was irreversible
- Optimisation was applied to reverse engineer the model by minimising the error between the predicted and target surface roughness value
- Genetic Algorithm was used for optimisation
  - Based on natural selection, i.e. “survival of the fittest”

Optimisation Architecture

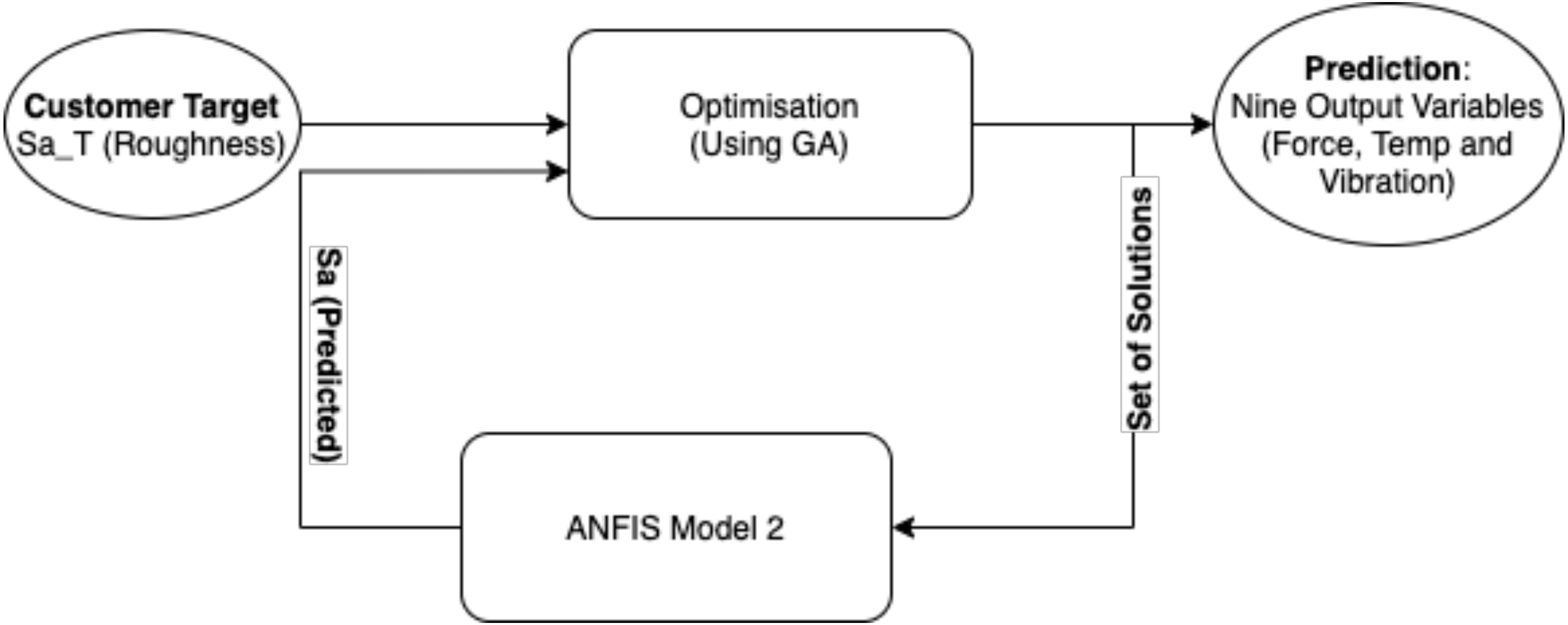


Fig 9: Shows the reverse engineering framework to predict the optimal surface parameters

Stage 3
Designing a GUI

Features

- Easy deployment to industry as a single software package
- Minimal staff training required to operate this tool
- Easy to understand without the need of much domain knowledge

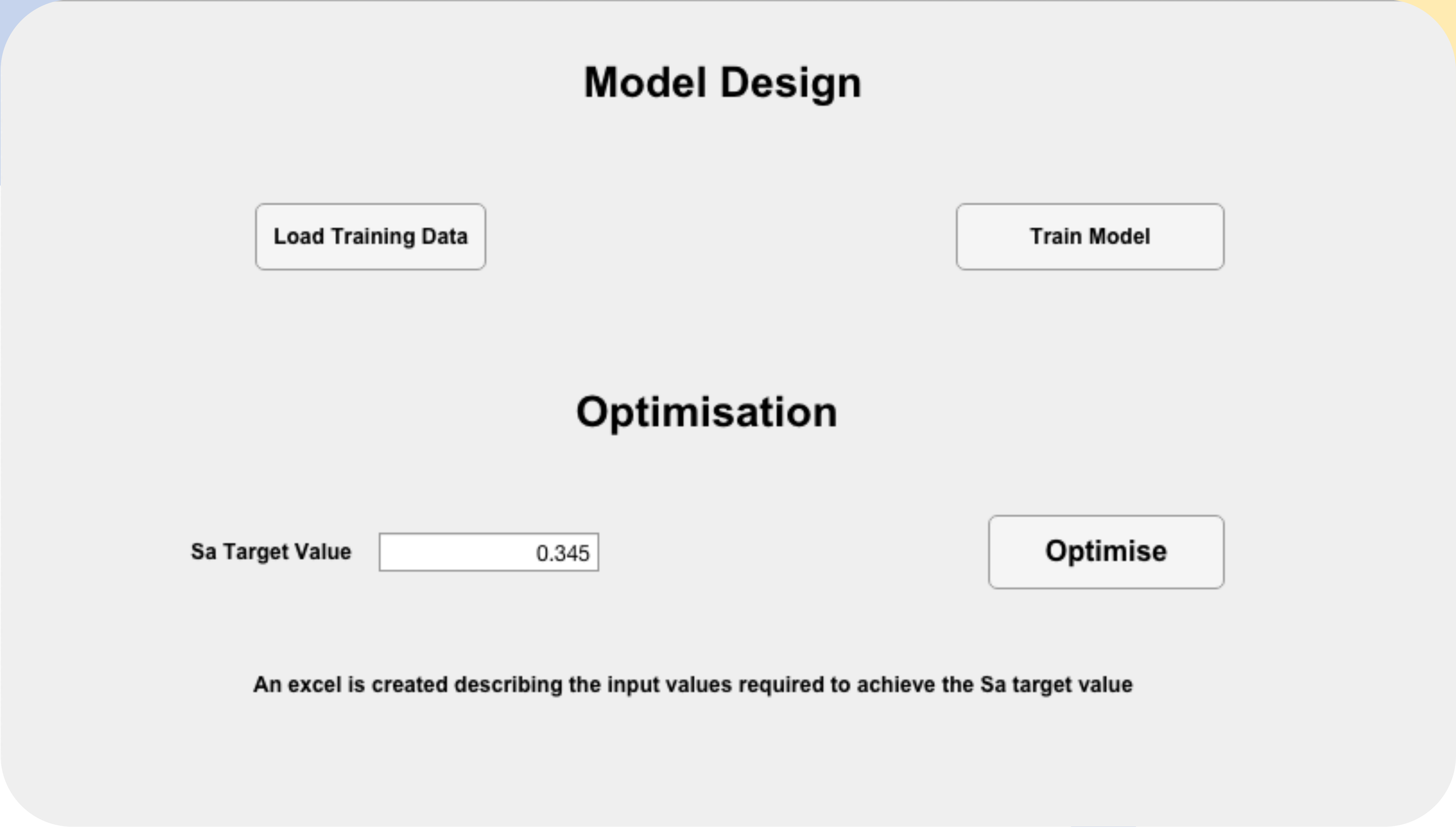


Fig 10: *Shows the GUI developed*

Conclusion

- Designed an ANFIS model to predict the surface roughness using vibration, force and temperature dataset
- Applied optimisation to reverse engineer the ANFIS model for predicting the optimal surface metrology parameters
- Developed a GUI with an aim to discard the physical inspection and testing of end products
- **Future Work**: Conducting more experiments, Investigating other ML models, Implementing Cloud Computing

Acknowledgements

Professor Mahdi Mahfouf

Dr. Olusayo Obajemu

References

- *[1]: Papananias, M., McLeay, T., Mahfouf, M. and Kadirkamanathan, V., 2019, April. An intelligent metrology informatics system based on neural networks for multistage manufacturing processes. In Procedia CIRP. Elsevier.*