U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO
SYSTEC

Sensor System for Predictive Maintenance in Industrial Environment

Master's in Electrical and Computer Engineering

André Cunha Enes Gonçalves

Supervisor: Professor Vítor H. Pinto

Table of contents

01 Context and Motivation

02 Objective

03 Background and Related Work

04 Implementation

05 Results

06 Conclusion and Related Work

01

Context and Motivation

Context and Motivation

Maintenance **costs**:

- **15 to 60%** of **all** manufacturing operations[1]
- Highly dependent on industry type

Worker **well being**:

- Prolonged exposure to noisy environments
- Decreased productivity[2]
- Increased accident risk[2]

Industry **dependence on legacy equipment**:

- Retrofitting

1. (Zonta et al., 2020) Predictive maintenance in the industry 4.0: A systematic literature review. Computers and Industrial Engineering
2. (Tagawa et al., 2021) Acoustic anomaly detection of mechanical failures in noisy real-life factory environments.

Context and Motivation

Predictive Maintenance

Monitor component state;

Repairs or replacements only **when necessary**.

Wireless Sensor Module

Retrofit legacy equipment;

Wirelessly **detect faults**;

Alert necessary maintenance.

02

Objective

Objective

Sensor system
for
Predictive Maintenance

→

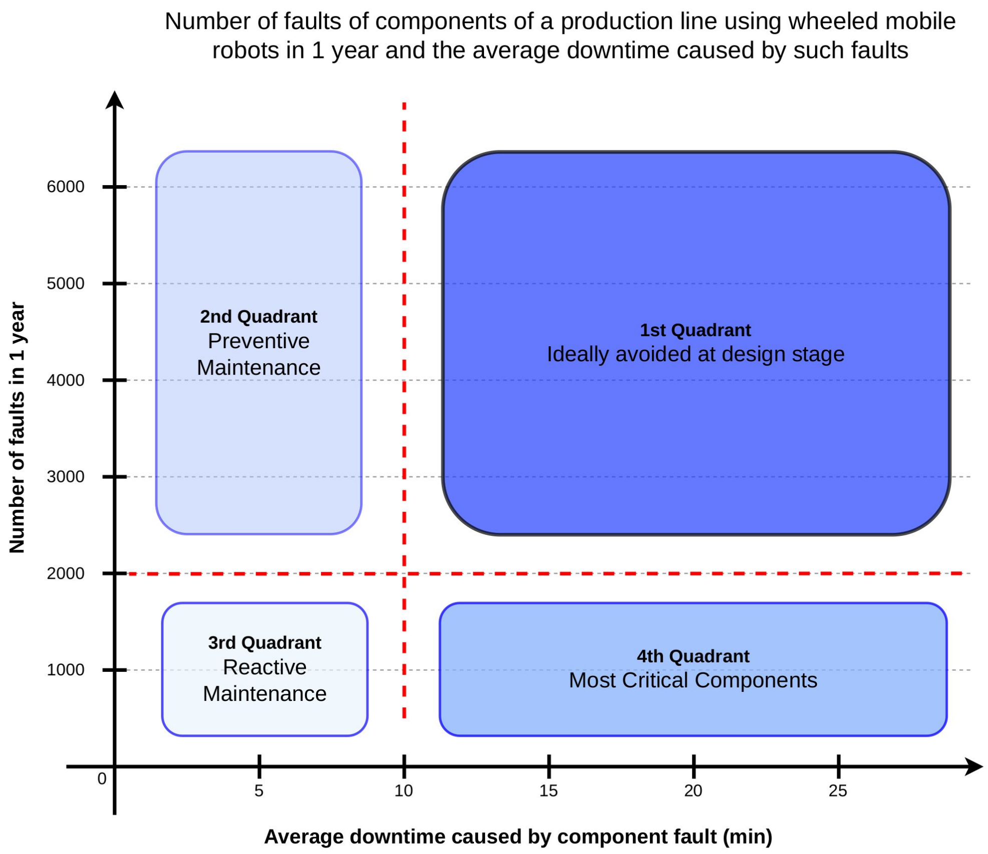
Detect anomalies in an Automated Guided Vehicle and surrounding machines

- Build custom testing platform
- Cost-effectiveness

03

Background and Related Work

Critical Components



Typical **4th quadrant** components:

- Bearings
- Gearboxes
- Induction motors

Adapted from (Lee et al. 2014) Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. Mechanical Systems and Signal Processing

Physical Quantities in Predictive Maintenance

- Vibration
- Sound
- Acoustic Emission
- Temperature
- Electric Current

Prediction Problem

Objective

Detect faults in the Automated Guided Vehicle and surrounding machines

Challenge

No theoretical model

Proposed Solution

Anomaly Detection using Machine Learning

Identify **points that deviate** from the expected **normal behaviour** within a dataset

Anomaly Detection Insights

- **Binary** classification
  - Multi-class Anomaly Detection also exists
- Supervised Learning
  - **All** classes represented in the training dataset
- Semi-supervised Learning
  - Only **part** of all classes represented in the training dataset
  - **Only normal** instances
- Unsupervised Learning
  - **No** predefined classes
- **Lack** of anomalous samples

Testing Platforms

Main characteristics:

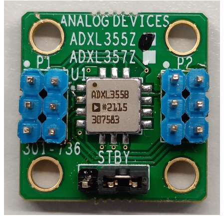
- Induction motor (around 750 W)
- Gearbox
- Bearings
- Shaft
- Meant to replicate **heavy machinery**

Machinery Fault Simulator from SpectraQuest

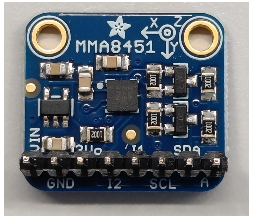
04

Implementation

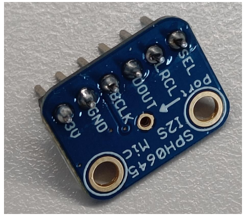
Hardware



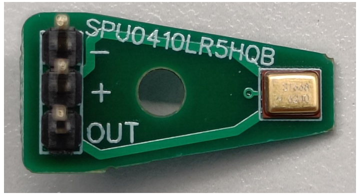
Accelerometer 1



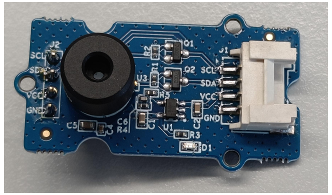
Accelerometer 2



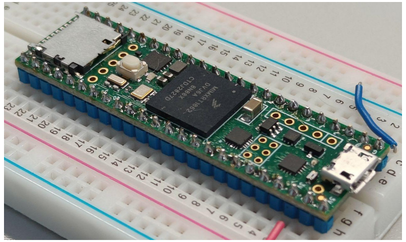
Digital Microphone



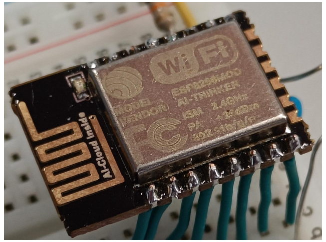
Ultrasonic Microphone



Infrared
Thermometer



Microcontroller
Teensy 4.1

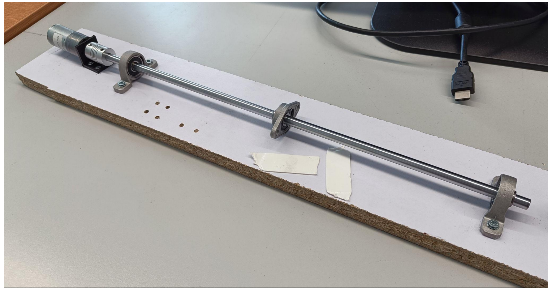


WiFi connection
ESP-12E

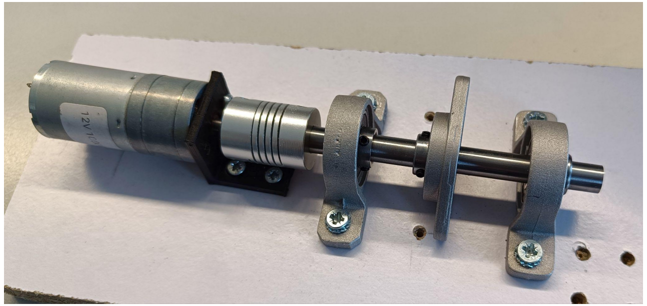
Custom Testing Platforms

- Available **public datasets**
  - **Not suitable** for the problem at hand
- **Validation** of sensor module
  - Sensor efficacy
  - Recording program structure and debugging
  - Controlled noise sources
  - Components similar to the AGV
- **More than 1** platform
  - Test multiple scenarios
  - Compare method
- **Adaptation** from the literature

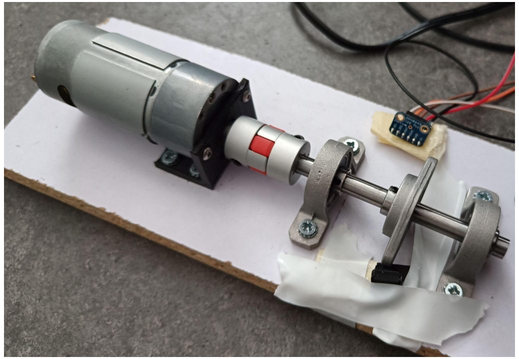
Custom Testing Platforms



Testbed 1



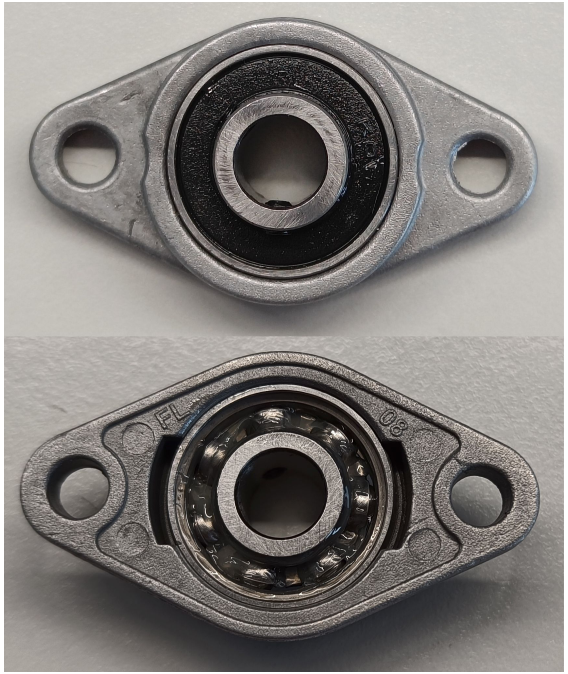
Testbed 2



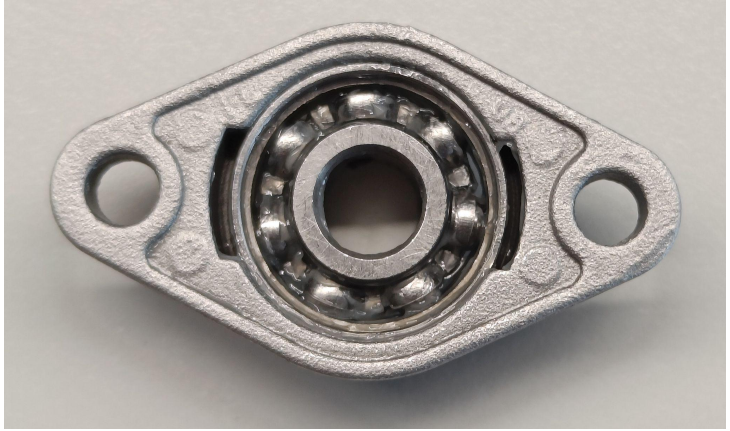
Testbed 3

	Testbed 1	Testbed 2	Testbed 3
12V DC motor	1000 rpm	1000 rpm	2640 rpm
Shaft length	40 cm	10 cm	10 cm

Tested Components



Normal



Anomalous

Software Structure

- Save **raw** sensor data in integrated SD card
  - Avoid information loss
  - An application layer is not necessary
  - Test preprocessing methods
- **1 second** recordings
  - Number of samples according to sensor sample rate
  - Join different data types
  - Capture system dynamics

Preprocessing Steps

- **Record** data from the sensors for **1 second**
  - Single values to represent the whole data
- Central tendency-based **time-domain** features
  - Less data to send wirelessly
  - Potentially less reliance on sensor bandwidth
  - Less computation
- Feature **scaling**
  - Vibration and sound: *RobustScaler*
  - Temperature: *StandardScaler*

$$RMS = \left(\frac{1}{N}\sum_{i=1}^{N}[X(i)^2]\right)^{\frac{1}{2}} \qquad Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X(i)-\mu}{\sigma}\right)^3 \qquad ImpulseFactor = \frac{max(|X|)}{\frac{1}{N}\sum_{i=1}^{N}|X(i)|}$$

Dataset Structure

355_rms	mma_var	mic_kurtosis	obj_temp	anomalous
0.3190	-0.2343	0.2479	0.9574	0
-0.2697	-0.3115	0.0923	0.9638	1

Machine Learning Models

Supervised

- k-Nearest Neighbors (k-NN)
- Support Vector Machine (SVM)
- Random Forest (RF)
- AdaBoost
- XGBoost

Unsupervised

- One-Class SVM
- Isolation Forest
- Local Outlier Factor (LOF)

05

Results

Metrics

In the scenario:

- **False Negatives** more **detrimental** than **False Positives**

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1\,Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

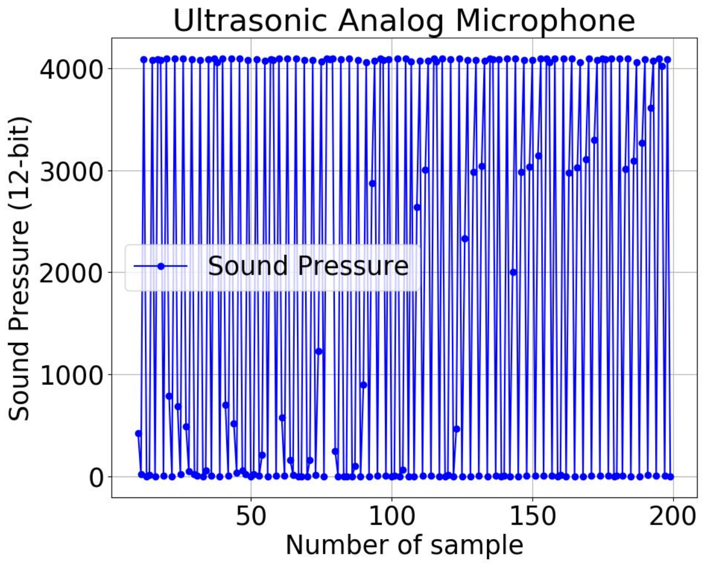
TP: True Positive TN: True Negative FP: False Positive FN: False Negative

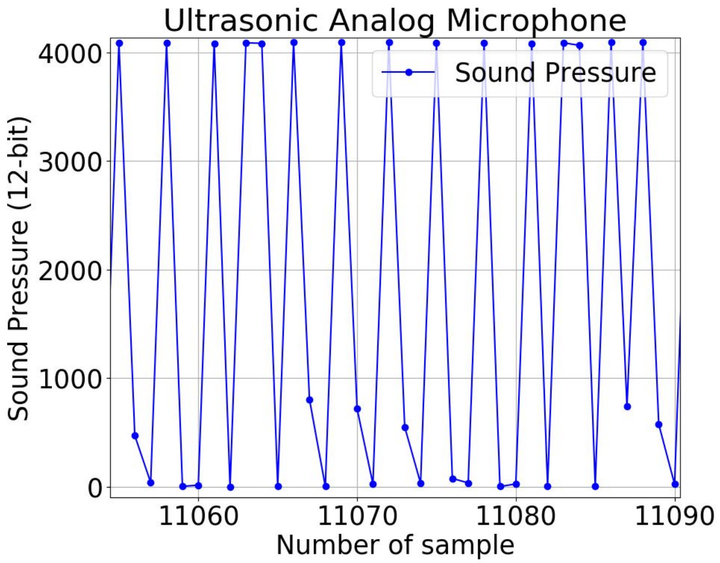
Test Structure

- **Binary** classification task
- **Train Test Split** for Supervised models
    - 80% for training, 20% for testing
- Dataset **unbalance**
    - Train models with different amounts of anomalous samples
    - Simulate lack of samples
    - 9%, 20%, 33%, 43% and 50%
- Sensor **comparison**

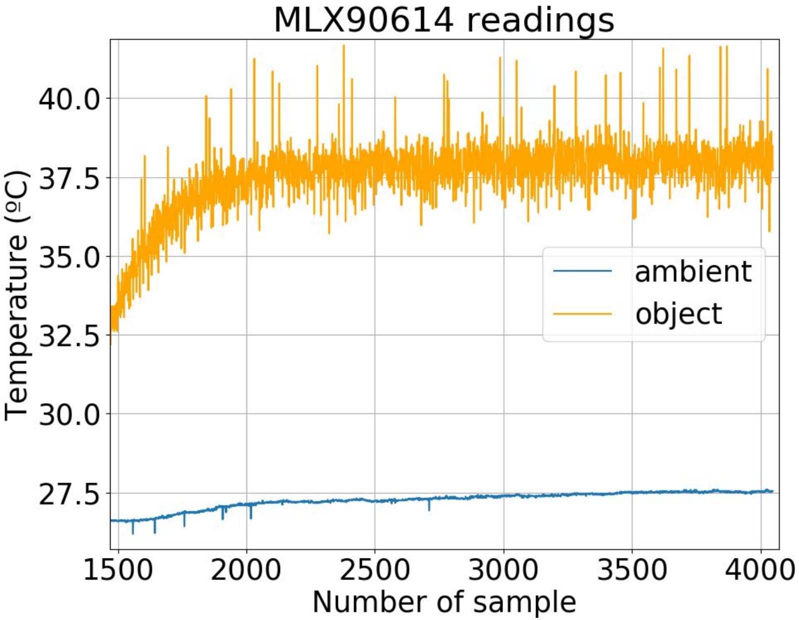
No. samples	Testbed 1	Testbed 2	Testbed 3
Normal	3018	4049	4161
Anomalous	3058	4323	3966

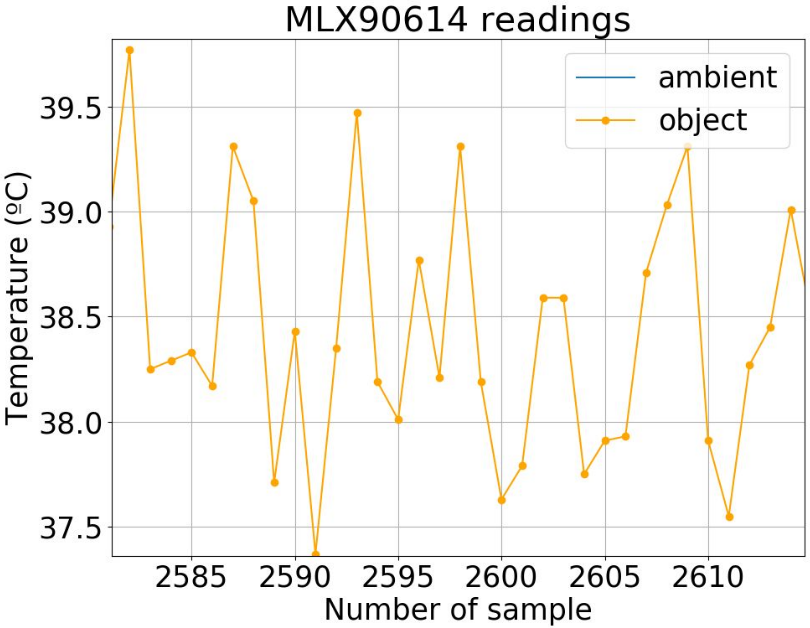
Sensor Analysis – Ultrasonic Microphone





Sensor Analysis – Infrared Thermometer





Unsupervised Models

Model	Testbed	Sensors	Anomaly (%)	Recall	Precision	F1-Score	Accuracy
One-Class SVM	1	All	50	**0.59**	**0.59**	**0.59**	**0.59**
	2	All		0.46	0.45	0.46	0.45
	3	No temperature[1]		0.46	0.45	0.46	0.45
Isolation Forest	1	All	20	0.87	0.34	0.89	0.81
	2	All	9	**0.91**	**<u>0.17</u>**	**0.91**	**0.85**
	3	No temperature		0.90	0.060	0.90	0.83
LOF	1	All	9	0.91	0.073	0.93	0.87
	2	All		**0.91**	**<u>0.14</u>**	**0.92**	**0.85**
	3	No temperature		0.93	0.34	0.94	0.89

1. No temperature refers to using the data from all sensors except for the temperature data

Supervised Models

Most **challenging** scenario / **Best** model:

Model	Testbed	Sensors	Anomaly (%)	Recall	Precision	F1-Score	Accuracy
XGBoost	1	No temperature[1]	9	1	1	0.99	0.99
	2			1	1	0.99	0.99
	3			1	1	1	1

1. No temperature refers to using the data from all sensors except for the temperature data

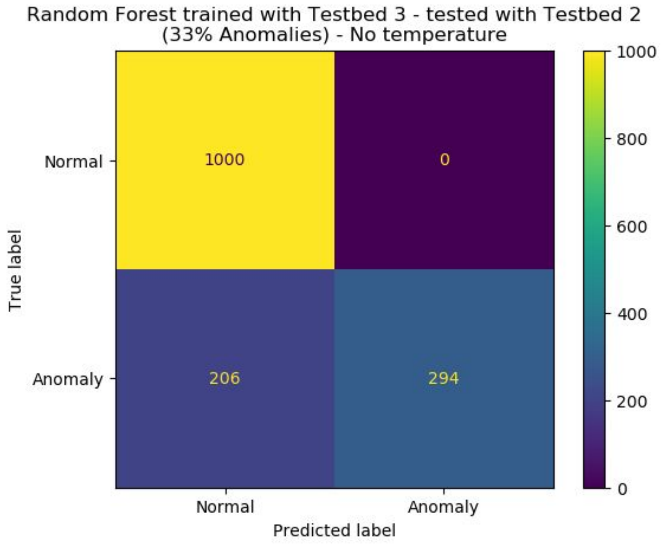
Sensor Comparison

Model	Testbed	Sensors	Anomaly (%)	Recall	Precision	F1-Score	Accuracy
K-NN	2	No temperature[1]	33	0.98	0.99	0.98	0.99
		Accelerometer 1		**1**	**1**	**0.99**	**0.99**
		Accelerometer 2		0.87	0.76	0.82	0.87
		Digital Microphone		0.89	0.95	0.77	0.86
		Accel. 2 + Microphone		**0.87**	**0.93**	**0.87**	**0.91**
SVM	2	No temperature	50	0.94	0.95	0.91	0.92
		Accelerometer 1		**0.9**	**0.91**	**0.79**	**0.81**
		Accelerometer 2		0.74	0.75	0.79	0.78
		Digital Microphone		0.65	0.8	0.45	0.57
		Accel. 2 + Microphone		**0.74**	**0.72**	**0.79**	**0.79**

1. No temperature refers to using the data from all sensors except for the temperature data

Unknown Anomalies

- Anomalies not present in the dataset
  - Made possible due to having 3 testbeds
- Test Supervised models
  - Trained with dataset from certain testbed
  - Tested with anomalies from different testbed



Model	Sensors	Anomaly (%)	Recall	Precision	F1 Score	Accuracy
RF	No temperature[1]	33	0.59	1	0.74	0.86

1. No temperature refers to using the data from all sensors except for the temperature data

06

Conclusion and Future Work

Conclusion

Testing Platforms

Validation of **method**

Sensors

Validation of **selection** and **efficacy**

Software

Delineated **strategy**

Preprocessing

Suitable for Supervised Models; Further **exploration** is required

Supervised

Near-ideal results

Unsupervised

Notably **poor** results

Future Work

- Selection of **tested components**
  - Replicate Automated Guided Vehicle
- Environmental **noise**
  - Replicate environment of final deployment
- **Hardware** integration
  - Improve sensor fidelity
  - Vibration stability
- Microphone **array**
  - Pinpoint fault location
- **Data collection** method
  - Increase number of samples
- **TinyML**

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

SYSTEC

Sensor System for Predictive Maintenance in Industrial Environment

Master's in Electrical and Computer Engineering

André Cunha Enes Gonçalves

Supervisor: Professor Vítor H. Pinto