

FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Development of an automatic welding inspection system

Vasco Manuel Mendes Dias

MASTER'S DISSERTATION



Mestrado em Engenharia Mecânica
Automação

Supervisor at FEUP: Prof. Dr. João Manuel R.S. Tavares

Supervisor at Faurecia: Eng. Nuno Pires

July 14, 2023

Development of an automatic welding inspection system

Vasco Manuel Mendes Dias

Mestrado em Engenharia Mecânica
Automação

July 14, 2023

Abstract

Currently, there is a huge demand for process automation in the industry, and it is within this context that this project arises. Faurecia aims to study the implementation of automated solutions for welding inspection in its factories, using this study as a basis for initiating this transformation.

This dissertation presents the internship conducted at Faurecia Frames, during which an integrated system for welding inspection was developed. The main objectives of this project are to replace the current manual inspection conducted on a production line with an automated process. The system needs to be compact, user-friendly, and interactive with the operator, providing feedback on the inspection results.

To address this issue, an initial study of the welding process on the production line was conducted, gathering information about the main defects that may occur and the product under examination. Subsequently, research was carried out on the theoretical foundations in this field and the state-of-the-art of automated systems for welding inspection.

Throughout the development process of this system, various tasks involving different areas were undertaken. The first step involved selecting the key components of the system, namely a collaborative robot and an automated vision system. The collaborative robot was responsible for positioning the vision system for each weld, which would then inspect it and provide a subsequent result. To enable this integration and real-time data transmission, communication between the two components was established.

Regarding the inspection aspect, two image classification methods were developed to determine which one yielded better results. Both methods classified the images as either "OK" or "NOK". In order to track the parts and their respective welds, a solution was created to store all acquired images, referencing the Data Matrix of the corresponding part. Additionally, buttons and light signals were added to allow interaction with operators during the inspection process.

Subsequently, the code was developed to enable the seamless operation of the components as a unified system. Finally, two tests were conducted: the first evaluated the system's performance in welding inspection, comparing both classification methods developed, while the second assessed the variations in inspection under different lighting conditions.

Keywords: Welding inspection, Defects, Automatic system, Robotics, Image classification, Computational vision

Resumo

Atualmente, existe uma procura imensa pela automatização dos processos na indústria e é neste sentido que surge este projeto. A Faurecia pretende estudar a implementação de soluções automáticas na inspeção de soldaduras nas suas fábricas, servindo este estudo como base para início desta transformação.

Nesta dissertação, é apresentado o estágio realizado na Faurecia Metal, durante o qual foi concebido um sistema integrado para a inspeção de soldaduras. Os principais objetivos deste projeto consistem em substituir a inspeção manual, atualmente realizada numa linha de produção da fábrica, por um processo automatizado. O sistema em questão precisa de ser compacto, de fácil utilização e interativo com o operador, fornecendo feedback sobre o resultado da inspeção.

Para abordar essa questão, foi realizado inicialmente um estudo do processo de soldagem na linha, coletando informações sobre os principais defeitos que podem ocorrer e sobre o produto a ser avaliado. Em seguida, foi conduzida uma pesquisa sobre os fundamentos teóricos neste âmbito e sobre o estado da arte de sistemas automáticos para inspeção de soldaduras.

No processo de desenvolvimento deste sistema, foram realizadas diversas tarefas abrangendo diferentes áreas. A primeira etapa consistiu na seleção dos principais componentes do sistema, que foram, um robô colaborativo e um sistema de visão automática. O robô colaborativo foi responsável por movimentar o sistema de visão até cada cordão, para que este inspecione e forneça um resultado posteriormente. Para permitir essa integração e a transmissão de dados em tempo real, foi estabelecida uma comunicação entre os dois componentes. No âmbito da inspeção, foram desenvolvidos dois métodos de classificação de imagens, com o objetivo de determinar qual deles obtém os melhores resultados. Ambos os métodos classificavam a imagem como "OK" ou "NOK". Para rastrear as peças e seus respectivos cordões de solda, uma solução foi desenvolvida para armazenar todas as imagens adquiridas, fazendo referência ao Data Matrix da peça correspondente. Além disso, foram adicionados botões e sinais luminosos que permitem a interação com os operadores durante o processo de inspeção. Em seguida, foi desenvolvido o código que permite o funcionamento integrado dos componentes como um sistema unificado. Para concluir, foram realizados dois testes: o primeiro avaliou o desempenho do sistema na inspeção de soldas, comparando os dois métodos de classificação elaborados, enquanto o segundo permitiu avaliar as variações na inspeção quando submetido a diferentes condições de iluminação.

Keywords: Inspeção de soldaduras, Defeitos, Sistema automático, Robótica, Classificação de imagens, Visão computacional

Acknowledgements

The development of this dissertation would not have been possible without the contributions of everyone involved along the way. Hence, I would like to extend gratitude to all those who have played a part in this project:

To my supervisor at FEUP, Prof. João Tavares for the support, guidance and availability throughout the entire work.

To Eng. Nuno Pires, my supervisor at Faurecia, who has consistently shown dedication and genuine concern, providing me with the necessary support, while giving complete autonomy, contributing to my personal growth. Thanks for your patience, good humor, and friendship throughout this journey.

To the engineering team for the warm welcome and for creating an excellent work environment from the very beginning. Their companionship, professionalism, and teamwork have made this experience even better. I'm grateful for the enjoyable moments we shared, particularly the long walks after lunch.

Lastly, I would like to express my gratitude to my family and friends for their support throughout the years. Their encouragement, understanding, and belief in me have been crucial in reaching this milestone.

Contents

1	Introduction	1
1.1	Forvia Faurecia	1
1.1.1	Forvia Faurecia Frames São João da Madeira	2
1.2	Project background	3
1.3	Objectives	5
1.4	Dissertation Outline	6
2	Fundamentals and Literature Review	7
2.1	Introduction	7
2.2	Gas metal arc welding	7
2.2.1	Principles of operation	7
2.2.2	GMAW system and parameters	8
2.3	Type of defects	10
2.3.1	Surface defects	10
2.3.2	Internal defects	12
2.3.3	Dimensional defects	12
2.4	Non-destructive testing methods	14
2.4.1	Visual inspection	14
2.4.2	Magnetic particle testing	15
2.4.3	Liquid penetrant testing	16
2.4.4	Eddy current testing	17
2.4.5	Ultrasonic testing	17
2.4.6	Radiography testing	18
2.5	Automatic weld inspection State-of-art	19
2.5.1	Search method	19
2.5.2	Research results	19
2.6	Conclusion	21
3	Automatic welding inspection system	23
3.1	Introduction	23
3.2	Solution proposed	23
3.2.1	Universal Robots UR10	23
3.2.2	Vision sensor selection	25
3.2.3	Production process layout	26
3.3	Mechanical Project	27
3.3.1	Requirements	27
3.3.2	Tables and Jig	29
3.3.3	In-Sight 2800 support and protection case	31

3.3.4	Final System	33
3.4	Communication UR10 - In-Sight 2800	34
3.4.1	Communication solution	34
3.4.2	Communication setup	35
3.5	In-Sight Vision Suite	39
3.5.1	Image classification	39
3.5.2	Image storage	43
3.6	Human Machine Interface	46
3.7	Script development	48
3.7.1	Scenarios	48
3.7.2	Routine	50
3.8	Conclusion	52
4	Statistical validation	59
4.1	Introduction	59
4.2	Confusion matrix	59
4.2.1	Method A	61
4.2.2	Method B	62
4.2.3	Discussion	63
4.3	Gage R&R	64
4.4	Conclusion	65
5	Conclusions and future perspectives	67
5.1	Conclusions	67
5.2	Future perspectives	68
A	Script	69
B	Results	71
B.1	Confusion matrix results	71
B.1.1	Method A	71
B.1.2	Method B	71
B.2	Gage R&R	71
	References	97

List of Figures

1.1	Forvia Faurecia logo [1].	2
1.2	Faurecia Frames São João da Madeira facilities.	2
1.3	Front cushion and backrest metallic structure and mechanisms.	3
1.4	Inspection part - Backrest: (a) front and (b) back views.	4
1.5	Production line current layout.	5
2.1	GMAW gun assembly and process illustration (adapted from [2]).	8
2.2	Gas Metal Arc Welding system [2].	9
2.3	Magnetic particle testing method (adapted from [3]).	15
2.4	Liquid penetrant inspection steps.	16
2.5	Eddy current testing inspection (a) without and (b) with defects.	17
2.6	Ultrasonic testing proceedings (adapted from [4]).	18
2.7	Radiography ability for detecting different types of defects.	19
2.8	PRISMA diagram of the performed literature search process.	20
3.1	Universal Robot UR10 [5].	24
3.2	CB3 teach pendant and control box [5].	24
3.3	Cognex In-Sight 2800 [6].	25
3.4	Keyence IV2 [7].	25
3.5	Proposed production process layout.	26
3.6	Top view sketch of the system's layout with dimensions in mm.	28
3.7	Front view of system's with dimensions in mm.	28
3.8	Aluminium base for UR10 attachment.	29
3.9	UR10 table structure.	30
3.10	Jig table structure.	30
3.11	Jig Table views illustrating inclinations.	30
3.12	In-Sight 2800 - UR10 attachment support.	31
3.13	Protection cases for In-Sight 2800.	32
3.14	UR10 - In-Sight 2800 Assembly.	32
3.15	MarkForged Mark Two 3D printer [8].	33
3.16	Final system assembled.	33
3.17	Communication solution diagram.	35
3.18	Beckhoff Ethernet switch CU2008 [9].	36
3.19	Ethernet properties, TCP/IPv4 enable.	36
3.20	TCP/IPv4 properties, IP address and subnet mask configuration.	36
3.21	In-Sight Vision Suite network configuration.	37
3.22	UR10 network settings.	38
3.23	Classification methods.	40

3.24	Classification diagram - Method A.	40
3.25	In-Sight Vision Suite - Classification environment window Method A.	41
3.26	Classification diagram - Method B.	41
3.27	Spreadsheet of final inspection value.	42
3.28	In-Sight Vision Suite - "OK Classifier" environment window Method B.	43
3.29	Classification diagram - Part detection.	43
3.30	In-Sight Vision Suite - "Detection Classifier" environment window.	44
3.31	Data matrix of backrest.	44
3.32	FTP server, users setup.	45
3.33	FTP configuration - In-Sight Vision Suite.	46
3.34	Image storage diagram.	47
3.35	Control box and I/O terminal blocks.	48
3.36	Push buttons electrical circuit.	49
3.37	Lights indicators electrical circuit.	50
3.38	Emergency button electrical circuit.	51
3.39	Control box, with light indicators and blue button.	52
3.40	Green button control box.	53
3.41	Emergency button control box.	53
3.42	HMI available in In-Sight Vision Suite.	53
3.43	Scenario A Grafcet.	54
3.44	Scenario B Grafcet.	54
3.45	Scenario C Grafcet.	54
3.46	Scenario D Grafcet.	55
3.47	Scenario E Grafcet.	55
3.48	Scenario F Grafcet.	55
3.49	Main flowchart of the script.	56
3.50	Weld inspection flowchart.	57
4.1	Confusion matrix	60
4.2	Porous weld 8 from part 10.	63

List of Tables

2.1	Typical surface defects, their causes and illustrations [10, 11].	11
2.2	Typical internal defects, their causes and illustrations [10, 11].	12
2.3	Typical dimensional defects, their causes and illustrations [10, 11].	13
2.4	Overview on NDT methods [12].	14
3.1	Native commands.	38
3.2	URscript commands.	38
3.3	Inputs/Outputs description.	47
4.1	Confusion matrix results for method A.	62
4.2	Confusion matrix results for method B.	64
4.3	Gage R&R results.	66
B.1	Weld 1 confusion matrix values method A, threshold = 80.	71
B.2	Weld 1 confusion matrix components method A, threshold = 80.	71
B.3	Weld 2 confusion matrix values method A, threshold = 85.	72
B.4	Weld 2 confusion matrix components method A, threshold = 85.	72
B.5	Weld 3 confusion matrix values method A, threshold = 60.	72
B.6	Weld 3 confusion matrix components method A, threshold = 60.	72
B.7	Weld 4 confusion matrix values method A, threshold = 85.	73
B.8	Weld 4 confusion matrix components method A, threshold = 85.	73
B.9	Weld 5 confusion matrix values method A, threshold = 85.	73
B.10	Weld 5 confusion matrix components method A, threshold = 85.	73
B.11	Weld 6 confusion matrix values method A, threshold = 85.	74
B.12	Weld 6 confusion matrix components method A, threshold = 85.	74
B.13	Weld 7 confusion matrix values method A, threshold = 85.	74
B.14	Weld 7 confusion matrix components method A, threshold = 85.	74
B.15	Weld 8 confusion matrix values method A, threshold = 80.	75
B.16	Weld 8 confusion matrix components method A, threshold = 80.	75
B.17	Weld 9 confusion matrix values method A, threshold = 85.	75
B.18	Weld 9 confusion matrix components method A, threshold = 85.	75
B.19	Weld 10 confusion matrix values method A, threshold = 85.	76
B.20	Weld 10 confusion matrix components method A, threshold = 85.	76
B.21	Weld 11 confusion matrix values method A, threshold = 85.	76
B.22	Weld 11 confusion matrix components method A, threshold = 85.	76
B.23	Weld 12 confusion matrix values method A, threshold = 85.	77
B.24	Weld 12 confusion matrix components method A, threshold = 85.	77
B.25	Weld 13 confusion matrix values method A, threshold = 75.	77
B.26	Weld 13 confusion matrix components method A, threshold = 75.	77

B.27 Weld 14 confusion matrix values method A, threshold = 85.	78
B.28 Weld 14 confusion matrix components method A, threshold = 85.	78
B.29 Weld 15 confusion matrix values method A, threshold = 85.	78
B.30 Weld 15 confusion matrix components method A, threshold = 85.	78
B.31 Weld 16 confusion matrix values method A, threshold = 80.	79
B.32 Weld 16 confusion matrix components method A, threshold = 80.	79
B.33 Weld 17 confusion matrix values method A, threshold = 85.	79
B.34 Weld 17 confusion matrix components method A, threshold = 85.	79
B.35 Weld 1 confusion matrix values method B, threshold = 75.	80
B.36 Weld 1 confusion matrix components method B, threshold = 75.	80
B.37 Weld 2 confusion matrix values method B, threshold = 80.	80
B.38 Weld 2 confusion matrix components method B, threshold = 80.	80
B.39 Weld 3 confusion matrix values method B, threshold = 70.	81
B.40 Weld 3 confusion matrix components method B, threshold = 70.	81
B.41 Weld 4 confusion matrix values method B, threshold = 75.	81
B.42 Weld 4 confusion matrix components method B, threshold = 75.	81
B.43 Weld 5 confusion matrix values method B, threshold = 65.	82
B.44 Weld 5 confusion matrix components method B, threshold = 65.	82
B.45 Weld 6 confusion matrix values method B, threshold = 85.	82
B.46 Weld 6 confusion matrix components method B, threshold = 85.	82
B.47 Weld 7 confusion matrix values method B, threshold = 85.	83
B.48 Weld 7 confusion matrix components method B, threshold = 85.	83
B.49 Weld 8 confusion matrix values method B, threshold = 80.	83
B.50 Weld 8 confusion matrix components method B, threshold = 80.	83
B.51 Weld 9 confusion matrix values method B, threshold = 80.	84
B.52 Weld 9 confusion matrix components method B, threshold = 80.	84
B.53 Weld 10 confusion matrix values method B, threshold = 85.	84
B.54 Weld 10 confusion matrix components method B, threshold = 85.	84
B.55 Weld 11 confusion matrix values method B, threshold = 85.	85
B.56 Weld 11 confusion matrix components method B, threshold = 85.	85
B.57 Weld 12 confusion matrix values method B, threshold = 85.	85
B.58 Weld 12 confusion matrix components method B, threshold = 85.	85
B.59 Weld 13 confusion matrix values method B, threshold = 60.	86
B.60 Weld 13 confusion matrix components method B, threshold = 60.	86
B.61 Weld 14 confusion matrix values method B, threshold = 75.	86
B.62 Weld 14 confusion matrix components method B, threshold = 75.	86
B.63 Weld 15 confusion matrix values method B, threshold = 85.	87
B.64 Weld 15 confusion matrix components method B, threshold = 85.	87
B.65 Weld 16 confusion matrix values method B, threshold = 80.	87
B.66 Weld 16 confusion matrix components method B, threshold = 80.	87
B.67 Weld 17 confusion matrix values method B, threshold = 75.	88
B.68 Weld 17 confusion matrix components method B, threshold = 75.	88
B.69 Gage R&R study values, Weld 1.	88
B.70 Gage R&R study values, Weld 2.	89
B.71 Gage R&R study values, Weld 3.	89
B.72 Gage R&R study values, Weld 4.	90
B.73 Gage R&R study values, Weld 5.	90
B.74 Gage R&R study values, Weld 6.	91

B.75 Gage R&R study values, Weld 7.	91
B.76 Gage R&R study values, Weld 8.	92
B.77 Gage R&R study values, Weld 9.	92
B.78 Gage R&R study values, Weld 10.	93
B.79 Gage R&R study values, Weld 11.	93
B.80 Gage R&R study values, Weld 12.	94
B.81 Gage R&R study values, Weld 13.	94
B.82 Gage R&R study values, Weld 14.	95
B.83 Gage R&R study values, Weld 15.	95
B.84 Gage R&R study values, Weld 16.	96
B.85 Gage R&R study values, Weld 17.	96

Abbreviations

ANN	Artificial Neural Network
CAD	Computer-aided Design
EC	Eddy Current
FN	False Negatives
FP	False Positives
FTP	File Transfer Protocol
GMAW	Gas Metal Arc Welding
HMI	Human Machine Interface
I/O	Input/Output
LPT	Liquid Penetrant Testing
LUT	Laser Ultrasonic Technique
MAG	Metal Active Gas
MIG	Metal Inert Gas
MPT	Magnetic Particle Testing
NDT	Non-destructive Testing
RIA	Reflection Image Area
R&R	Repeatability and Reproducibility
RT	Radiography Testing
SAFT	Synthetic Aperture Focusing Technique
TCP/IP	Transmission Control Protocol / Internet Protocol
TN	True Negatives
TP	True Positives
UT	Ultrasonic Testing

Chapter 1

Introduction

The present dissertation was developed under the scope of the Master in Mechanical Engineering, from the Faculty of Engineering of the University of Porto. The project took place as a 4 month internship, in the second semester of the 2022/2023 academic year at the company Forvia Faurecia Frames based in São João da Madeira.

This chapter starts by providing a presentation of the company, followed by a description of the project developed, with the title Automatic welding inspection system. Subsequently, an overview of the objectives for this project is provided, along with a reference to the structure of the dissertation.

1.1 Forvia Faurecia

Faurecia has a long history dating back to 1914, when its founder Bertrand Faure established a small workshop near Paris that produced seats for trams and the metro. Over time, the company has become one of the top 10 suppliers of automotive products globally. Faurecia's areas of specialisation include creating complete interior and seating systems, developing innovative solutions for eco-friendly and emission-free mobility, and creating technologies that enable automated vehicles to function efficiently.

Prior to 2021, Faurecia was majority-owned by Groupe PSA, a French multinational that manufactured Peugeot, Citroën, DS, Opel, and Vauxhall cars. However, when Groupe PSA merged with Fiat Chrysler to create Stellantis, Faurecia became an independent entity. Following this change, Faurecia acquired a controlling stake in Hella, which is a company established in Germany in 1899 and is a major provider of advanced lighting technology and automotive electronics. Hella is a listed company that was majority privately owned by the Hueck and Roepke families before Faurecia became the majority shareholder.

The merge between Faurecia and Hella has resulted in the formation of a powerful global force in the field of automotive technology, Forvia. With a deep understanding of the latest trends

that are reshaping the automotive industry - such as the shift towards electrification, automation, and customisation of onboard experiences. The name Forvia (FOR as forward and VIA, the latin word for road) stand for movement and agility and has the view to the current transformation of mobility. The logo is visible in Figure 1.1.



Figure 1.1: Forvia Faurecia logo [1].

Forvia is currently the world's seventh-largest automotive supplier, operating in over 40 countries with a workforce of more than 157,000 employees. Their advanced technology is integrated into approximately half of all vehicles manufactured worldwide [1].

1.1.1 Forvia Faurecia Frames São João da Madeira

Forvia Faurecia has categorised its operations into four distinct areas, which are clean mobility, Seating, Interiors, and Electronics. In São João da Madeira, Faurecia operates a plant that specifically focuses on Seating and is where this project takes place.

The factory is comprised of two separate buildings, SJM1 and SJM2, with SJM1 occupying an area of 7 000 square meters and SJM2 occupying an area of 13 000 square meters. Figure 1.2 illustrates the facilities of Faurecia Frames in São João da Madeira, identifying each building.



Figure 1.2: Faurecia Frames São João da Madeira facilities.

This factory primarily manufactures the metallic frames for car seats, front cushions, front backrests, rear cushions, and rear backrests. It not only fabricates the metallic structure but also

develops the mechanisms responsible for enabling the seats to perform the desired motions. On a daily basis, it consistently produces an average of 50,000 parts. Figure 1.3 illustrates the metallic structures and the mechanisms of a front cushion and backrest.

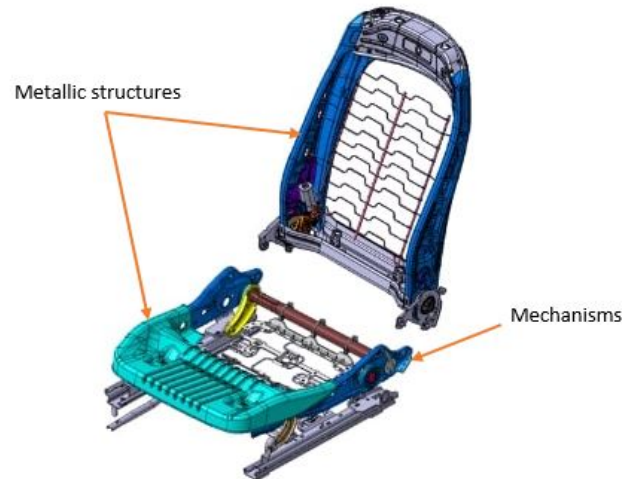


Figure 1.3: Front cushion and backrest metallic structure and mechanisms.

Faurecia frames currently has 916 employees, of which 786 are direct labor, responsible for production, and 130 are indirect labor responsible for support functions for production. They are maintenance, quality, process engineering, product engineering, times and methods, logistics, management control, purchasing and human resources. Faurecia Metal has a total of 32 customers, which includes Renault, Peugeot, Nissan, Ford, and others. Their sales value in 2022 amounted to 280 million euros.

Over the years, Faurecia Frames has embraced technological advancements and integrated a range of techniques into their fabric manufacturing process. Currently, they employ the following technologies: laser welding, MAG welding, tube end forming, automatic expanding, electric and MAG welding, riveting, screwing, painting, and assembly.

Faurecia is actively working towards implementing new technologies, being one of them the automatic weld inspection in their fabric production process. Being a huge step for enhancing the production efficiency and product quality control.

1.2 Project background

Currently the weld inspection in the fabric is done manually by operators which can be time-consuming, costly, and subject to human error, making them less reliable. Therefore, there is a need for automated systems that can accurately and efficiently inspect welds.

This project serves as a proof of concept, laying the foundation for the integration of automatic weld inspection in Faurecia Frames' production process. By successfully demonstrating the

feasibility and benefits of automated inspection in this context, it sets a precedent for the future integration of this technology across all fabric production operations.

This pivotal step not only showcases the potential for enhanced efficiency and accuracy but also establishes a solid framework for further research and development in automating weld inspection across the industry.

This study was conducted in a production line of the HJB project, which is one of the many ongoing projects at Faurecia Frames. This production line is responsible for manufacturing backrests, each with 17 weld seams that require inspection. The welding technique employed in the production of this particular product is gas metal arc welding (GMAW).

The product is illustrated in Figure 1.4, with the red seams indicating higher susceptibility to errors and the green seams less prone to such issues.

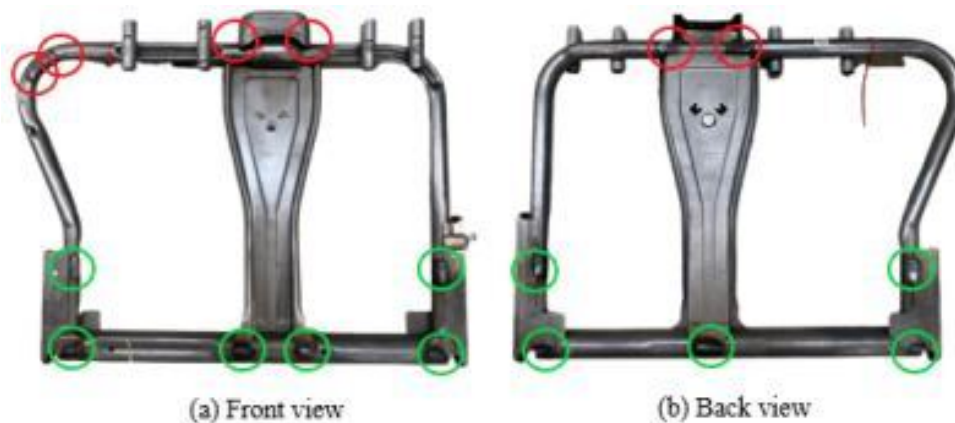


Figure 1.4: Inspection part - Backrest: (a) front and (b) back views.

At the moment, the visual inspection in this line is performed by an operator, which is prone to making mistakes, due to the high volume of parts that are produced daily. The current production process is described in the following points and in Figure 1.5:

1. Sub-assemblies are supplied to K03 station;
2. K03 operator loads parts for backrest closing;
3. After welding, K03 operator hangs parts between K03 and K04 station;
4. K04 operator visually inspects welding seams;
5. K04 operator loads parts for backpanel welding;
6. Operator from final inspection (FI) removes welded backrests from K04 station;
7. FI operator labels and package parts.

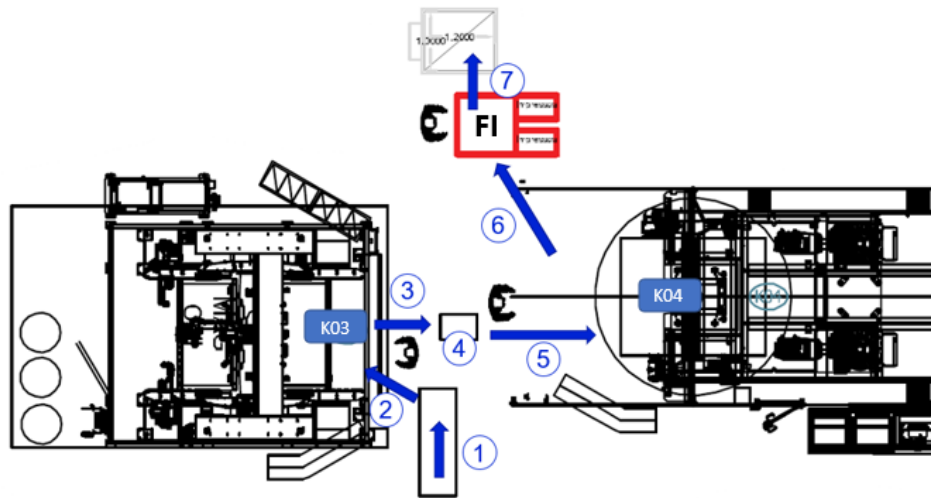


Figure 1.5: Production line current layout.

1.3 Objectives

Having established the context for the development of this project, let's delve into its specific objectives.

The main aim of this project was to eliminate step 4 from Figure 1.5. Replacing the manual inspection with an automatic system that accurately inspects all the 17 backrests weld seams.

In terms of the line layout, specific requirements have been outlined for the integration of the automated inspection system. The system need to integrate the existing production line at the same position where the manual inspection currently takes place, between stations K03 and K04. However, no modifications can be made to either the K03 or K04 stations. Therefore, the automated inspection system needs to be compact enough to satisfy these constraints while still fulfilling the necessary inspection functions.

The productivity of the production line is of utmost importance, and therefore, integrating this system must not result in a decline in output. Consequently, it is crucial to ensure that the cycle time of the inspection process does not exceed a certain value (54 seconds), which is determined by the cycle time of the stations.

The system need to be easy to use and provide clear indications of the inspection status for each part inspected, as either OK or NOK. In case of NOK result, the part must be locked and held until an authorised person performs a detailed analysis.

The system developed should be evaluated through statistical methods, to assess the performance of the inspection.

1.4 Dissertation Outline

The dissertation is structured into five chapters, which are designed to divide and organise the contents in a manner that facilitates easy reading and comprehension.

In the second chapter, the fundamental theory behind the project is presented. It begins with an overview of the welding process, parameters, and defect types. Non-destructive methods for weld inspection are also discussed. Additionally, a state-of-the-art review is conducted on automatic weld inspection, exploring the latest advancements and research in the field.

In the third chapter of the dissertation, the practical aspects of the project are presented. It begins by explaining the proposed solution and then proceeds to describe the development process of the system components. The chapter further discusses the communication and data exchange within the system, followed by an explanation of the classification methods employed for detecting and categorising weld defects. Additionally, it covers the devices used for operator interaction and provides insights into the development of the script used in the system.

In the fourth chapter, tests are conducted to evaluate the performance of the developed system. Initially, a confusion matrix is employed to assess the system's accuracy in correctly inspecting welds. Furthermore, a Gage R&R study is carried out to examine the influence of light on the inspection process, assessing the system's consistency and reproducibility under different lighting conditions.

In the fifth, the ending conclusions are presented followed by the future perspectives for the system.

Chapter 2

Fundamentals and Literature Review

2.1 Introduction

Weld quality assessment and inspection play a critical role in ensuring the structural integrity and reliability of welded components. This chapter delves into the comprehensive examination of various aspects related to gas metal arc welding (GMAW) quality assessment, including the welding process itself, types of defects that can occur, non-destructive testing (NDT) methods employed for inspection, and the current state of the art in automatic inspection of welds. Understanding these aspects is essential for improving weld quality, enhancing productivity, and reducing the risk of failure in welded structures.

2.2 Gas metal arc welding

There are numerous welding techniques available, each with its own set of benefits and typically ideal for specific applications. Among them, the GMAW method is one of the most used due to its low initial cost and high productivity.

In the late 1940s, the GMAW welding process, also known as metal inert gas (MIG) or metal active gas (MAG), was first introduced to the industry. This process can be either manual or automatic, but in most cases, industrial welding production is performed using automatic devices and robotic systems. Welding in an industrial setting is usually repetitive and can emit hazardous substances to human operators, making it challenging and that's why welding robots play a crucial role in addressing these challenges and enhancing welding efficiency and quality [13].

2.2.1 Principles of operation

In GMAW the coalescence of metals is done by heating them to their melting points through an electric arc. In this process, the consumable filler wire is continuously fed through the contact tip and reaches the arc zone, where an electrical arc is generated between the wire and the workpiece.

This arc generates intense heat, melting the electrode wire and the base material, forming a weld puddle. To protect the weld puddle from atmospheric contamination, a shielding gas is introduced through the nozzle of the welding gun. This shielding gas, typically a mixture of argon and carbon dioxide, creates a protective atmosphere around the weld zone, preventing oxidation and ensuring the integrity of the weld. Figure 2.1 provides a detailed view of the Gun and cable assembly in a GMAW setup. Additionally, allows for an examination of important properties and elements during the welding process, such as the weld puddle, the shielding gas, and the electric arc [2, 14].

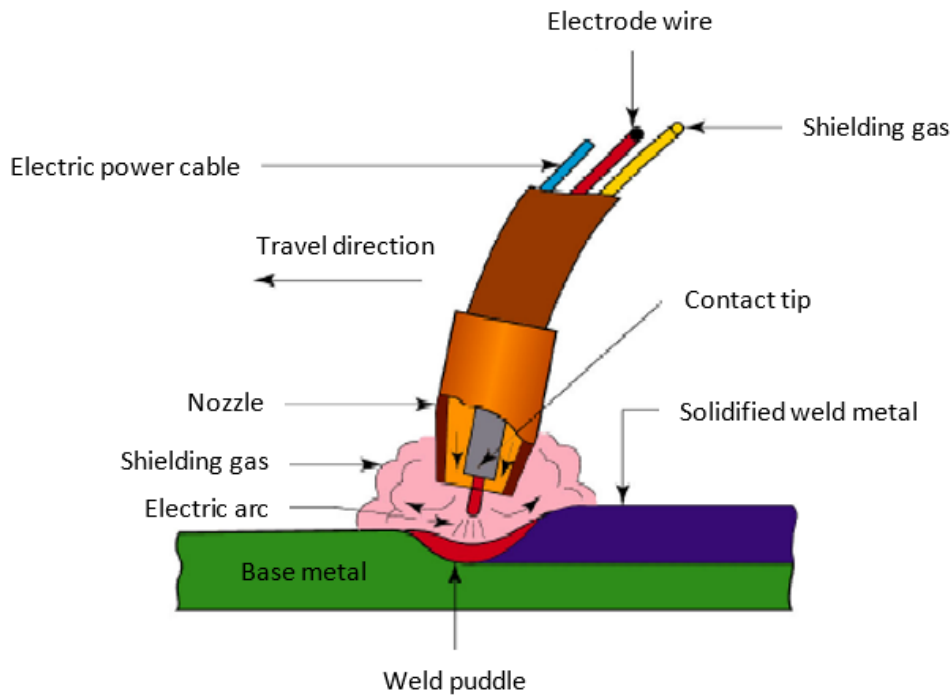


Figure 2.1: GMAW gun assembly and process illustration (adapted from [2]).

Since the equipment provides for automatic self-regulation of the electrical characteristics of the arc and deposition rate, the GMAW operation can be executed in three different manners, that is, semiautomatic welding, machine welding, and automatic welding.

In semiautomatic welding, a human operator controls the gun positioning, guidance, and travel speed. However, in machine welding, the welding gun is attached to a robot. Rather than straight user intervention, a worker operates and regulates the commands for the motion of the robot. Automatic welding is a procedure where equipment like robotic actuators is used to perform welding with only intermittent or no surveillance from the operator [2].

2.2.2 GMAW system and parameters

The GMAW system is represented schematically in Figure 2.2, with all its components. At the center of the image, we can see the power source, which provides the necessary electrical energy for the welding process. Adjacent to the power source is the wire feeder unit, responsible for

feeding the consumable electrode wire into the welding gun through a cable conduit that also covers a gas hose and the electrical power cable.

The filler wire, comes from the wire spool and is guided through motor-driven rollers that can be adjusted to control its speed. It is important to maintain a balance between the rate at which the wire is consumed or burnt off from the welding gun tip and the rate at which it is fed [15].

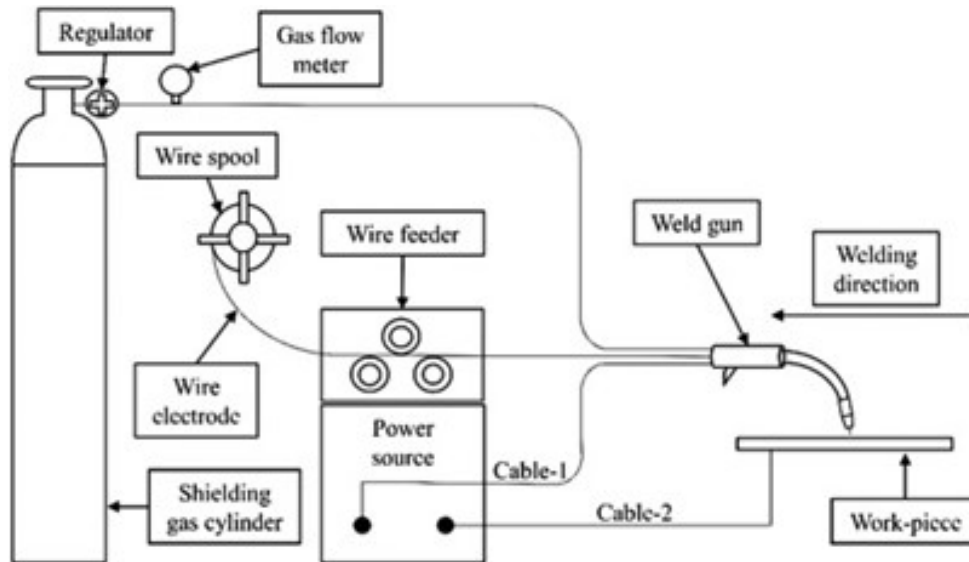


Figure 2.2: Gas Metal Arc Welding system [2].

GMAW encompasses a range of variables and parameters that significantly influence the welding process and the resulting weld quality. These variables are:

- **Wire feed speed:** refers to the rate at which the consumable electrode wire is fed into the welding zone. It directly affects the amount of metal deposition and the welding current. Adjusting the wire feed speed allows control of the size and shape of the weld bead, as well as the overall weld penetration;
- **Welding current:** plays a crucial role in determining the heat input during GMAW. It affects the melting rate of the electrode wire and the base material, influencing the depth of penetration and the fusion between the workpieces. By adjusting the welding current, we can achieve optimal heat distribution and control the overall weld quality;
- **Arc voltage:** voltage in GMAW influences the arc length and the energy delivered to the weld zone. It affects the stability and intensity of the arc, thereby influencing the heat input. Controlling the voltage enables to manage the arc length, control the weld puddle size, and achieve the desired weld appearance and mechanical properties;
- **Travel speed:** refers to the speed at which the welding gun moves along the joint. It influences the amount of heat input and the cooling rate of the weld. Controlling the travel speed

helps maintain proper fusion of the base materials. The increase in the travel speed causes a decrease in the maximum temperature;

- **Shielding gas composition:** the composition of the shielding gas is another critical parameter in GMAW. The choice of shielding gas depends on the base material and the desired weld properties. Commonly used gases include argon, carbon dioxide, and mixtures of these gases. The shielding gas protects the weld zone from atmospheric contamination, such as oxygen and nitrogen, ensuring a clean and sound weld;
- **Electrode size:**
 - **Electrode diameter:** the diameter of the electrode wire used in GMAW affects the current density, heat input, and weld bead shape. Thinner wires generally provide better control over the welding process and are suitable for welding thinner materials, while thicker wires can handle higher welding currents and provide higher deposition rates;
 - **Electrode stick-out:** refers to the length of the electrode wire protruding from the welding gun's contact tip. Proper stick-out ensures stable arc formation and facilitates good control over the welding process. It influences the arc length, heat input, and the shape of the weld bead.

By controlling and adjusting these process parameters, it's possible to optimise the GMAW process to achieve consistent, high-quality welds with desired characteristics such as penetration, fusion, bead shape, and mechanical properties [16, 17, 13].

2.3 Type of defects

GMAW is one of the most widely used welding processes in the manufacturing industry, owing to its versatility and efficiency. This process produces a high-quality, consistent weld, making it ideal for high-volume production. However, despite its numerous advantages, GMAW is not without its challenges. Defects can occur during the welding process, which can weaken the joint and compromise its structural integrity. These defects will be classified according to ISO 6520 and Faurecia quality standards in MAG welding [18] [11].

To have a better understanding of the defects that can occur during GMAW, we can divide them into three categories: surface defects, internal defects, and dimensional defects.

2.3.1 Surface defects

Surface defects in welds are often apparent to the naked eye on the external surface of the weld and can have a negative impact on the strength and structural integrity of the joint. However, these defects can sometimes be so small or subtle that they are not easy detectable by visual inspection

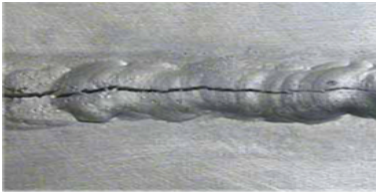
alone. In such cases, NDT methods are employed to identify and evaluate these minute defects accurately. While they may seem minor or superficial, surface defects should not be underestimated, as they can act as stress concentration points and significantly weaken the weld.

The most common surface defects are the following:

- **Cracks:** imperfections produced by a local rupture in the solid state which can arise from the effect of cooling or stresses. Cracks can be longitudinal or transverse in relation to the material surface and/or welding direction. They can appear in any part of the welding zone and depending on their formation or location, cracks are named differently, for instance, cold/hot cracks, segregation cracks, end crater cracks, etc;
- **Surface porosity:** refers to the presence of small air cavities within the weld that breaks the surface, which can weaken the joint and make it more susceptible to failure. It is often caused by the presence of contaminants, such as moisture or oil, on the surface of the base metal or filler wire;
- **Spatter:** globules of weld metal or filler metal expelled during welding and adhering to the surface of base metal or solidified weld metal. Spatter can be permitted unless these impact the product function, the product aesthetic, or for instance paint adherence.

Table 2.1 provides a overview of the primary causes or factors associated with each of the previous defects, as well as an illustration for each defect.

Table 2.1: Typical surface defects, their causes and illustrations [10, 11].

Defect	Main Causes	Example
Cracks	High cooling rates. Localised stresses surpass the ultimate strength of the material. Some metals require preheat before starting welding.	
Surface porosity	Contamination, due to inadequate cleaning of the base metal or the electrode. Insufficient shielding gas coverage, resulting in inadequate protection.	
Spatter	Amperage and voltage settings used during welding. Improper gun angle or travel speed. Using wrong contact tip size for the wire diameter. Inconsistent or improper wire stick-out.	

2.3.2 Internal defects

In contrast to surface defects, internal defects in welds are not visible to the human eye. As their name implies, these defects occur within the material itself and significantly impact the reliability and performance of the weld joint.

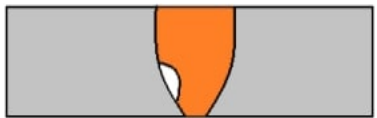
Unlike surface defects that may be detected through visual inspection, internal defects require more advanced techniques such as others non-destructive testing to identify their presence accurately.

The most common internal defects are the following:

- **Solid inclusions:** Solid foreign substances can become entrapped in the weld metal, and these are referred to as inclusions. They can have a significant effect on the quality of the weld, reduce its strength, and lead to cracking or other defects;
- **Lack of fusion:** The filler material must be well bonded to the base metal on both sides. If there are voids, gaps, or poor adhesion, the joint will be structurally impaired;
- **Incomplete root penetration:** It happens when one or both fusion faces of the root are not melted. Lack of root penetration may negatively impact the joint's mechanical performance.

Table 2.2 offers a comprehensive summary of the key causes linked to each of the aforementioned defects, along with a corresponding visual representation for better understanding.

Table 2.2: Typical internal defects, their causes and illustrations [10, 11].

Defect	Main Causes	Example
Solid inclusions	Improper torch speed or electrode manipulation. Low amperage settings. Improper cleaning of the weld between passes.	
Lack of fusion	Electrode incorrect size. Moving the torch to fast. Not keeping the amperage high enough for the job. Insufficient heat input.	
Incomplete root penetration	Excessive gap between the base metal pieces, or misalignment. Use of a diameter electrode that is too large. Heat input set to low.	

2.3.3 Dimensional defects

Dimensional defects on welds refer to deviations or errors in the size or shape of the welded joint or surrounding areas, compared to the intended or specified dimensions. Dimensional defects can

compromise the quality and integrity of the welded joint, leading to reduced strength, durability, or performance.

- **Undercut:** irregular groove thinning of the parent material just next to the fusion line, most often a severe geometry change resulting in stress concentration during mechanical loading. A loss of thickness reduces the strength of the weldment and makes the joint susceptible to fatigue.
- **Overlap:** Excessive weld metal covering the parent material surface without being fused to it. In this case, the weld pool flows excessively and extends beyond the toe.
- **Burn-Through:** Is a collapse of the molten material resulting in a hole in the weld or in the side of the weld.
- **Misalignment:** Misalignment can occur in several ways, such as when the two pieces of metal being welded are not properly aligned, or when the welding torch is not positioned correctly in relation to the joint. This can lead to incomplete fusion between the two pieces of metal, which in turn can result in a weaker joint.

Table 2.3 presents a comprehensive overview of the main causes or factors linked to each of the above defects, accompanied by illustrative examples that help visualise the specific characteristics of each defect.

Table 2.3: Typical dimensional defects, their causes and illustrations [10, 11].

Defect	Main Causes	Illustration
Undercut	Welding current is too excessive, leading to excessive heating. Improper manipulation of the electrode or moving the gun too quickly.	
Overlap	Using oversized electrodes or using high welding current.	
Burn-Through	Excessive heating, due to high currents. Very low travel speed. Use the incorrect wire size.	
Misalignment	Variations in the shape and thickness of components. Bad welding technique. Bad positioning of the base metals or of the gun.	

2.4 Non-destructive testing methods

Welding is one of the most important processes in manufacturing industries, providing strong and reliable bonds between metal parts. However, the quality of the weld can vary greatly, depending on various factors such as welding technique, material properties, and environmental conditions. In order to ensure the quality and safety of welded structures, it is important to perform thorough testing of the welds.

There are two main types of testing for welds: destructive and NDT (non-destructive testing). Destructive testing involves physically damaging the weld in order to assess its properties and performance. This can include methods such as tension tests, bend tests, and impact tests, which can provide valuable information about the weld's strength and resistance to forces. NDT, on the other hand, does not damage the weld and can be used to evaluate its properties without affecting its integrity. Non-destructive testing is often preferred over destructive testing because it allows for more efficient and cost-effective evaluation of welds, while minimising the risk of damaging the welded structure. [14]

In the subsequent subchapters, it will be presented the most commonly utilised NDT methods, elucidating their respective procedures and providing other pertinent information. Table 2.4 provides an overview of all the NDT methods discussed. It not only lists these methods but also highlights their specific capabilities and limitations.

Table 2.4: Overview on NDT methods [12].

NDT technique	Capabilities	Limitations
Visual inspection	Visible surface defects	Small defects are difficult to detect
Magnetic particle	Surface and layer defects	Only suitable for magnetic material
Ultrasonic	Surface and interior defects	Testing material must be a conductor of sound
Radiography	Internal defects	Sensitive to defect orientation
Liquid penetrant	Surface defects	Not suitable for porous material
Eddy current	Surface and near surface defects	Only effective on conductive materials

2.4.1 Visual inspection

Is the most simple and common method used to evaluate the quality of a weld, and is usually low in cost. It involves a thorough examination of the weld directly with the eyes or indirectly using optical instruments. A simple visual test can reveal gross surface defects thus leading to an immediate rejection of the component and consequently saving a significant amount of time and money [12].

While being less complicated than other NDT methods, that does not imply that just anyone can effectively perform this operation. It is therefore essential that welding inspectors have the necessary skills and training to carry out visual inspection of welds successfully. When a defect is discovered during a visual inspection, the standard practice is to mark the weld and isolate the

part for rework. However it is important to note that the interior of the weld cannot be inspected using this method, which means that only visible surface defects can be detected.

Frequently, it is required to inspect the welding seam to detect any small flaws that may exist. To accomplish this, various visual techniques have been developed to a great level of accuracy. Nowadays, visual inspections can be performed with high reliability and at a low cost, thanks to the availability of charge coupled device cameras, microprocessors, and computers. Image processing, pattern recognition and automatic accept/reject choice are used when large number of components are to be evaluated [14].

2.4.2 Magnetic particle testing

Is a widely used NDT method for detecting surface and slightly subsurface discontinuities in ferromagnetic materials. The method requires magnetising the area to be inspected and coating the surface with magnetic particles. The presence of defects causes a flux leakage field in the magnetized component. The magnetic particles are attracted to the flux leakage and thereby cluster at the defect. The particles will form visible indications at the location of any surface or near-surface discontinuities, as shown in Figure 2.3 [4].

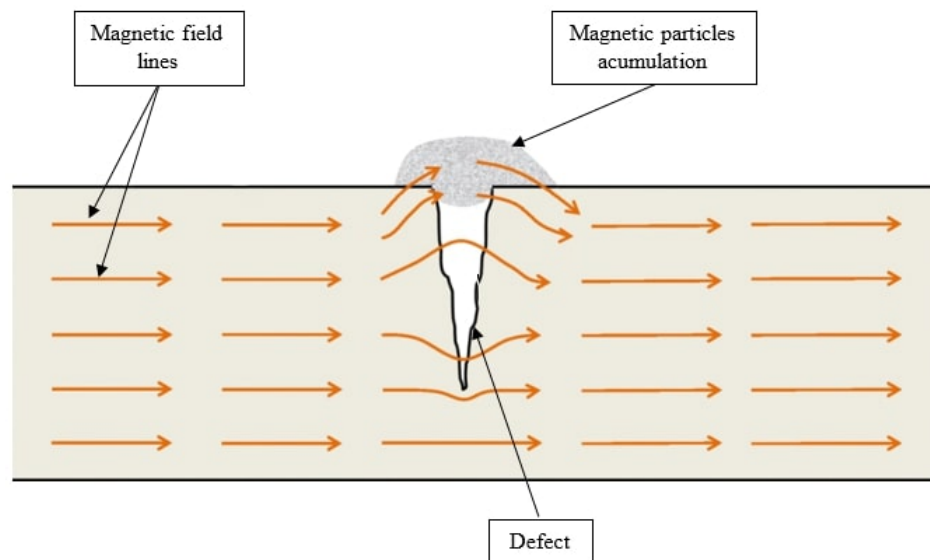


Figure 2.3: Magnetic particle testing method (adapted from [3]).

Weld defects such as cracks, lack of fusion, porosity, and inclusions can be detected using magnetic particle testing. The sensitivity of the technique depends on various factors such as the size and shape of the defect, the orientation of the magnetic field, and the magnetic particle properties. Proper preparation of the surface to be tested is critical to obtain accurate and reliable results. The surface should be cleaned thoroughly to remove any contaminants that may interfere with the inspection process [14].

Magnetic particle testing (MPT) on welds has several benefits. The technique is fast, efficient, and cost-effective compared to other NDT methods. MPT can be performed on complex shapes and surfaces, making it suitable for inspecting various types of welded structures. The results are immediate, and the indications are visible, making it easy for the inspector to identify the location and size of the defects.

However, magnetic particle testing on welds also has its limitations. The technique is limited to ferromagnetic materials, meaning it cannot be used to inspect non-magnetic materials such as aluminum or copper. The sensitivity of the technique may also be affected by the surface condition, the magnetic field strength, and the particle concentration. Additionally, MPT can only detect surface or slightly subsurface defects and may not be able to detect defects deeper in the material [12].

2.4.3 Liquid penetrant testing

Liquid penetrant testing (LPT) is one of the oldest and simplest NDT method. Is a process that is used to reveal the surface discontinuities by bleed out of a colored visible and fluorescent dye from the defected area. It involves three materials: cleaner, penetrate and developer [12].

First the component surface is cleaned (Figure 2.4 (a)), and then the liquid penetrant is applied, which is a colored dye that can seep into any surface-breaking cracks, pores, or other discontinuities in the surface of the weld (Figure 2.4 (b)). After sufficient penetration time, the excess penetrant is removed (Figure 2.4 (c)), and a developer is applied. The developer reacts with the dye, drawing it out from the defect onto the surface to form a visible indication, commonly known as bleed-out (Figure 2.4 (d)). [4].

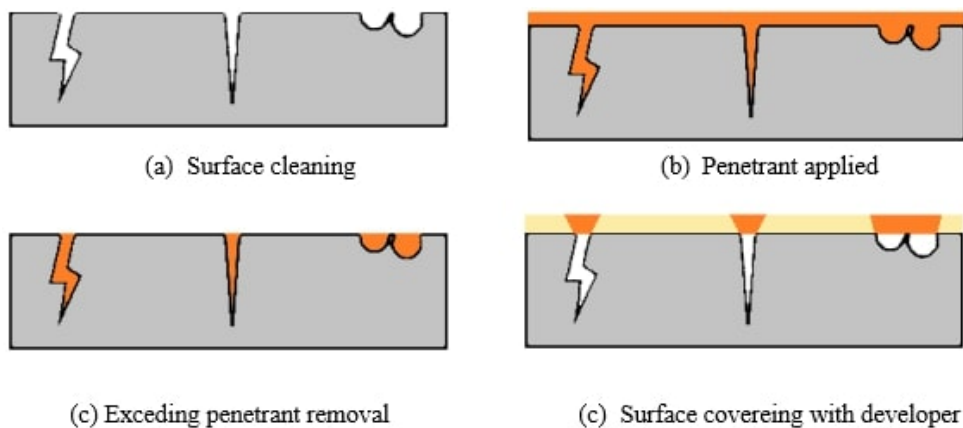


Figure 2.4: Liquid penetrant inspection steps.

To conduct an inspection, the part is observed for a difference in color between the penetrant and the surface background, which indicates the presence of a defect. If the penetrant contains visible dye, the inspection is carried out using white light, while fluorescent dyes require ultraviolet

or black light. It is crucial to search for even the slightest amount of penetrant, as this can signal the existence of a flaw in the material being inspected [14].

2.4.4 Eddy current testing

Eddy current (EC) inspection method is widely used to inspect metallic components for surface cracks and corrosion damage. Figure 2.5 shows the EC process of inspection. This method involves passing an alternating current through a coil that is located close to the surface of the weld. This current creates an electromagnetic field that induces eddy currents in the metal. Surface and near-surface defects disturb the eddy current flow, and this is detected by changes in the coil's impedance. EC testing only works on conductive materials and can't be used to inspect insulating materials with low electrical conductivity [14].

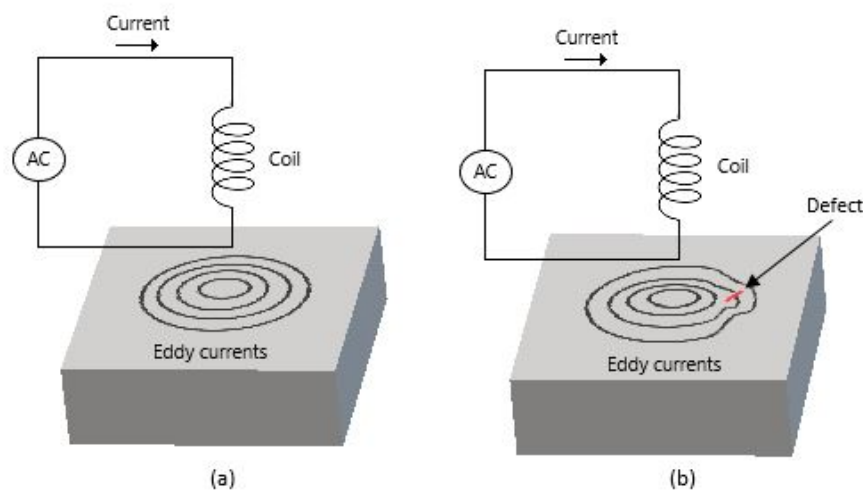


Figure 2.5: Eddy current testing inspection (a) without and (b) with defects.

Defects that intersect the path of the eddy currents are easily identified. However, defects that are parallel to the direction of the current may not be detected, as they do not cause any disturbance to the eddy currents. By passing the eddy current equipment, which is a hand-held device, above the component surface it is possible to detect defects that may be less than 50 mm deep. Therefore, in some applications, access to both sides of the weld is necessary for complete inspection [4].

2.4.5 Ultrasonic testing

Ultrasonic testing (UT) was first implemented as a non-destructive testing method for weld inspection during the 1960s. Over time, this technique has been significantly refined and improved, and it has become widely recognised and utilised in the industry [19].

The UT process involves the use of a transducer, which emits sound waves into the material being tested. These travel through the weld until they encounter a boundary or a flaw, then they are reflected back to the surface, being detected by the same transducer. The transducer converts

the sound waves into an electrical signal, which is then processed by a computer. The computer produces a visual image of the material being tested, which is displayed on a monitor. This process can be seen in Figure 2.6 [14].

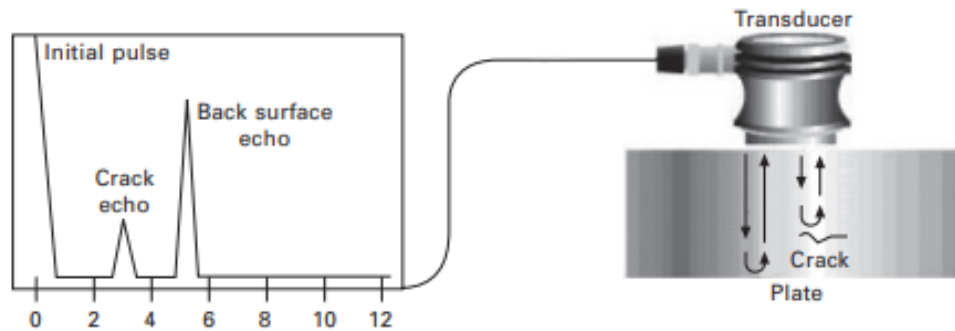


Figure 2.6: Ultrasonic testing proceedings (adapted from [4]).

Ultrasonic inspection offers several benefits when compared to other NDT methods. Firstly, it possesses exceptional penetrating power, enabling the inspection of components with thicknesses as substantial as 5 meters. Secondly, it exhibits high sensitivity, enabling the detection of extremely minute flaws. Additionally, it provides high accuracy in determining the precise location of internal defects and estimating their size [14]. However, the technique is not well suited to detecting damage aligned parallel with the propagation direction of the acoustic waves [4].

2.4.6 Radiography testing

The process of radiography testing (RT) involves directing X-rays or gamma rays through the weld and onto a piece of film positioned on the other side of the weld, this film will then have different contrasts based on the differential adsorption of the penetrating radiation into the weld. The rays that pass through the weld create an image that shows the internal structure of the weld, which can be analysed to detect any defects or areas of concern, the process is illustrated in Figure 2.7 [12].

RT can provide information on the size and location of defects, as well as the overall quality of the weld. This information can be used to make informed decisions about the acceptability of the weld and to guide any necessary repairs.

However, there are some limitations to radiography testing that must be considered. One of the main limitations is the potential health risks associated with exposure to X-rays or gamma rays. Personnel conducting radiography testing must follow strict safety protocols to minimise the risk of exposure to radiation. Additionally, radiography testing can be time-consuming and requires specialised equipment and personnel with specific training and certification.

Smaller discontinuities such as small inclusions and micro fissures are hard or impossible to detect using this technique. The direction of the crack is also an important determining factor using radiography technique. Cracks perpendicular to the radiation are less likely to be detected

since they are similar to small discontinuities in terms of radiation path length, as we can see in Figure 2.7 [20].

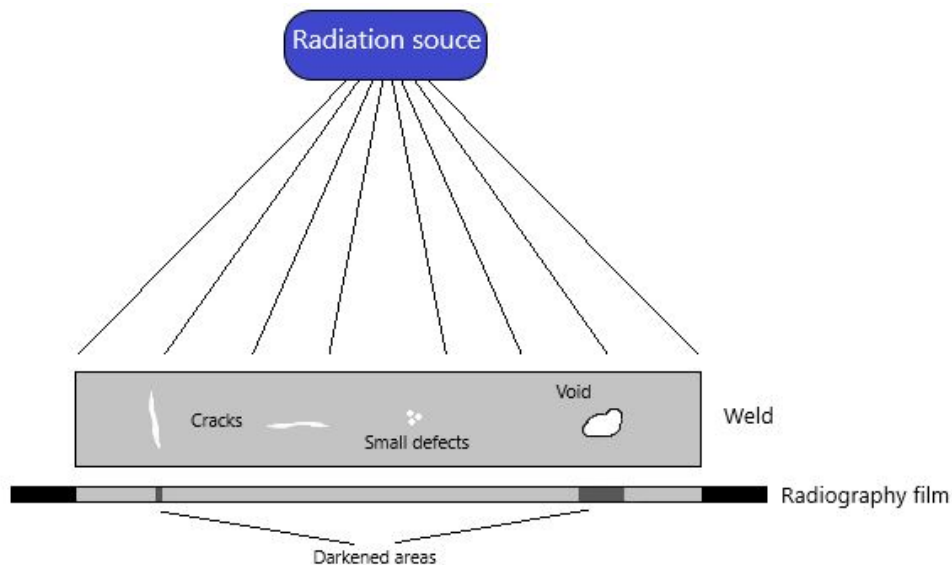


Figure 2.7: Radiography ability for detecting different types of defects.

2.5 Automatic weld inspection State-of-art

2.5.1 Search method

Between February and March 2023, a systematic literature search was conducted using SCOPUS database, Figure 2.8. The search query employed was: "inspection" and "arc" and "welding" and ("image" or "imaging" or "computer vision" or "machine vision" or "computational vision") and ("automatic" or "automated"). As a result, a collection of 30 distinct results was obtained.

After careful examining the title and abstract, 13 studies were excluded as they were found to be unrelated to the objective of this research. Out of the remaining 17 studies, a comprehensive evaluation of the complete works resulted in the inclusion of 9 studies.

2.5.2 Research results

The integration of computer vision techniques with weld inspection methods, such as NDT, has revolutionised this field, significantly enhancing the overall capabilities of inspections. In the 11 studies included in this research, 2 performed inspection of radiographic images, another 3 used ultrasonic methods, and the rest used 2D images taken from a conventional camera.

Before the 2000's there were 3 studies published. The first one was an automated spatter detection system that was developed in 1998 by Bidanda, Rubinovitz, and Raman, using a computer vision system. This approach demonstrated a high level of reliability, particularly when employing

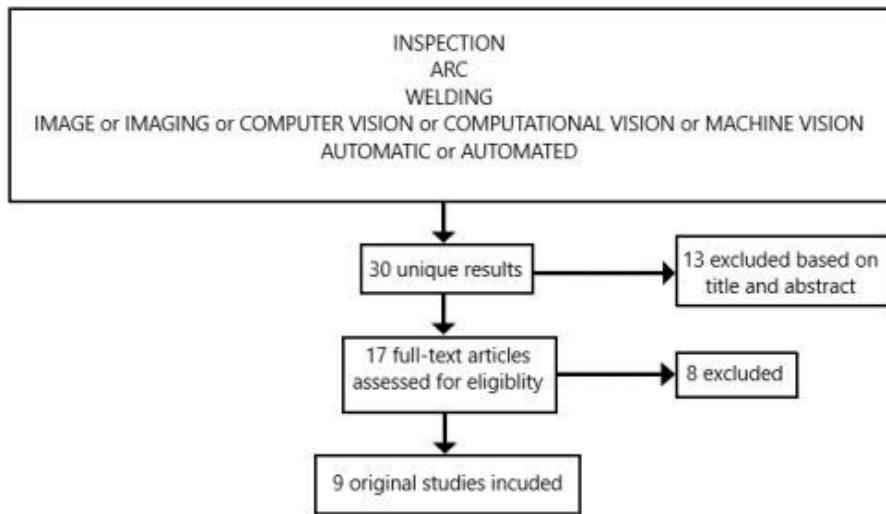


Figure 2.8: PRISMA diagram of the performed literature search process.

a low angle of light incidence [21]. In [22] it is presented a method to analyse real-time radiographic images of welds pool depression. Guu and Rokhlin used this information to determine the depth and width of the pool depression and by comparing this values to predefined threshold levels, they were able to automatically adjust the welding conditions in order to achieve the desired weld penetration. Lastly, [21] examine the variation of weld profiles to determine the quality of the weld. A high quality weld would generally yield minimal variation in the weld profiles while low quality weld profiles would vary significantly. George Cook and colleagues developed a method for the weld profile evaluation that was consistent and generally agrees with the quality evaluations of a human expert.

After the year 2000, the most advanced studies started to arise. In 2004, an expert vision system for automatic inspection of welding defects from radiographic films was developed. Three different algorithms were used, the AutoWDA algorithm to detect defects, the DIA to identify defects and the ADA to take an acceptance decision. The proposed algorithms were capable of identifying and inspecting all defects accurately [23].

In 2009, Wang and Chen were able to reconstruct a 3D shape of welding pool from a 2D image of a real welding pool. This allowed the extraction of the weld pool height. For this, the shape from shading algorithm was used, with some improvements related to noise and brightness. This method was prove to be accurate and precise [24].

In [25], Lévesque and colleagues used Laser ultrasonic technique (LUT) combined with the synthetic aperture focusing technique (SAFT). A CCD camera was used to simultaneously acquire the surface profile of the weld for correction in the SAFT processing. All the defects were detected by this technique, showing the potential of using the LUT with SAFT for the automated inspection of arc welds.

Zhang, proposed an innovative method that detects the dynamic change of the reflection image area (RIA) for the laser pattern reflected by the weld pool surface. The changes in the RIA were found to be determined by the weld pool surface, which was determined by the weld penetration. Because of this phenomenon, the RIA demonstrated two peaks that corresponded to the occurrences of the complete joint penetration and excessive penetration, respectively. To analyse the characteristics of the reflection laser images, an image processing algorithm was developed and tested in experiments, verifying the effectiveness of this method [26]. Mazloun in 2019, presented the only study to use neural networks in this research. The proposed system was named Phased Array for Characterizing Discontinuities, which combined 2D S-scan images into 3D images (volumetric scan). The system is able to check the shape, location and dimensions of each discontinuity. These image features are used as inputs to the artificial neural network (ANN) to characterise 12 types of common defects. This study conclude that characterising discontinuities from 3D images is more reliable and accurate than 2D images and the ANN can solve complex welding discontinuities classification with no errors [27].

Lastly, in this study [28], the effect of the weld sample surface on the Laser ultrasonic inspection was explored. Zeng established LU finite element models for defect detection with different surface morphologies using COMSOL software. The propagation of acoustic wave and its interaction with surface morphology and defects were numerically analysed. These acoustic waves will interact with defects of different shape, depth, orientation and size, then form different imaging features in the scan map. The finite element method can be used to reveal the interaction process and law between acoustic wave and defect, and obtain the theoretical defect imaging feature which provides a theoretical basis for the defect identification. The experimental results were in good agreement with the numerical results and validate the proposed Finite element modeling method.

With this research we can conclude that image processing and analysis techniques have become a useful tool in automatic weld inspections. They have been used allied with a variety of NDT methods, and extracting different information on the weld seam to determine the weld final inspection result.

2.6 Conclusion

This chapter covers the theoretical aspects involved in the project. It begins by providing an overview on the welding process used in the production of the inspection part, GMAW. It explains its principles of operation, the overall system setup and the adjustable parameters. Following this, the most common defects are described, showing the main reasons for the occurrence of each.

There are several methods to inspect weld seams, and in this chapter, the main NDT methods are presented. This allow us to have a better understanding of each technique, knowing in which applications they should be used. Given that our project consists of an automated inspection system, we conclude this chapter by conducting a state-of-the-art review of automatic inspection systems for welds. This review provides us with as overview of the studies conducted over the years, where machine vision played a significant role.

Chapter 3

Automatic welding inspection system

3.1 Introduction

In this chapter, the practical aspects of the project are discussed. It begins by introducing the proposed solution and the reasoning behind the decisions made. The chapter then delves into the description of all the developed components, starting with the project requirements.

The focus then shifts to the data exchange within the system, explaining the theoretical solution for communication and its implementation in the devices. The work carried out in the In-Sight Vision Suite is also covered, including image classification methods and the storage of images for traceability purposes.

Furthermore, the devices allowing system-operator interaction are described, along with their setup processes. Finally, the chapter concludes with an explanation of the script development process. This includes presenting various inspection scenarios and utilising flowcharts to illustrate the script's steps effectively.

3.2 Solution proposed

In this section the solution proposed is presented, along with the reasons that support these decisions.

3.2.1 Universal Robots UR10

During the development of the solution for this project, several crucial considerations were taken into account. One essential requirement is the inspection of all 17 weld seams, necessitating a system capable of capturing images at each of these specific points. Therefore, the solution requires a mechanism that enables the movement of the imaging device to precisely capture images of each weld seam. Given the limited space available within the production line and the close proximity to operators, an optimal solution for this project is a collaborative solution.

Faurecia Frames has a established partnership with Universal Robots and possessed an available UR10 from previous applications. The UR10, Figure 3.1, is a highly versatile collaborative robot, capable of handling significant payloads of up to 12.5 kg and with a reach of 1300 mm [5].



Figure 3.1: Universal Robot UR10 [5].

In the current project, the payload requirement is minimal as the weight of the imaging devices is not substantial. Given that the inspection part have a width of 630 mm, the reach of the UR10 cobot is adequate to access and inspect all the welds effectively.

Therefore, the UR10 proved to be the ideal choice for the system as it meets all the necessary requirements for the project.

The UR10 is programmed through his teach pendant, the CB3, Figure 3.2, using the graphical programming interface and the programming language of Universal Robots, the URscript.



Figure 3.2: CB3 teach pendant and control box [5].

In Figure 3.2 it is also represented the control box, which serves as a central hub for managing various functionalities and facilitating seamless interactions within the system. It incorporates a power supply unit, ensuring a stable and reliable source of energy for the connected equipment. The Input/Output (I/O) ports within the Control Box enable precise control over numerous devices and processes and can efficiently receive/send signals and commands from/to external sources such as sensors, switches, or other digital devices. The UR10 supports several communication protocols, including MODBUS, ProfiNet, EtherNet/IP and TCP/IP [5].

3.2.2 Vision sensor selection

The selection of the vision sensor is a crucial step for this project since the chosen sensor will be responsible for acquiring the necessary images and providing the inspection tools for analysing those images. In this case, Faurecia already has two options available: the Cognex In-Sight 2800, Figure 3.3, and the Keyence IV2, Figure 3.4. These are turnkeys solutions, which are designed to be versatile and suitable for generic applications. Compared to customised solutions tailored for specific applications, turnkey solutions are most cost-effective options.

Now, it becomes essential to evaluate and compare the features and capabilities of both devices to determine which one better suits the specific requirements and objectives for this weld inspection system.



Figure 3.3: Cognex In-Sight 2800 [6].



Figure 3.4: Keyence IV2 [7].

Both the Cognex In-Sight 2800 and the Keyence IV2 utilise artificial intelligence algorithms for inspection purposes. However, the In-Sight 2800 goes a step further by incorporating deep learning algorithms, enabling it to handle various applications such as part location, defect detection, and classification. This means that the In-Sight 2800 can not only detect defects but also classify them into different categories. Additionally, it has the ability to assign multiple classifications models within a single image. In contrast, the IV2 is limited to distinguishing between a pass or fail inspection without the capability for detailed defect categorisation.

When it comes to connectivity and integration, both the Cognex In-Sight 2800 and the Keyence IV2 support various communication protocols. These protocols include TCP/IP, Ethernet/IP, Profinet, and more. This compatibility allows for connections with devices like the UR10 cobot, which also

support these protocols. Additionally, both devices provide FTP (File Transfer Protocol) support, enabling exchange of files, inspection results, and captured images.

When it comes to dimensions, the Keyence IV2 offers a more compact solution, weighing approximately 75g. On the other hand, the Cognex In-Sight 2800 provides a more robust solution, weighing around 300g [6, 7].

Based on the presented comparisons, the Cognex In-Sight 2800 was selected as the vision sensor for this application. In the context of weld inspection, the advanced capabilities of the In-Sight 2800 become crucial. Welds often exhibit significant variations in nature, which can pose challenges in image analysis. The In-Sight 2800's advanced capabilities, including deep learning algorithms and defect classification, provide the necessary tools to effectively analyse and interpret complex weld images.

3.2.3 Production process layout

In Chapter 1 was presented the objective of replacing manual visual inspection with automatic visual inspection. As a result, a new production process layout and flux is proposed, as shown in Figure 3.5.

When comparing the proposed layout, to the current layout (Figure 1.5), an important change is observed. Specifically, step 4 in the production process has been eliminated. Consequently, the responsibility of inspecting the part no longer falls on the K04 operator. Instead, the K03 operator now handles the task of loading the part into the inspection system and initiating the inspection process. Once the inspection is completed, the K04 operator takes charge of unloading the part and loading it onto the K04 station for further processing, as per usual procedures.

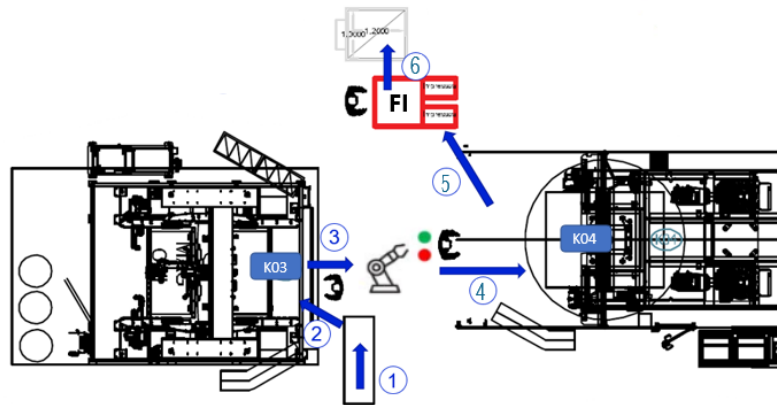


Figure 3.5: Proposed production process layout.

During the development of the new layout, several factors must be taken into consideration to ensure its effectiveness. Optimisation of the workflow plays a crucial role in minimising disruptions and maximising efficiency.

Ergonomics and safety considerations also play a vital role in the new layout design. It is important to create a work environment that promotes the well-being of the operators and reduces the risk of injuries. This may involve adjusting the height and positioning of the system to reduce strain on the operators' backs and limbs, when loading/unloading the backrest. It is also crucial to take into account the distance that operators have to cover while loading and unloading the parts. Minimising the distance travelled can have a significant impact on operational efficiency and operator productivity. Thus, the overall time taken for each task can be shortened, leading to increased productivity and throughput. This can be achieved by strategically positioning the inspection system in the production line.

3.3 Mechanical Project

This section begins by establishing the project requirements. Then, it proceeds to describe the mechanical project development, which involves designing and creating various essential components for the system to function. These components include tables, supports, and a protection case.

3.3.1 Requirements

One of the objectives of this project is to develop and design every component that integrates into the system. This subchapter outlines the specific requirements that must be taken into consideration during the design and development process for each component, which can be summarised in the following:

- It must be possible to take pictures of every weld seam;
- Ergonomics;
- Flexibility;
- Safety;
- Compact system;
- Total price.

In order to ensure the first point is accomplished, some tests were carried out prior to starting the system's design. These tests were conducted in a simulated environment, utilising CAD models of both the cobot and the inspection part. By manipulating the cobot, it was possible to determine the optimal orientation and arrangement of the system, that allows the cobot to reach every weld seam.

In Figure 3.6 a top view is illustrated showing a sketch of the system's layout, and also an estimated distance of 350 mm between the cobot's base and the inspection part.

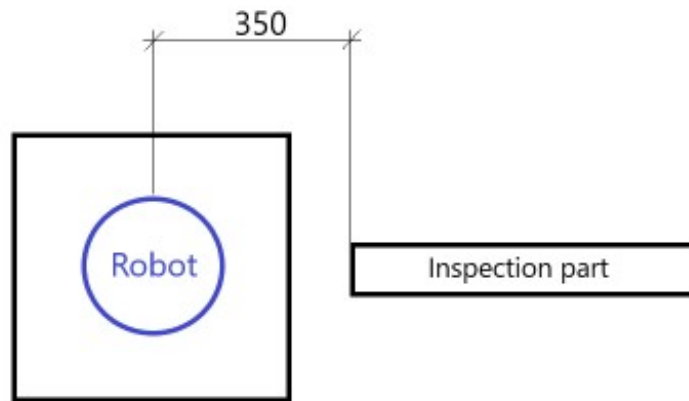


Figure 3.6: Top view sketch of the system's layout with dimensions in mm.

In addition to the first sketch, Figure 3.7 presents a front view that shows the height difference between the cobot's base and the jig base, which should be approximately 500 mm.

Considering that the positioning and removal of the part in the system are carried out by an operator, it is essential to take into account the ergonomic aspect. In order to meet the ergonomic standards set by Faurecia, the part should be positioned at a height of at least 800 mm. Since our goal is to minimise the overall system height as much as possible, 800 mm was chosen as the optimal height for the part in order to ensure compliance with ergonomic requirements.

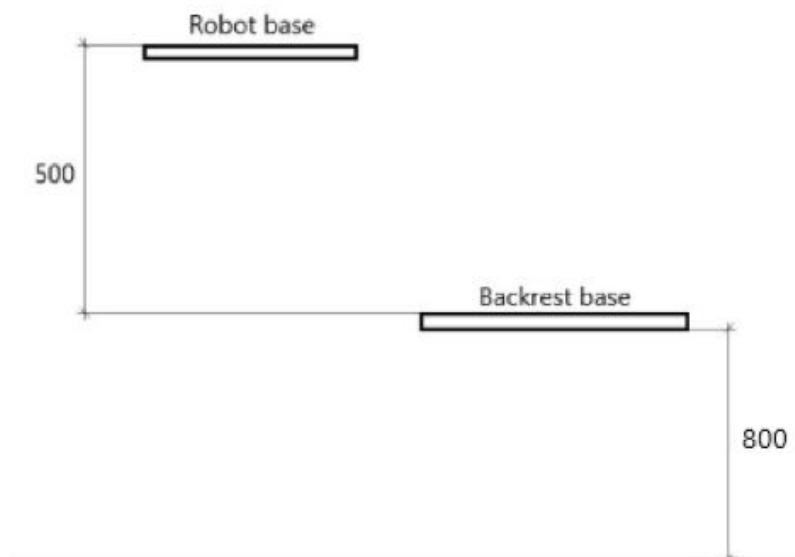


Figure 3.7: Front view of system's with dimensions in mm.

3.3.2 Tables and Jig

The designed system consists of two separate tables: one dedicated to the cobot and another specifically designed for the inspection jig that holds the inspection part. The decision to opt for this configuration, instead of a single table supporting both the cobot and the inspection part, was driven by higher flexibility. By employing two distinct tables, the system gains the advantage of easy reconfiguration in the future, if another product is wanted to inspect for example.

The table that supports the UR10 is composed of two primary components: the metallic structure and the base for cobot installation. The primary focus during the development process was ensuring a secure attachment for the cobot. To achieve this, the UR10's documentation was consulted. The cobot arm is mounted using four M8 bolts, and two Ø8 holes are provided for precise positioning using a pin.

Subsequently, the base where the cobot is mounted was developed, ensuring the appropriate design to enable the proper fixation of the cobot. The visual representation of this base can be seen in Figure 3.8.

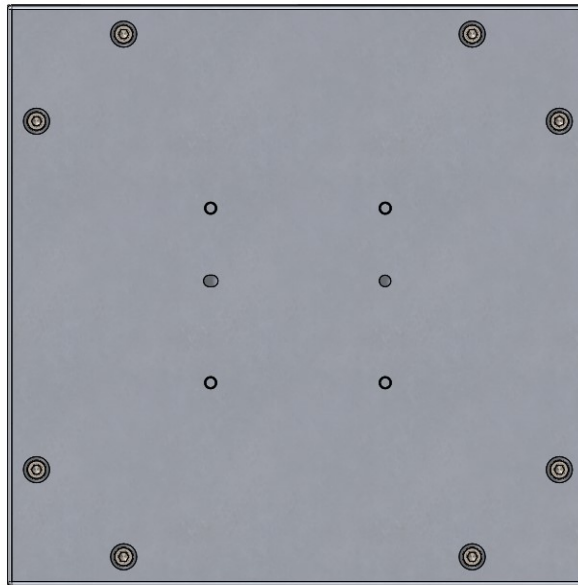


Figure 3.8: Aluminium base for UR10 attachment.

A metallic structure was designed to provide support for this base. The height of the structure was determined based on the previously mentioned requirements ($500 + 800 = 1300$ mm). The assembly between this structure and the cobot's base is presented in Figure 3.9.

The jig table is designed to securely hold the inspection backrest, and therefore requires a supporting mechanism, named jig. To ensure the support is well designed, the dimensions and tolerances of the backrest were carefully analysed. This table assembled with the jig that supports the backrest, is illustrated in Figure 3.10.

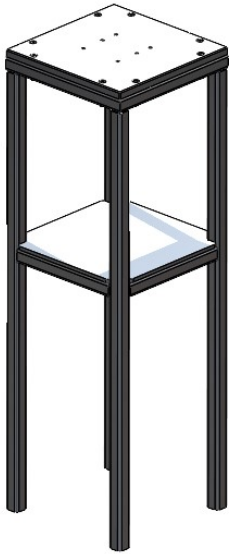


Figure 3.9: UR10 table structure.

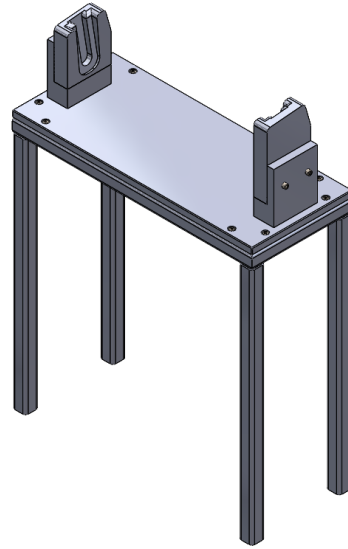


Figure 3.10: Jig table structure.

The system will be programmed to move to specific positions for each weld, and these positions will remain constant. To guarantee that the part remains in the desired location when loaded onto the jig, two inclinations were created at approximately 5 degrees, allowing the part to slide into the designated spot as intended. Figure 3.11 demonstrates this concept, showing a front view and a side view of this assembly.

This feature is important because if the part is positioned differently each time, the camera may fail to capture the weld seam accurately, leading to incorrect inspection results.

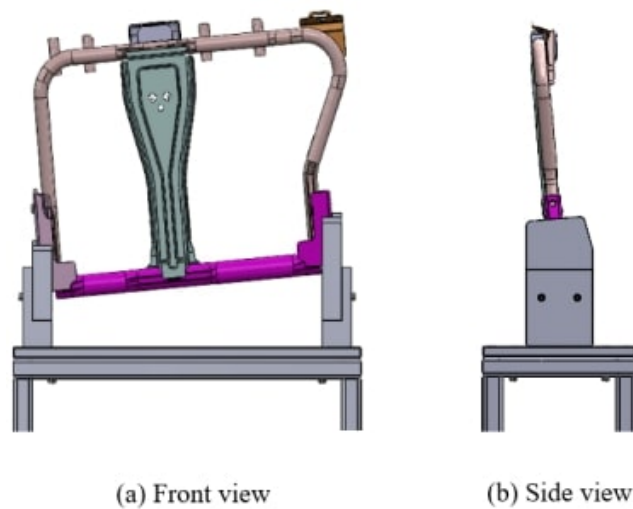


Figure 3.11: Jig Table views illustrating inclinations.

The metallic structures are made of stainless steel while the bases are composed of aluminium. These materials were reused from old parts that Faurecia had, aiming to minimise waste and cost. The jig responsible for supporting the backrest is divided into two parts, being the first made of stainless steel and the other, that is in contact with the backrest made in a polymeric material.

In the initial design of both tables, they were larger, offering a significantly higher level of stability. However, to make efficient reuse of materials and considering that both tables were going to be securely fixed to the floor, they were reduced in size.

The fabrication of all the elements mentioned in this section took place at an external company, near Faurecia installations.

3.3.3 In-Sight 2800 support and protection case

In order to mount the camera onto the cobot, it was necessary to create a support structure that provides stability. To ensure the stability is achieved effectively, the specifications of both the UR10's tool output flange and the camera itself were consulted. The design of the support structure, is presented in Figure 3.12.

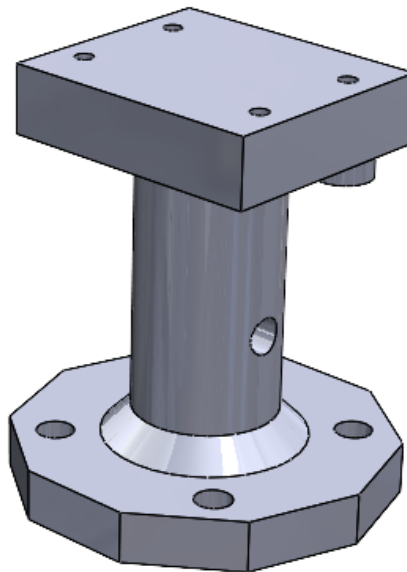


Figure 3.12: In-Sight 2800 - UR10 attachment support.

The camera is a delicate device that requires protection, especially in this system where it will be in continuously motion and susceptible to potential collisions. It is essential to provide safeguards to ensure the camera's integrity and prevent any damage that may occur during operation.

The design for protecting the camera consists of two separate cases that are securely fastened to each other and to the previously support using bolts and nuts. These cases were specifically designed to provide the highest level of effectiveness based on the structure of the camera. Figure 3.13 illustrates the two separate cases that make up the protective design.



Figure 3.13: Protection cases for In-Sight 2800.

Figure 3.14, provides the assembly of the camera onto the cobot, using the attachment support designed, including the incorporation of the protective cases designed.

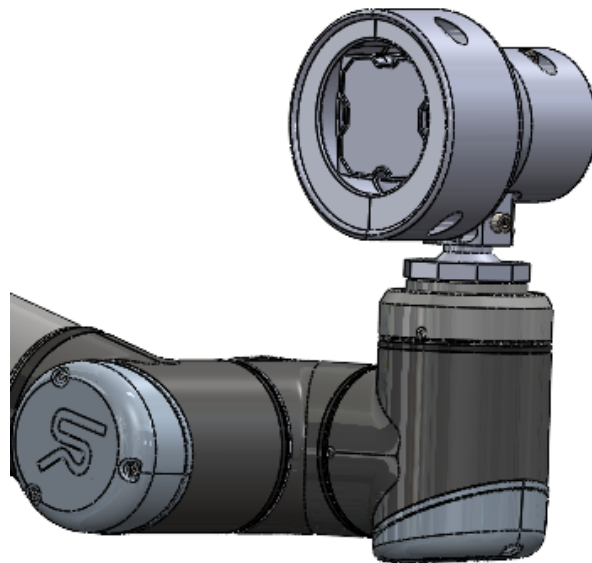


Figure 3.14: UR10 - In-Sight 2800 Assembly.

The three parts presented previously were produced using 3D printing technology, utilising a Markforged Mark Two 3D printer, Figure 3.15, available at Faurecia's facilities. The material chosen for printing all the parts was Onyx, which is a fusion of nylon with micro carbon fiber, offering high strength and toughness [29]. The attachment support took 8 hours, and each case took 19 hours to be completed.

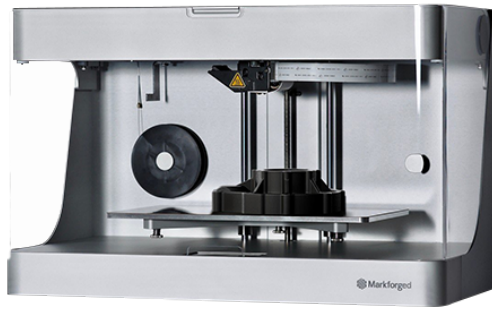


Figure 3.15: MarkForged Mark Two 3D printer [8].

3.3.4 Final System

Once all the parts were prepared and received at Faurecia's facilities, the assembly process was carried out, resulting in the system illustrated in Figure 3.16. The system is installed within the production line at a strategically chosen location that fulfills the previously stated requirements.



Figure 3.16: Final system assembled.

3.4 Communication UR10 - In-Sight 2800

This subchapter begins by presenting the solution obtained for exchanging data in the system, explaining decisions and problems. Subsequently, a detailed description of the steps needed to implement the solution is provided.

3.4.1 Communication solution

Real-time information sharing is vital for the success of an automatic system. The functioning of this system relies on the exchange of two key types of data between the cobot and vision system: the trigger command and inspection results. The trigger command is sent by the cobot and is essential to prompt the vision system to capture an image. Once the image is captured, the inspection process begins, and the results must be shared in real-time with the cobot.

In order to accomplish this, it is necessary to setup the connection between the two. To do this, an industrial communication protocol that is compatible with both the UR10 and the In-Sight 2800 is chosen. After conducting a research on both devices and industrial communication standards, the TCP/IP (Transmission Control Protocol/Internet Protocol) was selected as the most suitable protocol for the task at hand.

TCP/IP is a communication protocol widely used for networking. It provides a reliable and standardised method for data transmission and communication between computers and network devices. TCP/IP consists of two main protocols: TCP and IP [30].

The TCP ensures the reliable delivery of data guaranteeing it reaches the destination without errors or losses. It establishes a connection between the sender and receiver, and implements error detection and correction mechanisms. The IP is responsible for addressing and routing packets across networks. It assigns a unique IP address to each device connected to a network, enabling the identification and location of devices on the internet [31].

Socket communication was the method used to exchange data between the camera and the cobot. This means that they utilise sockets to establish a connection and exchange data. The main purpose of a socket is to identify the unique IP address of a device, along with its port number. The combination of an IP address and a port number forms a socket, which serves as a communication endpoint [32]. The decision to use socket communication in this system was driven by the availability of specific commands in URScript, the programming language used for the UR10 cobot. URScript provides various commands that allow for the opening and closing of sockets, as well as the sending and receiving of data in different formats.

The TCP/IP applications typically use a client/server architecture for communication, where the server provides services or resources, and the clients request and utilise those services [31]. In this particular system, neither the In-Sight 2800 nor the UR10 have the capabilities to behave as servers in a TCP/IP communication. As a result, a typical TCP/IP communication setup is not viable in this context. To solve this problem, the camera act as a telnet server, enabling the cobot to establish a connection and exchange data with it, via Telnet. Telnet is a network protocol used for

remote terminal access and communication over a TCP/IP network. It allows a client to establish a connection with a remote server and interact with it. [32].

The solution for the communication solution is illustrated in the diagram of Figure 3.17.

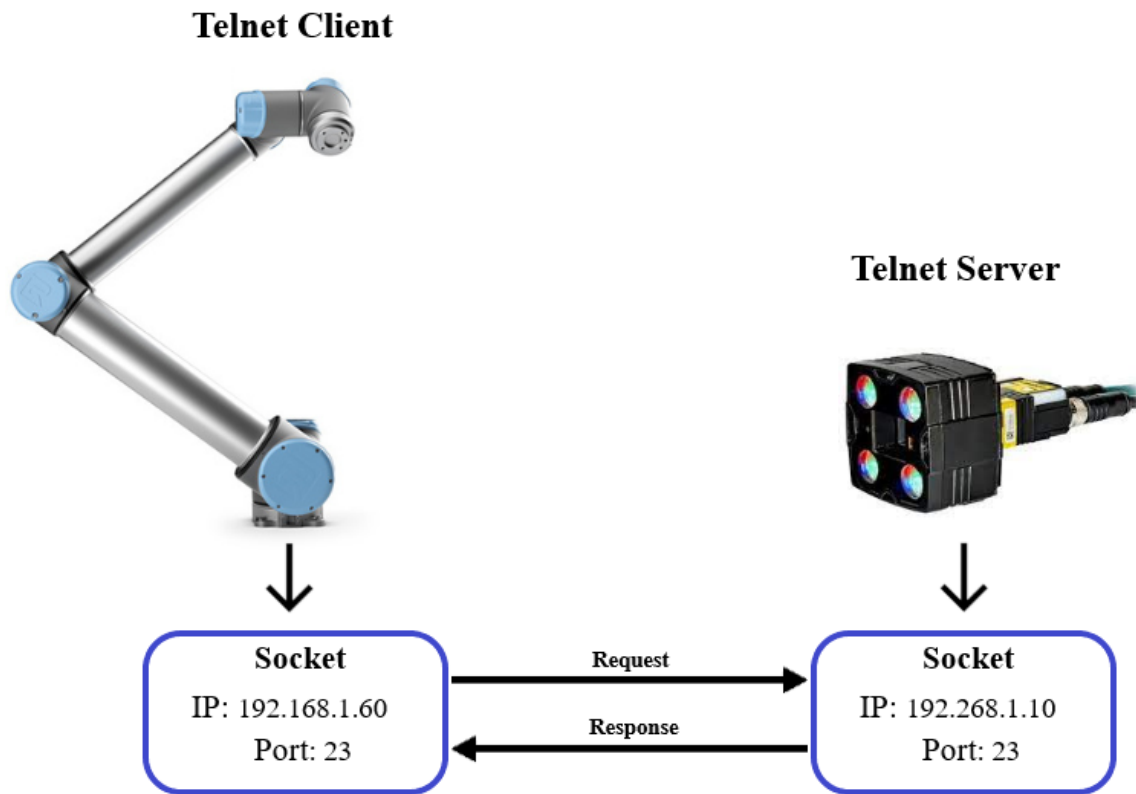


Figure 3.17: Communication solution diagram.

3.4.2 Communication setup

In this section, it will be described the steps done to achieve the desired communication that allow the exchange of data between the UR10 cobot and the In-Sight 2800 vision system.

To accomplish the communication between the UR10 cobot and the In-Sight 2800 vision system, it is essential for both devices to be connected within the same network. To achieve this, an Ethernet 8-port switch from Beckhoff, Figure 3.18, was employed as a networking device. This switch serves as a central hub, enabling the connection of multiple devices. To establish the physical connections, RJ45 cables were utilised to link the In-Sight 2800 and the UR10 cobot to the Ethernet switch.

In order to utilise the In-Sight 2800 software (In-Sight vision Suite) and allow the configuration and control of the vision system, a desktop is employed. The desktop is also connected to the same network through the CU2008 Ethernet port. The In-Sight 2800 and the desktop are also connected through TCP/IP.



Figure 3.18: Beckhoff Ethernet switch CU2008 [9].

Once the In-Sight Vision Suite is installed on the desktop, certain network settings in Microsoft Windows need to be configured to establish a connection with the In-Sight 2800. This involves enabling the Internet Protocol Version 4 (TCP/IPv4) and setting the appropriate IP address and subnet mask. Enabling TCP/IPv4 involves accessing the network connections properties and making sure the TCP/IPv4 option is checked, Figure 3.19. In the TCP/IPv4 properties dialog, the IP address and subnet mask are specified, Figure 3.20. The subnet mask helps determine which part of the IP address refers to the network and which part identifies the specific host. All devices within the same subnet share the same network part of the IP address, while the host part is unique to each device. Therefore in the desktop's IP address, the first three bytes are related to the network (192.168.1), while the last one is a unique identifier for the desktop (100).

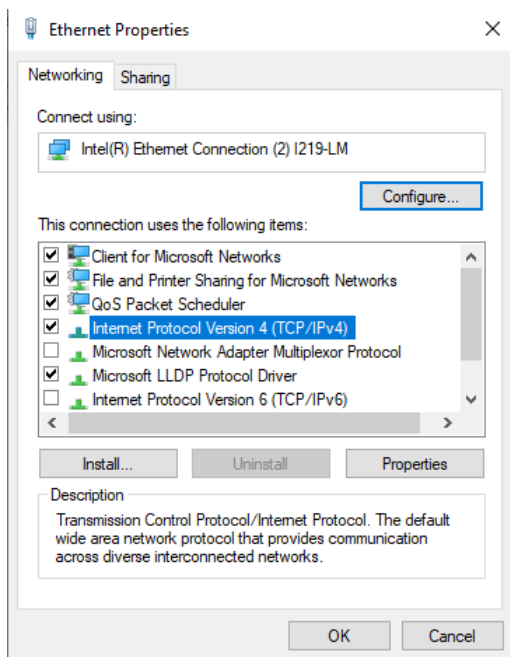


Figure 3.19: Ethernet properties, TCP/IPv4 enable.

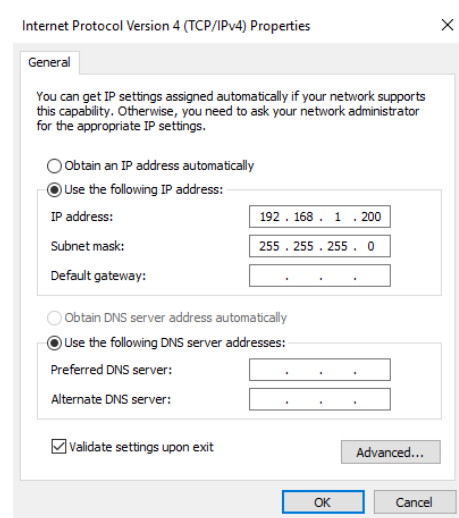


Figure 3.20: TCP/IPv4 properties, IP address and subnet mask configuration.

Next, the IP address of the vision system needs to be compatible with the desktop's network. To achieve this, the In-Sight software is used to change the system's IP address, as illustrated in Figure 3.21. The new IP address is set to match the first three bytes of the desktop's IP (192.168.1). However the last byte is modified to create a unique identifier for the vision system within the network (10).

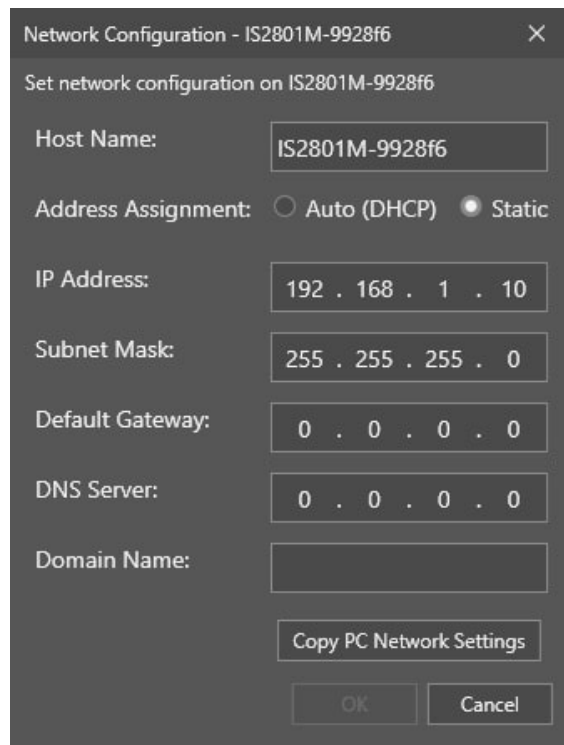


Figure 3.21: In-Sight Vision Suite network configuration.

By configuring this network settings, the In-Sight 2800 is now connected to the same network as the desktop. Therefore it's now possible to have full access to the In-Sight Vision Suite to configure and control the vision system.

The next step is configure the IP address of the UR10, using the teach pendant, following the same rules. This configuration is represented in Figure 3.22.

Once all three devices are successfully connected, data exchange can be initiated. This involves utilising the native commands provided by Cognex. Table 3.1 lists the three essential types of commands required for the project to operate. This commands are sent by the UR10 socket to the vision system socket, using the URscript commands of Table 3.2.

Figure 3.22: UR10 network settings.

Table 3.1: Native commands.

Commands	Syntax	Description
Set Job	SJ[ID]	Loads the [ID] job, making it the active job
Set event and wait	SW8	Acquire an image and update the spreadsheet
Get value	SV[tag]	Returns the contents of a specified symbolic tag

Table 3.2: URscript commands.

Command	Description
socket_open(address, port, socket_name="socket_0")	Attempts to open a socket connection
socket_send_string(str, socket_name)	Sends the "str" string through the socket
socket_read_string(socket_name)	Reads data from the socket and returns the data as a string

3.5 In-Sight Vision Suite

The In-Sight 2800 is programmed using In-Sight Vision Suite software. This software provides a variety of tools tailored to different applications. For this particular project, the tool used was the ViDi EL Classify. This tool uses deep learning to automatically identify and sort objects into classes based on the input data [6].

The inspection system examines all 17 welds, and due to the unique characteristics of each weld, it requires the existence of distinct jobs for every weld seam within the camera software. To address uncertainty regarding the optimal classification method, a decision was made to experiment with two different approaches and subsequently evaluate their performance to determine the superior method. Therefore each weld is inspected using two classification methods, resulting in a total of 34 jobs in the In-Sight software.

This subchapter explains the process of classifying the images captured by the In-Sight 2800. It provides details about two classification methods used for the quality inspection results, as well as an additional classification for detecting the backrest. Furthermore, it also covers the storage of the acquired images.

3.5.1 Image classification

Image classification is a fundamental task in computer vision that involves categorising or assigning labels to images based on their visual content. It plays a crucial role in numerous applications, including object recognition, scene understanding, medical diagnosis, autonomous driving, and more [33].

The In-Sight 2800 learns from labeled training data to make predictions or decisions based on new, unseen inputs. This is known as supervised learning, which involves training a model using input-output pairs, also known as training examples or labeled data, to learn the relationship between input variables and their corresponding output variables [33].

There are three main types of classification methods: binary classification, multi-class classification, and multi-label classification, Figure 3.23.

Binary classification involves tasks with two class labels, typically representing a normal state and an abnormal state. Multi-class classification involves tasks with more than two class labels. Multi-label classification involves tasks with two or more class labels, where it's possible to have one or more predicted labels [34]. This system uses two of these methods, the binary and the multi-class classification.

Before starting to configure the ViDi EL Classify tool, an important decision must be done regarding the labels included in the classification. This decision was based on an analysis of the most common defects observed in the production process. The selected labels were: "OK", "Porosity", "Misalignment", and "Burn through".

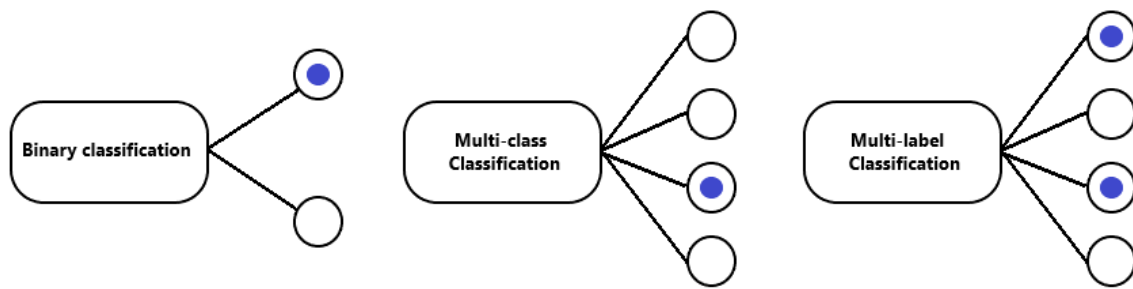


Figure 3.23: Classification methods.

3.5.1.1 Method A

The approach utilised in this method involves a single classifier that generates four possible outputs, as illustrated in Figure 3.24. This method follows the Multi-class classification technique. When the output is labeled as "OK," it indicates that the weld seam is of satisfactory quality, resulting in an inspection result denoted as "1". On the other hand, the remaining outputs, namely "Porosity," "Burn Through," and "Misalignment," indicate the presence of defects in the weld, signifying that it is not of acceptable quality, retrieving a "0" as inspection result.

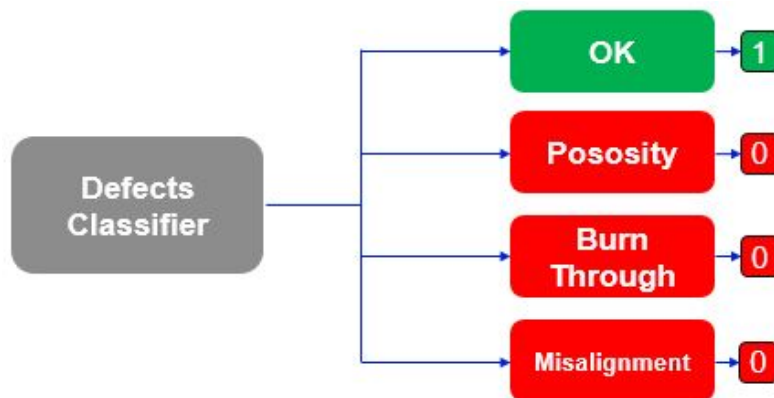


Figure 3.24: Classification diagram - Method A.

The training procedure for this model involved providing labeled data to each respective class. For instance, images representing welds of good quality were utilised as training examples for the "OK" class, while images displaying porous welds were employed as training examples for the "Porosity" class, and so forth. Figure 3.25, illustrates the training in In-Sight Vision Suite environment.

3.5.1.2 Method B

In contrast to the previous method, this alternative approach employs four distinct classifiers, each dedicated to one of the possible inspection outcomes, as demonstrated in Figure 3.26. This method

Class	Tool Result	Unlabeled Images	Labeled Images
Burn Through	Fail		
Misalignment	Fail		 
OK	Pass		 
Porosity	Fail		 

Figure 3.25: In-Sight Vision Suite - Classification environment window Method A.

uses binary classification for each classifier. For instance, the "OK Classifier" is responsible for determining whether the camera's prediction indicates a good quality weld. If the prediction aligns with an "OK" classification, the inspection result is assigned a value of "1", otherwise, it is assigned a value of "0". Similarly, the "Porosity Classifier" focuses on identifying porous welds, assigning a value of "1" to the inspection result if the camera predicts the presence of porosity and "0" otherwise.

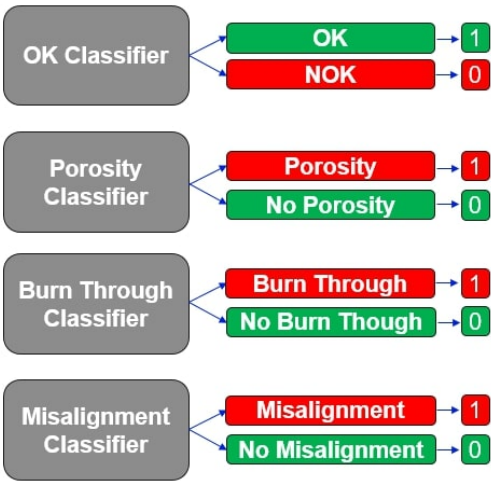


Figure 3.26: Classification diagram - Method B.

After the camera yield all the results for each classifier, the data obtained is processed logically to derive the final inspection result. For this procedure the spreadsheet provided by the In-Sight software was used, Figure 3.27.

In the spreadsheet the cells labeled "A0", "A1", "A2", and "A3", correspond to the results of each classifier, following the order shown in Figure 3.26. The two functions illustrated in Figure 3.27, specifically in cells "B0" and "B1", are used to determine the final inspection value.

Cell "B0" consolidates the results of the three defect classifiers into a single value. If the camera detects one or more defects, cell "B0" is assigned a value of "1", otherwise, it is assigned a value of "0". Subsequently, cell "B1" concludes the process by using the value from the "OK Classifier" and the value obtained earlier in cell "B0". The final inspection value is "1", indicating a good quality weld, only if the camera identifies the weld as "OK" and no defects are detected, otherwise the value is "0".

B0	=	if((A1+A2+A3) > 0, 1, 0)
B1	=	if((And(A0=1,B0=0))=1, 1, 0)

	A	B	C
0	1,000	0,000	
1	0,000	1,000	
2	0,000		
3	0,000		
4			

Figure 3.27: Spreadsheet of final inspection value.

The training procedure for this method differs from the previous one. In this case, the vision system evaluates each class individually in comparison to the rest.

Taking the "OK Classifier" as an example, it uses images of good quality welds in the "OK" class, while all images of different defects are used in the "NOK" class. Similarly, for the "Burn Through Classifier," images of burnt welds are used in the "Burn Through" class, and all other images, such as good quality, porous, and deviated welds, are used in the "No Burn Through" class.

Figure 3.28, illustrates the training proceeding in In-Sight Vision Suite, for the "OK Classifier".

3.5.1.3 Part detection classifier

This classifier is part of each job and serves the purpose of determining the presence of the weld and ensuring the part is placed in the jig.

It follows the structure of a binary classification, where the two labels are "Part" and "No Part", as demonstrated in Figure 3.29. When the prediction corresponds to the label "Part", a value of "1"

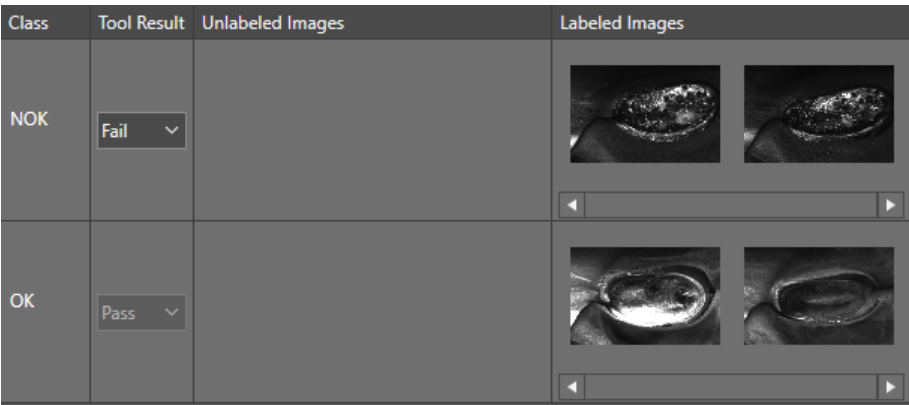


Figure 3.28: In-Sight Vision Suite - "OK Classifier" environment window Method B.

is assigned to the inspection result. Otherwise, if the prediction aligns with the label "No Part", a value of "0" is assigned.

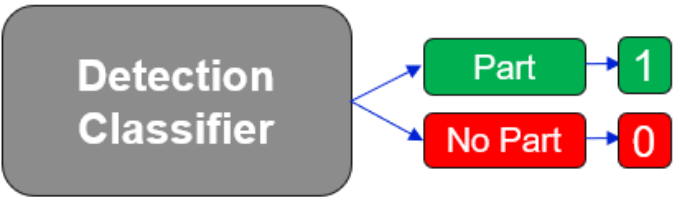


Figure 3.29: Classification diagram - Part detection.

The training process for this model is straightforward. An image of the weld is designated as a positive example and assigned to the "Part" label, while a black image is used as a negative example and assigned to the "No Part" label. Since a black image is the result when the part is not placed in the jig and the vision system captures an image, it serves as a suitable representation for the "No Part" classification. However, it's important to note that if the system is relocated to a different location, it would be necessary to verify and adapt the model to ensure its effectiveness in the new environment.

Figure 3.30 illustrates the training procedure of this classifier in the In-Sight Vision Suite.

3.5.2 Image storage

Image storage plays a crucial role in the inspection system, particularly in terms of traceability and maintaining a record of the inspection process. Storing images allows for future reference, analysis, and verification of inspection results.

Regarding traceability, in each inspection cycle, the vision system goes beyond capturing 17 images. It also captures the Data matrix located on the backrest, which contains crucial information that uniquely identifies each individual product. Figure 3.31 illustrates a data matrix of a

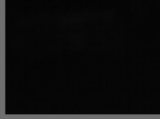
Class	Tool Result	Unlabeled Images	Labeled Images	
No Part	Fail v			
Part	Pass v			

Figure 3.30: In-Sight Vision Suite - "Detection Classifier" environment window.

backrest. This additional feature significantly enhances traceability by establishing a direct association between the captured weld images and their corresponding actual products.



Figure 3.31: Data matrix of backrest.

The File Transfer Protocol (FTP) is used to transfer the images from the In-Sight 2800 to designated folders in the desktop. To enable this, an FTP server software is installed in the desktop. A FTP server is a software application that allows for the transfer of files between a client and a server over a network. It provides means for upload, download, and manage files on the server using the FTP protocol [35].

Once the FTP server software is installed on the computer, certain configurations need to be set up. One of the initial steps involves determining the storage organisation. In this case, considering that 17 images are captured during each cycle, 17 distinct folders were created in the computer, with each folder dedicated to a specific weld.

With this information, the next step is to configure the FTP server accordingly. This involves creating 17 user accounts on the FTP server, where each user is assigned a specific folder for storing their respective images. This set up is illustrated in Figure 3.32.

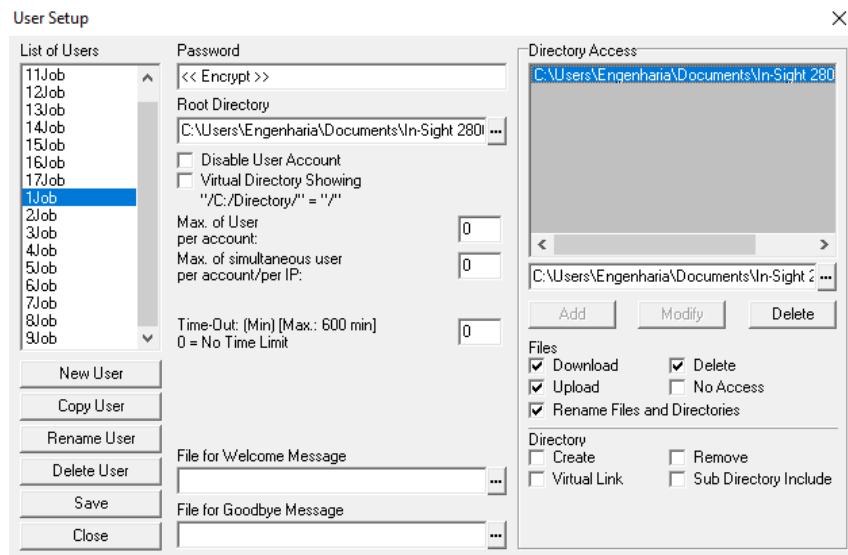


Figure 3.32: FTP server, users setup.

These users are then assigned to the correspondent job in the In-Sight Vision Suite, as illustrated in Figure 3.33. To accomplish this, the server's IP address, along with the username and password, are required. The passwords were established during the user account creation process within the FTP server application.

Several essential settings are worth noting during the configuration process. Firstly, the "File path" setting specifies the location of the folder where the captured images will be saved. Secondly, the "File name" setting determines the name given to the image based on the inspection result. In this specific scenario, the name used is "OK," indicating a successful inspection outcome. Finally, the "timestamp format" setting ensures that the exact time the image was acquired is included in the stored file's name.

Figure 3.34 presents a diagram that illustrates the process of transferring and storing images within this system. To summarise the image storage procedure, every job within the vision system is linked to a user in the FTP server. Consequently, each acquired image from a particular job is transmitted to the FTP server and saved in the designated folder specified in the user settings. For every image acquired, both a BMP file and an SVG document are saved. In terms of storage requirements, each part utilises a total of 26 MB.

Regarding the data matrix image, this one is acquired while the second job of the vision system is active, known as "2Job". Therefore it is stored in the "2Job" folder. Ideally, it would be created a new job, assign a new user, and create a separate folder specifically for the data matrix images. However, it was decided not to do this because it would increase the system's cycle time, which is not beneficial given the time constraints.

FTP Server	
Server	192.168.1.200
User Name	1Job
Password	•••••
Write Image	
Enabled	Yes
Storage	FTP Server
File Path	C:\Users\Engenharia\Documents\In-Sight 2800 FTP\1Job
File Name	OK
File Type	BMP
Overlay Graphics	Yes
Add Timestamp	Yes
Timestamp Format	HHMMSS
Append Value	No
Max Append Value	9999
File Name Preview	OK140359

Figure 3.33: FTP configuration - In-Sight Vision Suite.

3.6 Human Machine Interface

This system relies on effective control mechanisms and easily understandable status indicators to ensure smooth operation and monitoring between the system and operators. To accomplish this goal, the system incorporates the following components: two luminous push-up buttons (one green and one blue), three light indicators (green, red, and orange), and an emergency button. This subchapter provides a detailed explanation of the setup and role of these devices.

In Figure 3.35, an overview of the I/O terminal blocks included in the control box of the UR10 is visible.

The circuit diagram, in Figure 3.36, illustrates the arrangement of both push buttons. To establish these connections, the digital inputs and outputs terminal blocks are utilised.

Figure 3.37 showcases the circuit diagram for the light indicators. To establish these connections, the digital output terminal block is used. Therefore the system can control the behavior of the light indicators, allowing to display the desired colors and convey relevant information to the users.

Finally, in Figure 3.38 the circuit for the emergency stop push button is illustrated. This particular button is connected using two normally close contacts for enhanced safety and reliability. These are connected to the emergency stop dedicated area in the safety terminal block.

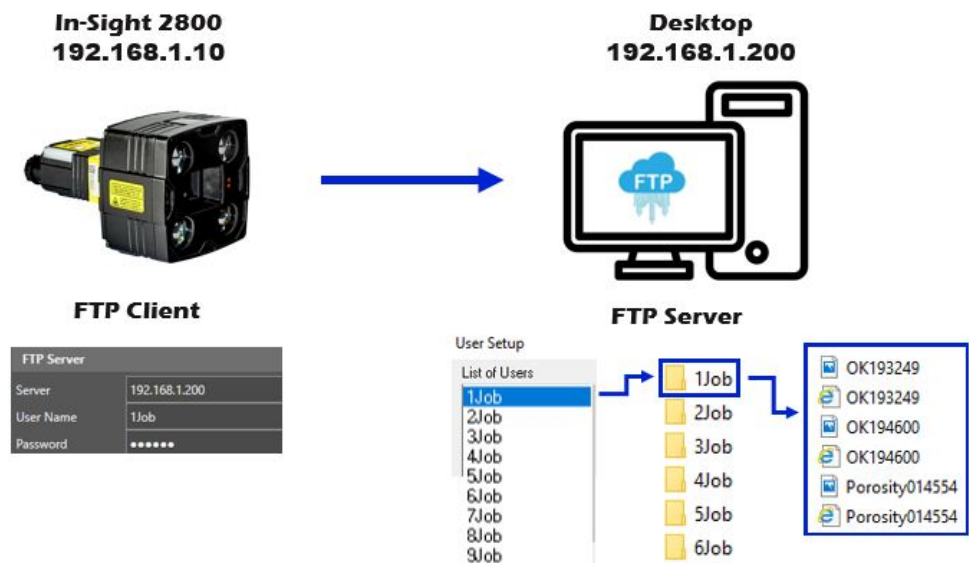


Figure 3.34: Image storage diagram.

In summary, Table 3.3 provides an overview of the input/output ports to which the aforementioned devices are connected, along with a brief description of the purpose of each device.

Table 3.3: Inputs/Outputs description.

Device	Input	Output	Purpose
Green button	DI1	DO4	Start the cycle
Blue button	DI2	DO5	Reset errors
Red light		DO2	NOK part indication
Orange light		DO6	Error indication
Green light		DO7	OK part indication

Figure 3.39 illustrates the buttons control box that houses the blue push button and all the light indicators. Figures 3.40 and 3.41 illustrate the assembly of the green push button and the emergency button, respectively. Each button and light has a tag, written in Portuguese due to safety standards, indicating the purpose of each device.

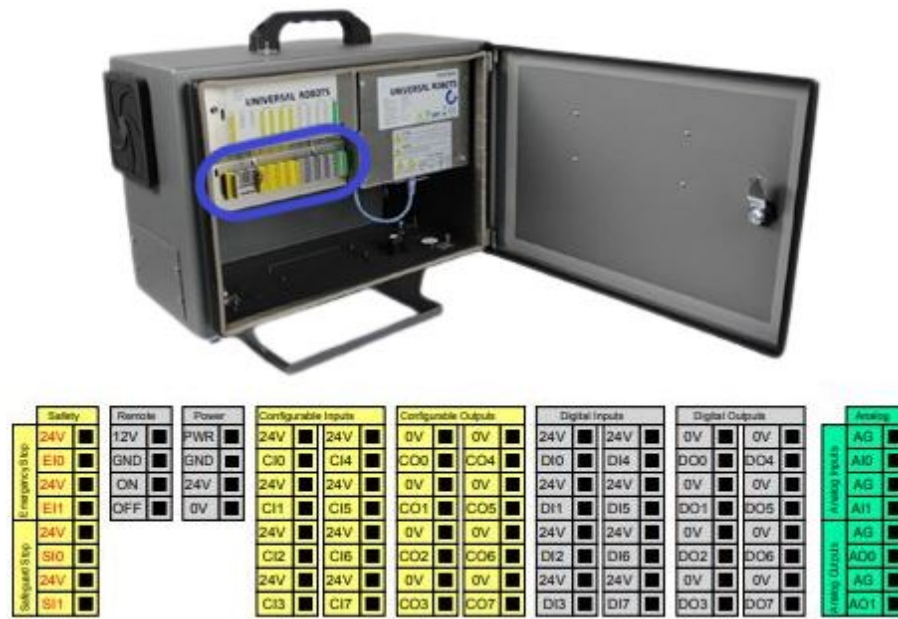


Figure 3.35: Control box and I/O terminal blocks.

To complement the interaction with the operators, an Human Machine Interface (HMI) is displayed in the desktop monitor, presented in Figure 3.42. This HMI is provided by the In-Sight Vision Suite, offering real-time images captured by the system along with their corresponding inspection results. This enables operators to easily monitor and interpret the visual data acquired by the system.

3.7 Script development

This subchapter delve into the phase of script development, starting by presenting the possible outcomes of the inspection, evaluating the behaviour of the system in each of this scenarios. After this the script is explained using two flowcharts, that describe the important steps of the inspection.

3.7.1 Scenarios

Prior to beginning the programming phase, an analysis was conducted to evaluate the potential outcomes of the inspection. As a result, six distinct scenarios were formulated. These process involved examining various factors and variables to anticipate different paths and developments. These scenarios act as a beneficial tool to guide the script development process.

3.7.1.1 Scenario A - Weld inspection, OK part

In this first scenario, Figure 3.43, the ideal process is described. It represents an optimal outcome, where the system functions with no errors and the part inspected is OK. Once the cobot completes the inspection process, the green light is turned on and the cobot returns to the home position.

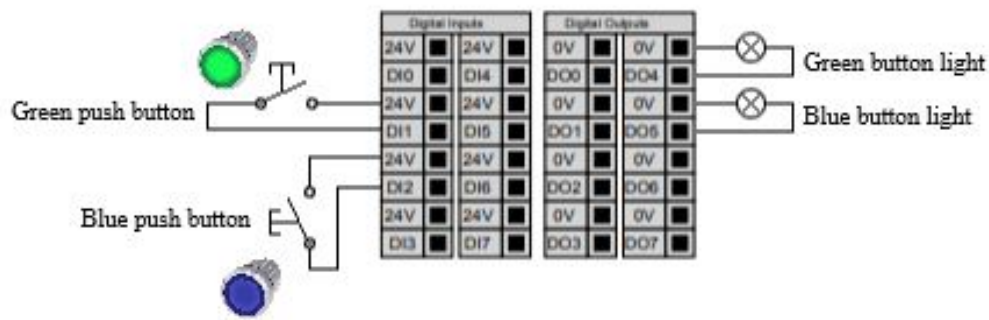


Figure 3.36: Push buttons electrical circuit.

3.7.1.2 Scenario B - Weld inspection, NOK part

In scenario B, Figure 3.44, similar to the previous scenario, the absence of errors persists. However, the inspected part is now considered NOK instead of OK. When such a situation arises, the red light is turned on and the cobot responds by locking the part in place by moving itself above the part, effectively preventing its extraction. This action ensures that the NOK part is securely held until the reset button is pressed. Once this happens the cobot returns to home position.

3.7.1.3 Scenario C - Weld inspection, Part removed before end of inspection

Scenario C, Figure 3.45, presents an unlikely situation where the operator unexpectedly removes the inspection part during the inspection process. While such incidents may be rare, it is crucial for the system to be prepared for all possibilities. In this scenario, when the system detects that the part has been removed prematurely, it activates an orange light and the cobot responds by instantly returning to the home position.

3.7.1.4 Scenario D - Weld inspection, absence of part

In a similar situation to the previous scenario, the system detects a missing part, but this time it happens at the start of the inspection. Figure 3.46 shows the grafcet for this scenario. The operator unintentionally forgets to place the part in the support and proceeds to press the start button. As a response, the system don't start the cycle and activates an orange light. Upon realising the mistake, the operator rectifies it by correctly positioning the part in the jig, the operator then can press the start button, and the system will initiate the inspection process.

3.7.1.5 Scenario E - Weld inspection, operator hits the cobot

In the event that the cobot encounters an obstacle or is struck by something while in motion, it activates a protective stop mechanism, Figure 3.47 illustrates the grafcet for this scenario. This safety feature is built into the collaborative cobot. In order to resume its operation, the operator is

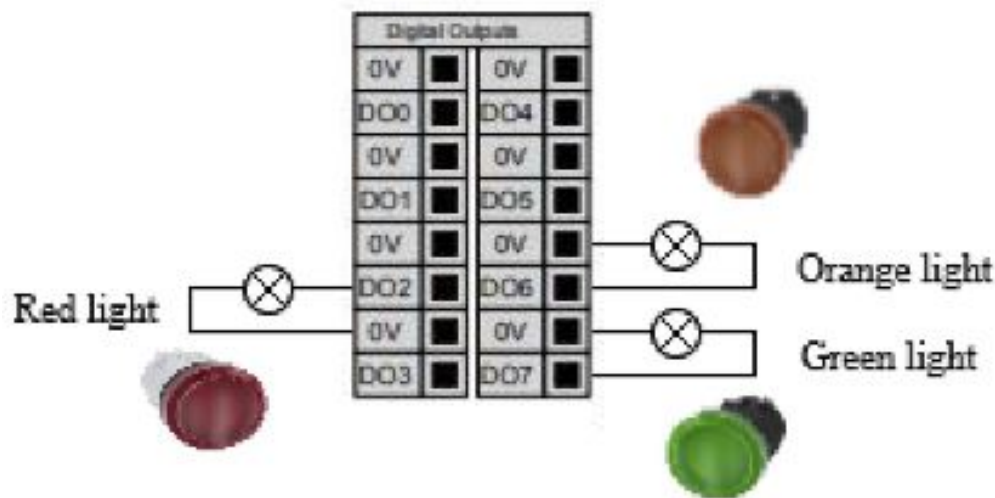


Figure 3.37: Lights indicators electrical circuit.

required to press the start button. Once the start button is pressed, the cobot resumes its inspection trajectory from where it left off, continuing its normal operations as usual.

3.7.1.6 Scenario F - Weld inspection, emergency button press

In this particular situation, there is an additional safety feature known as the emergency button. Figure 3.48 presents the grafcet of this scenario. This button can be activated at any moment during the inspection process. When the emergency button is pressed, it immediately halts the cobot's operation, and activates a red light.

3.7.2 Routine

Following the review of every outcome possible in the weld inspection, the script was developed. The script was written using Polyscope, accessible through the UR10's teach pendant, and a language called URcript. Essentially the main purposes of the script are controlling the cobot position, exchange data with the In-Sight 2800, and manage the I/O functionalities. The script is presented in Appendix A at Code A.1.

In this subchapter the script developed is explained using flowcharts. This allows for a comprehensive visualisation of the code's structure and the sequence of actions it performs. The routine is divided into two flowcharts.

The main flowchart, represented in Figure 3.49, initiates when the operator presses the green button. At this point, the cobot begins by establishing a socket connection between the UR10 socket and the vision system socket. Once this is successfully established, a login procedure is required to enable communication with the In-Sight 2800 system. With this accomplished, the

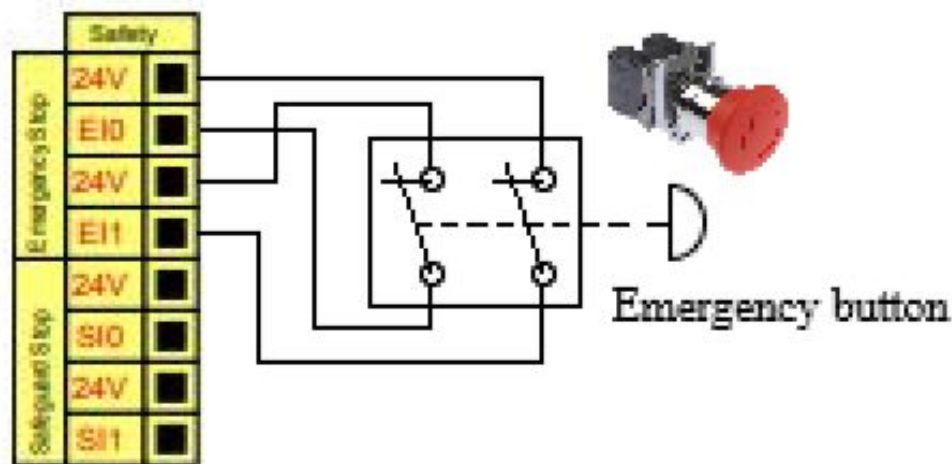


Figure 3.38: Emergency button electrical circuit.

actual weld inspection can begin, which is further elaborated in the flowchart illustrated in Figure 3.50.

The process of inspecting the weld begins by configuring the job for the specific weld being examined. Once the job is set, the system proceeds to move towards the designated weld waypoint. Upon reaching this waypoint, the camera is triggered, capturing an image of the weld. The captured image is initially inspected to determine if the part is present. In the event that the part is not detected, an error occurs, causing the orange light to activate. Subsequently, the system returns to the home position and halts the procedure.

However, if the part is detected, the inspection focuses on assessing the quality of the seam. In the case of a satisfactory weld (OK), the system increments a counter. On the other hand, if defects are identified in the weld (NOK), the counter step is skipped.

This process is repeated for a total of 17 welds, employing the same steps outlined in the flowchart depicted in Figure 3.50.

After completing the inspection of all the welds and obtaining the final counter value, the process transitions back to the main flowchart shown in Figure 3.49. If the counter reaches a total of 17, meaning the part deemed satisfactory, the system moves to the home position, activates the green light, and halts the procedure, signifying the completion of the inspection for that particular part.

However, if the counter total is not equal to 17, indicating the presence of defects in at least one seam, the system takes another actions. It moves to a designated waypoint that restricts the operator from unloading the part, activates the red light, and waits for the operator to press the blue button. Once the blue button is pressed, the system returns to the home position and halts the procedure, concluding the inspection process.

The inspection routine was carefully developed and optimised to meet the time requirements of the system. In Scenario A, where no errors occur and the backrest is deemed OK, the inspection process takes approximately 52 seconds. It's worth noting that this duration can vary depending



Figure 3.39: Control box, with light indicators and blue button.

on the chosen safety settings. The objective was to strike a balance between safety considerations and inspection time, to ensure that the inspection time remained below 54 seconds while still maintaining appropriate safety measures. This means that if a more restrict inspection time is required it can be achievable, with reduced safety measures.

3.8 Conclusion

In this chapter, the focus was on developing the automatic welding inspection system, which will be subjected to testing in the subsequent chapter. The development process involved several steps to ensure that all the system requirements were met.

By the conclusion of this chapter, a successful development of a compact system that fulfills all the specified requirements has been achieved. This system is capable of accessing and inspecting all the welds within the imposed cycle time. The script developed for the system covers all the possible scenarios of inspection. Furthermore, the system incorporates the capability to save data, thereby enhancing traceability. Overall, the developed system not only meets the required criteria but also offers improved efficiency and traceability, providing a reliable solution for automatic welding inspection.



Figure 3.40: Green button control box.



Figure 3.41: Emergency button control box.

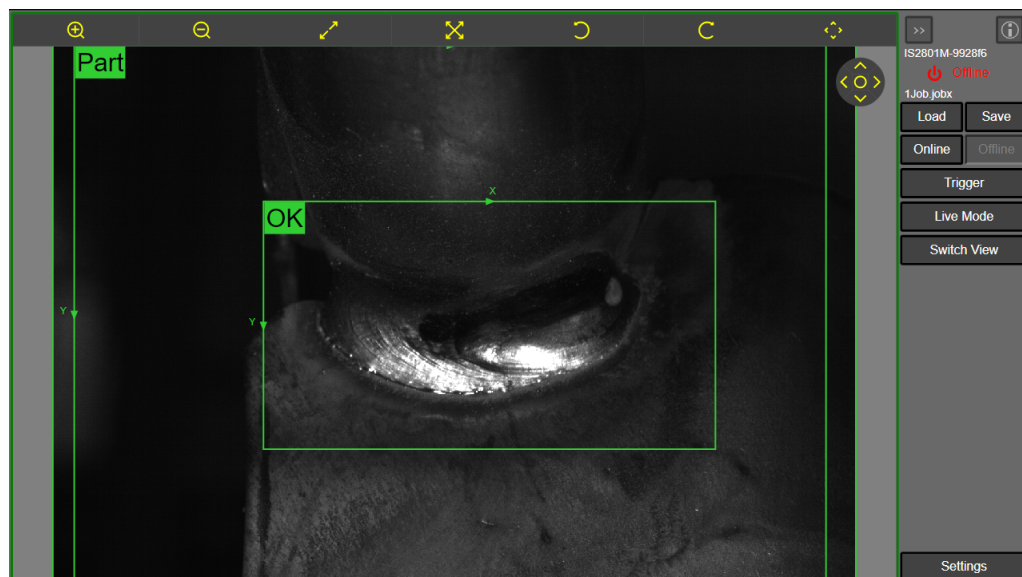


Figure 3.42: HMI available in In-Sight Vision Suite.

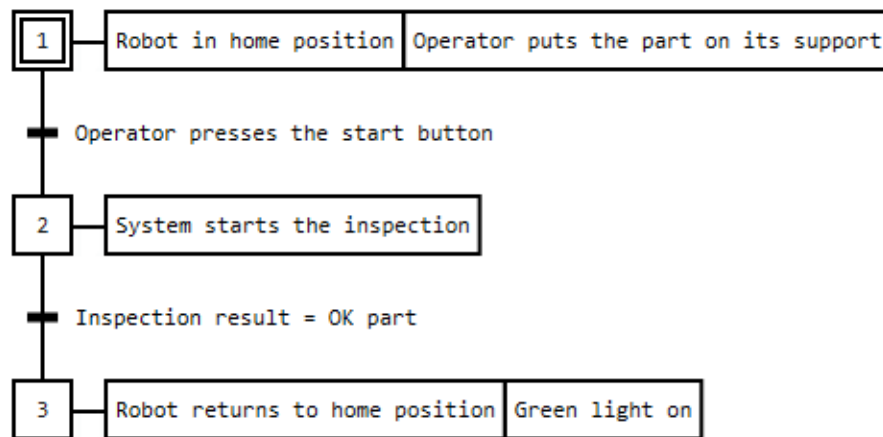


Figure 3.43: Scenario A Grafcet.

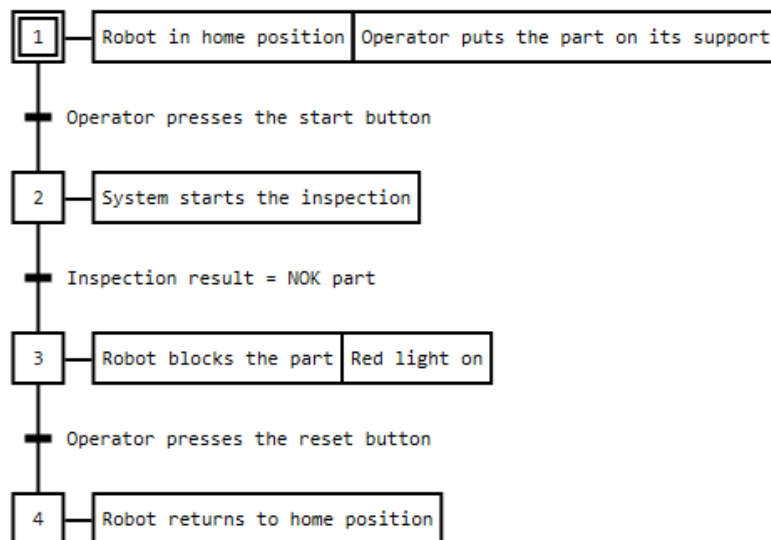


Figure 3.44: Scenario B Grafcet.

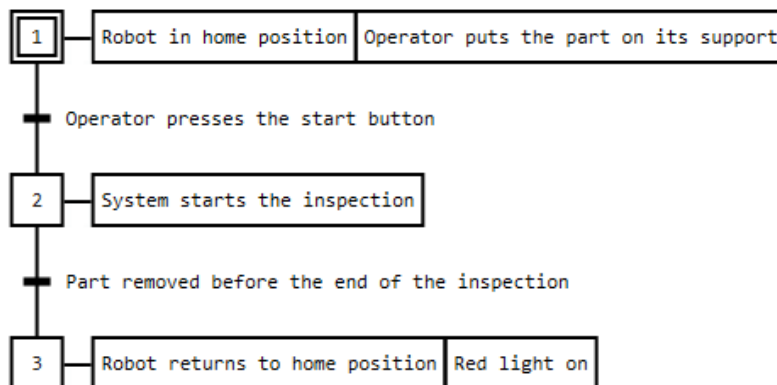


Figure 3.45: Scenario C Grafcet.

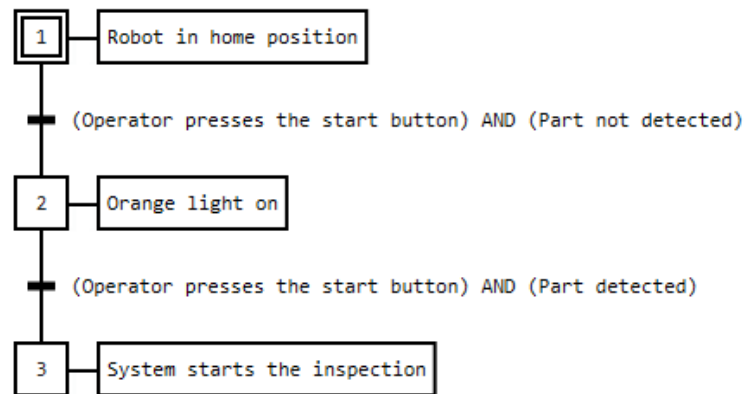


Figure 3.46: Scenario D Grafcet.

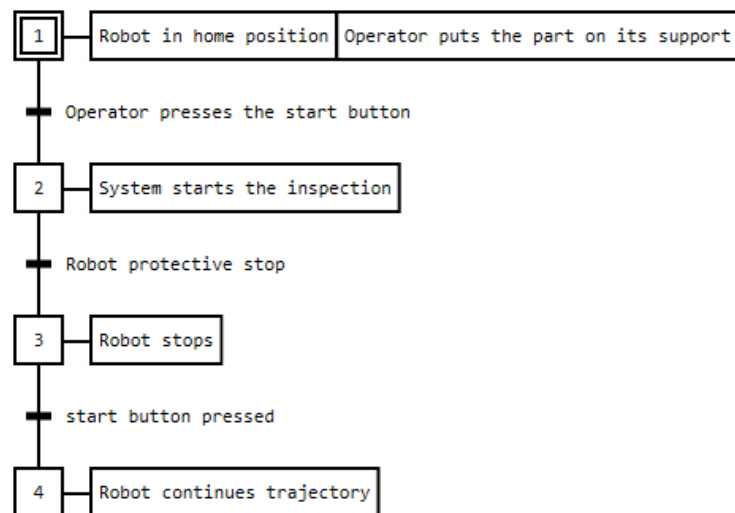


Figure 3.47: Scenario E Grafcet.

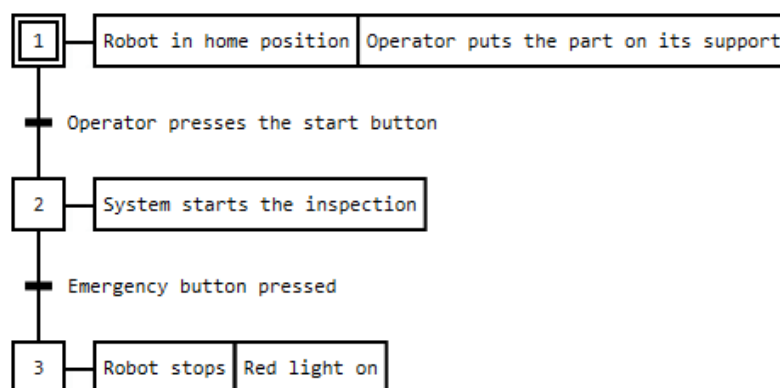


Figure 3.48: Scenario F Grafcet.

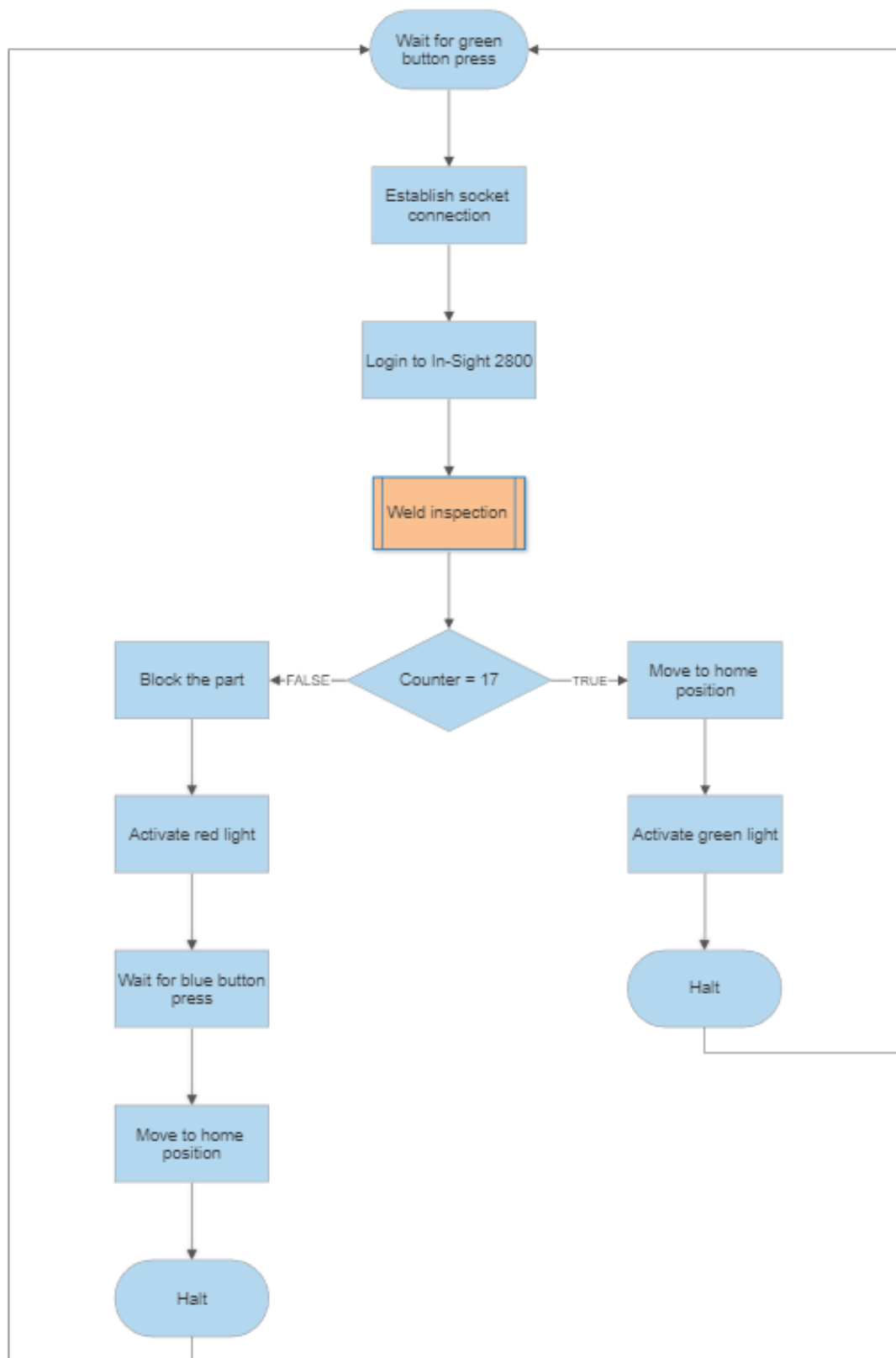


Figure 3.49: Main flowchart of the script.

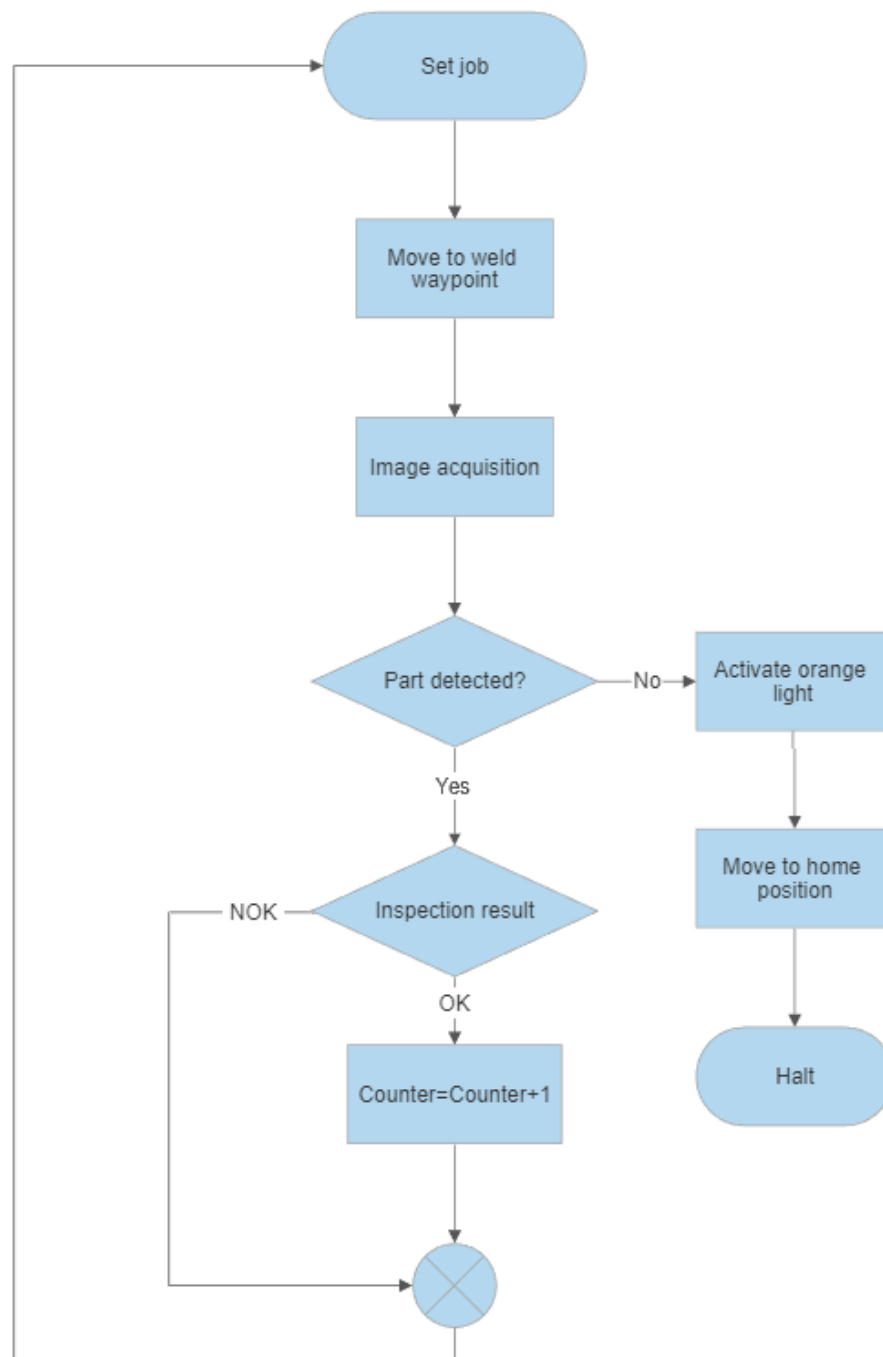


Figure 3.50: Weld inspection flowchart.

Chapter 4

Statistical validation

4.1 Introduction

In this chapter, the testing phase of the previously developed system is conducted, with a specific focus on evaluating the classification models proposed. The objective of this evaluation is to evaluate the performance, and the influence of light in the inspection.

4.2 Confusion matrix

The confusion matrix is one of the most commonly used tools for evaluating the classification accuracy of a model. It provides a comprehensive and intuitive representation of the model's predictions and their agreement with the true labels [36]. Figure 4.1, presents a diagram of this study.

A confusion matrix includes four important components: True positives (TP), False negatives (FN), False positives (FP), and True negatives (TN). These components help us evaluate the performance of a system or model.

True positives represent good welds that the system correctly identifies as good, indicating successful production. False negatives, on the other hand, are good quality welds that the system mistakenly categorises as not good, resulting in wastage. False positives refer to not good welds that the system incorrectly identifies as good, which is the worst-case scenario for inspections, potentially leading to client claims. Lastly, True negatives represent not good welds that the system correctly identifies as not good, providing client protection by avoiding acceptance of faulty products.

In the subsequent sections, the confusion matrix is utilised to assess the performance of the two methods developed in the previous chapter. This evaluation serves to determine the accuracy and effectiveness of the classification methods in detecting defects and conducting reliable inspections.

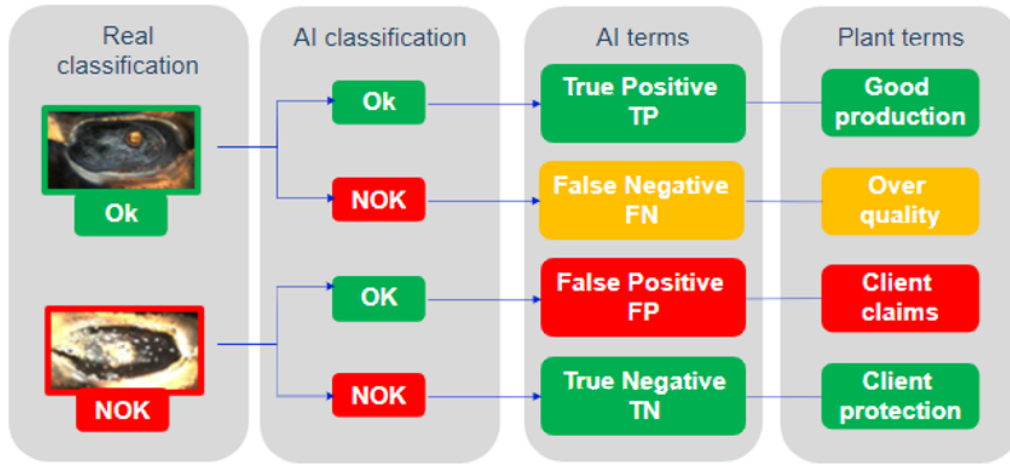


Figure 4.1: Confusion matrix

This study is made individually for each weld model, resulting in 17 studies for each method analysed.

The effectiveness of the inspection is determined by considering both the prediction score value and a threshold value. Prediction score is a number between 1 and 100 representing the confidence of the model in the result yield. The threshold value acts as a decision boundary, separating solid predictions from weak ones. Any prediction score greater than the threshold is considered a solid prediction. Conversely, predictions with scores below the threshold are considered weak or unreliable.

In order to validate the system, the optimal threshold is carefully selected in order to meet the specific requirements set by Faurecia. These requirements involve the percentage of False positives and False negatives. Firstly, the system should ideally achieve a percentage of False positives of zero. This means that no defects or anomalies should be incorrectly classified as good or acceptable. Secondly, the percentage of False negatives should not be very high. This implies that the system can tolerate a small margin in waste.

After the threshold is defined, some calculations are done to evaluate the performance of each model.

Accuracy measures the overall correctness of the classification model. It is determined using Equation 4.1.

$$Accuracy : \frac{TP + TN}{TP + FP + TN + FN} \quad (4.1)$$

Precision assesses the correctness of positive predictions made by the model. It is calculated using Equation 4.2.

$$\text{Precision} : \frac{TP}{TP + FP} \quad (4.2)$$

Recall evaluates the model's ability to correctly identify good quality welds. It is obtained using Equation 4.3.

$$\text{Recall} : \frac{TP}{TP + FN} \quad (4.3)$$

In both studies, the same set of eleven parts was used, and each weld seam was labeled from 1 to 17. Within these eleven parts, there was at least one poor quality weld for each type of weld seam.

4.2.1 Method A

The confusion matrix was used to evaluate the performance of the model of each weld seam using the method A. This method involved classifying the weld seams into multiple categories, as explained in the previous chapter. The main goal of this inspection system is to detect defects rather than determining the specific type of defect present. Therefore, the three types of defects were grouped together and labeled as "NOK". In this study, whenever the vision system predicted the presence of any defect, the output considered was "NOK".

To explain the threshold determination process, let's take the example of the weld 12 model. The classification results of the eleven inspected weld 12 can be found in the Appendix B, specifically in section B.1.1, Table B.23. In this particular example, there are three NOK welds and eight OK welds. The model accurately predicted all the OK welds as OK with a very high level of accuracy.

The NOK weld in Part 11 was also correctly predicted as NOK with a high level of confidence. However, the NOK welds in both Part 3 and Part 10 were mistakenly predicted as OK, but with relatively low prediction scores of 82 and 75, respectively. In order to address this issue, a threshold of 85 was chosen for the weld 12 model. This threshold ensures that the prediction scores of both wrongly predicted OK welds are not sufficient to be considered as solid predictions, resulting in an NOK classification. This adjustment of the threshold effectively prevents the occurrence of false positives, thereby increasing the accuracy and precision of the model.

After determining the optimal threshold for all the weld models, the results can be observed in Table 4.1. In this study, there was only one instance where a NOK weld was misclassified as OK, resulting in a False Positive and a decrease in precision. This misclassification occurred in the weld 8 model, specifically in part 10, where the system predicted it as OK with a high prediction score of 88. In reality, the weld had a very small pore, as depicted in Figure 4.2. This suggests that the vision system faces challenges in detecting such minute defects. In terms of false negatives, only two instances occurred.

Table 4.1: Confusion matrix results for method A.

	Threshold	Accuracy	Precision	Recall
Weld 1	80	1.000	1.000	1.000
Weld 2	85	1.000	1.000	1.000
Weld 3	60	0.971	1.000	0.900
Weld 4	85	0.971	1.000	0.900
Weld 5	85	1.000	1.000	1.000
Weld 6	85	1.000	1.000	1.000
Weld 7	85	1.000	1.000	1.000
Weld 8	80	0.971	0.889	1.000
Weld 9	85	1.000	1.000	1.000
Weld 10	85	1.000	1.000	1.000
Weld 11	85	1.000	1.000	1.000
Weld 12	85	1.000	1.000	1.000
Weld 13	75	1.000	1.000	1.000
Weld 14	85	1.000	1.000	1.000
Weld 15	85	1.000	1.000	1.000
Weld 16	80	1.000	1.000	1.000
Weld 17	85	1.000	1.000	1.000

The system demonstrates a good ability to correctly identify acceptable welds and a majority of the NOK welds. Nonetheless, when the defects are extremely small, the camera's prediction may encounter challenges. It is important to note that this study should be expanded by incorporating more parts for validation purposes. The usage of only eleven parts is insufficient to fully evaluate and validate the system's performance.

4.2.2 Method B

Method B of classification was also investigated using a confusion matrix. In Method B, four different binary classifiers are utilised, as explained earlier. In this study, the prediction score used was the average of the scores generated by these four classifiers. Essentially, these four classifiers were treated as a single classifier that determines whether the weld is OK or NOK, providing a single prediction value.

To illustrate the process of threshold definition in Method B, let's consider weld 6 as an example. The classification results of the eleven inspected welds can be found in the Appendix B, specifically in section B.1.2, Table B.45. In this particular case, there are ten OK welds and one NOK weld. The model correctly predicted nine out of ten OK welds, and incorrectly predicted the NOK weld of part 11 as OK, with a high prediction score. This misclassification should be avoided at all costs.

To address this issue, a threshold of 85 was defined. Setting such a high threshold ensures that the false positive prediction becomes a weak prediction, and instead of being labeled as OK, it is predicted as NOK, resulting in a true negative. However, defining such a high threshold in this model poses a problem. Some correct predictions, such as the welds from part 5, 6, 8, and 10, are



Figure 4.2: Porous weld 8 from part 10.

now considered weak predictions and are classified as false negatives. While false negatives are preferable to false positives, this is still not an ideal outcome.

After determining the thresholds for each model, the results are summarised in Table 4.2. Analysing these results, it becomes evident that Method B exhibits more difficulties in accurately predicting the correct labels compared to Method A. Method B produced a total of six false positives and fourteen false negatives, indicating that the vision system's performance is not satisfactory using this method.

4.2.3 Discussion

Based on the analysis of the confusion matrix studies for both Method A and Method B, it can be concluded that Method A is more accurate and precise compared to Method B. Despite the limited sample size of eleven parts used in the study, Method A demonstrates the ability of the vision system to effectively identify acceptable welds and detect the majority of defects, with only minor difficulties in detecting very small pores.

Collecting parts for both training and testing purposes was challenging due to the continuous operation and high demands of production. Acquiring NOK parts, in particular, was especially difficult as they are actively avoided in production and occur infrequently. Additionally, it was

Table 4.2: Confusion matrix results for method B.

	Threshold	Accuracy	Precision	Recall
Weld 1	75	1.000	1.000	1.000
Weld 2	80	1.000	1.000	1.000
Weld 3	70	0.818	1.000	0.800
Weld 4	75	0.909	1.000	0.900
Weld 5	65	0.818	1.000	0.900
Weld 6	85	0.545	1.000	0.500
Weld 7	85	1.000	1.000	1.000
Weld 8	80	0.909	0.900	1.000
Weld 9	80	0.909	0.800	1.000
Weld 10	85	0.909	1.000	0.900
Weld 11	85	1.000	1.000	1.000
Weld 12	85	0.909	0.800	1.000
Weld 13	60	1.000	1.000	1.000
Weld 14	75	0.909	1.000	1.000
Weld 15	85	1.000	1.000	1.000
Weld 16	80	1.000	1.000	0.700
Weld 17	75	0.818	0.900	0.889

necessary to ensure that the parts used for training the models were distinct from those used for testing. These factors contributed to the utilisation of a relatively small sample size in this study.

To evaluate the influence of light in the inspection, it is appropriate to continue using Method A. Since Method A demonstrated being superior compared to Method B, hence it is illogical to employ Method B in this context.

4.3 Gage R&R

Gage R&R is a statistical technique utilised to evaluate the repeatability and reproducibility of a measurement instrument or process. In this system context, the primary focus lies on assessing the reproducibility of the inspection. Typically, in Gage R&R studies, reproducibility measures variations caused by different operators, which does not pose a concern in this system since it is automated. Consequently, the reproducibility is measured in different light conditions so access the influence of light in the inspection system.

On the other hand, repeatability refers to the variation observed when the same weld is inspected multiple times in the same scenario. In this automated system, where the inspection device remains constant, it is expected that there should be minimal or no variation at all.

To perform this study, three distinct scenarios were utilised to evaluate the performance of the inspection system under varying light conditions. The scenarios employed were as follows:

- **Scenario A** - In this scenario, the inspection was conducted under very low light conditions. This was achieved by using cardboard covering the inspection area, limiting the amount of light entering the space.

- **Scenario B** - Normal light conditions were employed in this scenario.
- **Scenario C** - A spotlight was utilised in this scenario to maximise the amount of light available during the inspection. The spotlight was movable, allowing it to be positioned and directed directly towards the welds.

As mentioned in the conclusions of the previous study, only Method A is tested in this particular study. For this, a total of 10 different parts were utilised for evaluation and analysis purposes.

In this study, the evaluation does not focus on determining whether the prediction is correct or incorrect, as in the confusion matrix analysis. Instead, the study revolves around utilising the prediction scores obtained from inspecting a weld three times under three different scenarios.

For each part, three images were inspected for each weld in each of the three scenarios. This values are present in Appendix B, section B.2.

The Gage R&R study was conducted using an internal spreadsheet file from Faurecia. The results were evaluated based on this analysis, where the R&R Index was used as the metric for assessing the inspection system. If the R&R Index is below 10%, the system is considered to be adequate and reliable. In the range of 10% to 30%, the system may be acceptable for specific applications. However, if the R&R Index exceeds 30%, it indicates significant variability and inconsistency in the values, corresponding to an unacceptable system.

The results of this study can be observed in Table 4.3. Upon analysing these results, it is evident that each weld model exhibits an R&R Index below 10%. This indicates that the models are reliable under varying light conditions. It is worth noting that the models for welds 3 and 4 approached the 10% limit, suggesting the need for closer attention to their performance.

4.4 Conclusion

In this chapter, a comparison was conducted using the confusion matrix to evaluate the performance of the two previously developed classification methods. The results of this comparison led to the conclusion that method A outperformed method B in terms of accuracy and precision. Method A demonstrated the capability to accurately identify good welds and detect the majority of defects. However, it encountered challenges in detecting very small porous defects, which resulted in some instances of missed detection. This demonstrates that the effectiveness of the vision system improves when it categorizes distinct defects into separate classes rather than treating them as a single category.

The training phase of the models could have been more extensive if there were no challenges in gathering parts, particularly NOK welds. Consequently, the training phase was constrained in terms of diversity and quantity. Similar, the sample size used for the confusion matrix analysis was relatively small, and it would have been beneficial to have a larger sample with a greater number of NOK parts.

As previously mentioned, only method A was utilised for conducting the Gage R&R study to assess the impact of different light conditions on the predictions of the vision system. The

Table 4.3: Gage R&R results.

	$\sigma_{repeatability}$	$\sigma_{scenarios}$	$\sigma_{reproducibility}$	R&R INDEX
Weld 1	0	0.31	0.31	1.7 %
Weld 2	0	0.28	0.28	1.7 %
Weld 3	0	1.23	1.23	7.8 %
Weld 4	0	1.07	1.07	6.1 %
Weld 5	0	0.13	0.13	1.5 %
Weld 6	0	0.38	0.38	1.9 %
Weld 7	0	0.50	0.50	2.2 %
Weld 8	0	0.82	0.82	3.6 %
Weld 9	0	0.13	0.13	1.5 %
Weld 10	0	0.38	0.38	1.9 %
Weld 12	0	0.13	0.13	1.5 %
Weld 13	0	0.16	0.16	1.5 %
Weld 14	0	0.47	0.47	2.1 %
Weld 15	0	0.22	0.22	1.6 %
Weld 16	0	0.47	0.47	2.1 %
Weld 17	0	0.44	0.44	2.0 %
Weld 1	0	0.44	0.44	2.0 %

results of this study indicated that the vision system exhibited high reproducibility across different intensities of lighting. This finding is advantageous as it ensures that the placement of the system will not be hindered by concerns related to light variations. One particular concern addressed in the study was the presence of a skylight directly above the production line, which could potentially affect the system's inspection performance.

Regarding repeatability, the study confirmed that the system consistently provided the same results, as evidenced by the Gage R&R results. This outcome aligns with expectations, as the system's components and settings remained constant throughout the measurements.

Chapter 5

Conclusions and future perspectives

5.1 Conclusions

The four months of internship with the engineering team provided a firsthand experience of the day-to-day operations in a company of Faurecia Metal's scale. Throughout the internship period, there was a need to collaborate with various departments, which allowed interactions with a diverse group of people from different areas of expertise.

The main focus of this internship was the development of an automatic welding inspection system, which encompassed a wide range of engineering disciplines. The project involved various aspects, including mechanical design of the components, industrial communication protocols, I/O setups, electrical connections, robotics, and image classification models.

The project has achieved its objectives, resulting in the development of a fully functional system that fulfils all the required specifications. The developed system was tested and demonstrated good results in inspecting welds, taking into consideration the limited sample size used for training and testing. One notable aspect was the system's immunity to variations in lighting conditions, which was a concern for its implementation on the production line.

Among all the project phases, the most challenging aspect was establishing communication between the UR10 cobot and the In-Sight 2800 vision system. This particular task necessitated extensive research on both devices and the corresponding communication protocols. Multiple attempts were made to find a viable solution, involving various configurations and settings, before arriving at the final working solution. Establishing reliable and efficient data exchange between the cobot and vision system was a crucial foundation for the entire system, therefore it was one of the initial priorities to allow the progression of the project.

An issue appear regarding the time required to manufacture the developed components, particularly those produced by an external company. Numerous other tasks depended on these components, and as a result of the delay, they were also postponed. After receiving all the components

and completing the assembly, the system was successfully installed on the production line. However, complications arose with the health and safety department (HSE), which necessitated the removal and temporary repositioning of the system outside the line.

This project provided an opportunity to acquire a diverse set of skills across various project areas. Additionally, it offered valuable experience in a factory environment. As a result, Faurecia frames now possesses an automatic system for performing weld inspection, which has the potential to become a benchmark in revolutionising visual inspection within the company.

5.2 Future perspectives

For future perspectives, it is recommended to enhance the training procedure for the classification models by incorporating a more extensive dataset, particularly including a greater number of NOK parts. This will help improve the accuracy and effectiveness of the models in identifying and classifying faulty components. Additionally, it is advisable to conduct a comprehensive study using a larger sample size in the confusion matrix analysis. By doing so, more conclusive and reliable results can be obtained, providing deeper insights into the performance of the system.

To ensure safety measures are in place, it is recommended to conduct a thorough risk assessment to validate the system's safety. This assessment will help identify potential hazards, evaluate associated risks, and determine appropriate mitigation measures.

Appendix A

Script

Code developed in URscript language. Only the important steps were included.

```
1  #Establish socket connection
2
3  Loop ISconnection=False
4      ISconnection=socket_open("192.168.1.10",23,"is2800")
5
6  #LogIn
7
8  askUser=socket_read_string("is2800")
9  telnet_send("admin")
10 askPassword=socket_read_string("is2800")
11 telnet_send("")
12 login=socket_read_string("is2800")
13
14 #Weld 1 inspection
15
16 telnet_send("SJ1")                #Set Job
17
18 MoveJ                            #Move to weld waypoint
19     Waypoint_0
20     Waypoint_1
21
22 telnet_send("SW8")                #Send trigger command
23
24 telnet_send("GVMath_1.B1")        #Part detection inspection value
25 inspId=socket_read_string("is2800")
26 detect1=str_sub(inspId,0,1)
27
28 If detect1="0"                    #Part not detected
29     Set orange_light=On
30     MoveJ
31         Waypoint_0
32     Popup: Part missing
```

```

33     Set orange_light=Off
34     Halt
35
36 telnet_send("GVMath_1.A1")           #Weld quality inspection value
37 insp1=socket_read_string("is2800")
38 inspvalue1=str_sub(insp1,0,1)
39
40 If inspvalue1="1"
41     counterOK=counterOK+1             #In case of OK result add to "counterOK"
42
43
44 #The same procedure is done for all the 17 welds...
45
46 If counterOK=17                       #OK part procedures
47     MoveJ
48     Waypoint_0                       #Move to home position
49     Set green_light=On
50
51 ElseIf counterOK<17                  #NOP part procedures
52     Set red_light=On
53     MoveJ
54     Waypoint_20                      #Move to waypoint blocking the part
55     Set blueBT_light=On
56     Wait blue_button=HI              #Wait for the operator pressing the blue
57                                     button
57     Set blueBT_light=Off
58     MoveJ
59     Waypoint_1
60     Waypoint_0                      #Move to home position
61
62 Popup: end of inspection              #End of inspection
63 Halt

```

Code A.1: System script.

Appendix B

Results

B.1 Confusion matrix results

B.1.1 Method A

Table B.1: Weld 1 confusion matrix values method A, threshold = 80.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	99
Part 3	OK	OK	TP	88
Part 4	OK	OK	TP	98
Part 5	OK	OK	TP	93
Part 6	OK	OK	TP	95
Part 7	OK	OK	TP	96
Part 8	OK	OK	TP	97
Part 9	OK	OK	TP	98
Part 10	OK	OK	TP	97
Part 11	NOK	NOK	TN	89

Table B.2: Weld 1 confusion matrix components method A, threshold = 80.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

B.1.2 Method B

B.2 Gage R&R

Table B.3: Weld 2 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	OK	OK	TP	96
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	OK	OK	TP	100
Part 8	OK	OK	TP	99
Part 9	OK	OK	TP	100
Part 10	OK	OK	TP	98
Part 11	NOK	NOK	TN	96

Table B.4: Weld 2 confusion matrix components method A, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.5: Weld 3 confusion matrix values method A, threshold = 60.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	70
Part 2	OK	OK	TP	94
Part 3	OK	OK	TP	68
Part 4	OK	OK	TP	75
Part 5	OK	NOK	FN	73
Part 6	OK	OK	TP	79
Part 7	OK	OK	TP	95
Part 8	OK	OK	TP	96
Part 9	OK	OK	TP	91
Part 10	OK	OK	TP	99
Part 11	NOK	NOK	TN	81

Table B.6: Weld 3 confusion matrix components method A, threshold = 60.

True Positive	9	90%
False Negative	1	10%
False Positive	0	0%
True Negative	1	100%

Table B.7: Weld 4 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	99
Part 2	OK	OK	TP	94
Part 3	OK	OK	TP	99
Part 4	OK	OK	FN	64
Part 5	OK	OK	TP	90
Part 6	OK	OK	TP	96
Part 7	OK	OK	TP	89
Part 8	OK	OK	TP	98
Part 9	OK	OK	TP	99
Part 10	OK	OK	TP	99
Part 11	NOK	NOK	TN	96

Table B.8: Weld 4 confusion matrix components method A, threshold = 85.

True Positive	9	90%
False Negative	1	10%
False Positive	0	0%
True Negative	1	100%

Table B.9: Weld 5 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	OK	OK	TP	100
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	OK	OK	TP	100
Part 8	OK	OK	TP	100
Part 9	OK	OK	TP	100
Part 10	OK	OK	TP	96
Part 11	NOK	NOK	TN	100

Table B.10: Weld 5 confusion matrix components method A, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.11: Weld 6 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	98
Part 2	OK	OK	TP	100
Part 3	OK	OK	TP	97
Part 4	OK	OK	TP	99
Part 5	OK	OK	TP	99
Part 6	OK	OK	TP	99
Part 7	OK	OK	TP	99
Part 8	OK	OK	TP	99
Part 9	OK	OK	TP	100
Part 10	OK	OK	TP	99
Part 11	NOK	NOK	TN	99

Table B.12: Weld 6 confusion matrix components method A, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.13: Weld 7 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	94
Part 2	OK	OK	TP	98
Part 3	OK	OK	TP	97
Part 4	OK	OK	TP	99
Part 5	OK	OK	TP	99
Part 6	OK	OK	TP	98
Part 7	OK	OK	TP	96
Part 8	OK	OK	TP	98
Part 9	OK	OK	TP	98
Part 10	OK	OK	TP	99
Part 11	NOK	NOK	TN	98

Table B.14: Weld 7 confusion matrix components method A, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.15: Weld 8 confusion matrix values method A, threshold = 80.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	OK	OK	TP	98
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	NOK	NOK	TN	84
Part 8	OK	OK	TP	95
Part 9	OK	OK	TP	98
Part 10	NOK	OK	FP	88
Part 11	NOK	NOK	TN	85

Table B.16: Weld 8 confusion matrix components method A, threshold = 80.

True Positive	9	100%
False Negative	0	0%
False Positive	1	50%
True Negative	1	50%

Table B.17: Weld 9 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	NOK	NOK	TN	100
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	OK	OK	TP	100
Part 8	OK	OK	TP	100
Part 9	OK	OK	TP	100
Part 10	NOK	NOK	TN	98
Part 11	NOK	NOK	TN	99

Table B.18: Weld 9 confusion matrix components method A, threshold = 85.

True Positive	8	100%
False Negative	0	0%
False Positive	0	0%
True Negative	3	100%

Table B.19: Weld 10 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	OK	OK	TP	96
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	OK	OK	TP	95
Part 8	OK	OK	TP	100
Part 9	OK	OK	TP	100
Part 10	OK	OK	TP	99
Part 11	NOK	NOK	TN	98

Table B.20: Weld 10 confusion matrix components method A, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.21: Weld 11 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	NOK	NOK	TN	98
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	OK	OK	TP	100
Part 8	OK	OK	TP	100
Part 9	OK	OK	TP	100
Part 10	OK	OK	TP	100
Part 11	NOK	NOK	TN	100

Table B.22: Weld 11 confusion matrix components method A, threshold = 85.

True Positive	9	100%
False Negative	0	0%
False Positive	0	0%
True Negative	2	100%

Table B.23: Weld 12 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	NOK	OK	TN	82
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	OK	OK	TP	100
Part 8	OK	OK	TP	99
Part 9	OK	OK	TP	100
Part 10	NOK	OK	TN	75
Part 11	NOK	NOK	TN	93

Table B.24: Weld 12 confusion matrix components method A, threshold = 85.

True Positive	8	100%
False Negative	0	0%
False Positive	0	0%
True Negative	3	100%

Table B.25: Weld 13 confusion matrix values method A, threshold = 75.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	94
Part 2	OK	OK	TP	83
Part 3	OK	OK	TP	90
Part 4	OK	OK	TP	93
Part 5	OK	OK	TP	86
Part 6	OK	OK	TP	93
Part 7	OK	OK	TP	94
Part 8	OK	OK	TP	90
Part 9	OK	OK	TP	76
Part 10	OK	OK	TP	98
Part 11	NOK	NOK	TN	89

Table B.26: Weld 13 confusion matrix components method A, threshold = 75.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.27: Weld 14 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	98
Part 2	OK	OK	TP	93
Part 3	NOK	OK	TN	78
Part 4	OK	OK	TP	99
Part 5	OK	OK	TP	98
Part 6	OK	OK	TP	98
Part 7	OK	OK	TP	97
Part 8	OK	OK	TP	95
Part 9	OK	OK	TP	98
Part 10	OK	OK	TP	97
Part 11	NOK	NOK	TN	92

Table B.28: Weld 14 confusion matrix components method A, threshold = 85.

True Positive	9	100%
False Negative	0	0%
False Positive	0	0%
True Negative	2	100%

Table B.29: Weld 15 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	97
Part 2	OK	OK	TP	97
Part 3	OK	OK	TP	98
Part 4	OK	OK	TP	99
Part 5	OK	OK	TP	96
Part 6	OK	OK	TP	95
Part 7	OK	OK	TP	97
Part 8	OK	OK	TP	98
Part 9	OK	OK	TP	99
Part 10	OK	OK	TP	99
Part 11	NOK	NOK	TN	90

Table B.30: Weld 15 confusion matrix components method A, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.31: Weld 16 confusion matrix values method A, threshold = 80.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	86
Part 2	OK	OK	TP	94
Part 3	OK	OK	TP	88
Part 4	OK	OK	TP	95
Part 5	OK	OK	TP	96
Part 6	OK	OK	TP	98
Part 7	OK	OK	TP	97
Part 8	OK	OK	TP	89
Part 9	OK	OK	TP	94
Part 10	OK	OK	TP	95
Part 11	NOK	NOK	TN	93

Table B.32: Weld 16 confusion matrix components method A, threshold = 80.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.33: Weld 17 confusion matrix values method A, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	97
Part 2	OK	OK	TP	96
Part 3	NOK	OK	TN	73
Part 4	OK	OK	TP	84
Part 5	OK	OK	TP	96
Part 6	OK	OK	TP	94
Part 7	OK	OK	TP	93
Part 8	OK	OK	TP	97
Part 9	OK	OK	TP	96
Part 10	OK	OK	TP	95
Part 11	NOK	NOK	TN	93

Table B.34: Weld 17 confusion matrix components method A, threshold = 85.

True Positive	9	100%
False Negative	0	0%
False Positive	0	0%
True Negative	2	100%

Table B.35: Weld 1 confusion matrix values method B, threshold = 75.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	89
Part 2	OK	OK	TP	92
Part 3	OK	OK	TP	93
Part 4	OK	OK	TP	85
Part 5	OK	OK	TP	87
Part 6	OK	OK	TP	85
Part 7	OK	OK	TP	93
Part 8	OK	OK	TP	84
Part 9	OK	OK	TP	83
Part 10	OK	OK	TP	90
Part 11	NOK	NOK	TN	89

Table B.36: Weld 1 confusion matrix components method B, threshold = 75.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.37: Weld 2 confusion matrix values method B, threshold = 80.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	97
Part 2	OK	OK	TP	95
Part 3	OK	OK	TP	96
Part 4	OK	OK	TP	94
Part 5	OK	OK	TP	96
Part 6	OK	OK	TP	92
Part 7	OK	OK	TP	99
Part 8	OK	OK	TP	89
Part 9	OK	OK	TP	88
Part 10	OK	OK	TP	94
Part 11	NOK	NOK	TN	96

Table B.38: Weld 2 confusion matrix components method B, threshold = 80.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.39: Weld 3 confusion matrix values method B, threshold = 70.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	82
Part 2	OK	OK	TP	84
Part 3	OK	NOK	FN	88
Part 4	OK	OK	TP	92
Part 5	OK	NOK	FN	91
Part 6	OK	OK	TP	79
Part 7	OK	OK	TP	87
Part 8	OK	OK	TP	85
Part 9	OK	OK	TP	80
Part 10	OK	OK	TP	94
Part 11	NOK	NOK	TN	80

Table B.40: Weld 3 confusion matrix components method B, threshold = 70.

True Positive	8	80%
False Negative	2	20%
False Positive	0	0%
True Negative	1	100%

Table B.41: Weld 4 confusion matrix values method B, threshold = 75.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	95
Part 2	OK	OK	TP	81
Part 3	OK	OK	TP	94
Part 4	OK	OK	TP	84
Part 5	OK	OK	TP	90
Part 6	OK	OK	TP	91
Part 7	OK	OK	TP	89
Part 8	OK	OK	TP	87
Part 9	OK	OK	TP	88
Part 10	OK	OK	TP	84
Part 11	NOK	NOK	TN	86

Table B.42: Weld 4 confusion matrix components method B, threshold = 75.

True Positive	9	90%
False Negative	1	10%
False Positive	0	0%
True Negative	1	100%

Table B.43: Weld 5 confusion matrix values method B, threshold = 65.

	Real	Prediction	AI term	Score
Part 1	OK	NOK	FN	70
Part 2	OK	OK	TP	82
Part 3	OK	OK	TP	83
Part 4	OK	OK	TP	73
Part 5	OK	OK	TP	83
Part 6	OK	OK	TP	86
Part 7	OK	OK	TP	89
Part 8	OK	OK	TP	62
Part 9	OK	OK	TP	84
Part 10	OK	OK	TP	74
Part 11	NOK	NOK	TN	82

Table B.44: Weld 5 confusion matrix components method B, threshold = 65.

True Positive	9	90%
False Negative	1	10%
False Positive	0	0%
True Negative	1	100%

Table B.45: Weld 6 confusion matrix values method B, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	97
Part 2	OK	NOK	FN	88
Part 3	OK	OK	TP	90
Part 4	OK	OK	TP	91
Part 5	OK	OK	FN	79
Part 6	OK	OK	FN	84
Part 7	OK	OK	TP	90
Part 8	OK	OK	FN	80
Part 9	OK	OK	TP	93
Part 10	OK	OK	FN	81
Part 11	NOK	OK	TN	82

Table B.46: Weld 6 confusion matrix components method B, threshold = 85.

True Positive	5	50%
False Negative	5	50%
False Positive	0	0%
True Negative	1	100%

Table B.47: Weld 7 confusion matrix values method B, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	94
Part 2	OK	OK	TP	98
Part 3	OK	OK	TP	97
Part 4	OK	OK	TP	89
Part 5	OK	OK	TP	94
Part 6	OK	OK	TP	98
Part 7	OK	OK	TP	94
Part 8	OK	OK	TP	93
Part 9	OK	OK	TP	87
Part 10	OK	OK	TP	89
Part 11	NOK	NOK	TN	94

Table B.48: Weld 7 confusion matrix components method B, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.49: Weld 8 confusion matrix values method B, threshold = 80.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	98
Part 2	OK	OK	TP	97
Part 3	OK	OK	TP	95
Part 4	OK	OK	TP	89
Part 5	OK	OK	TP	97
Part 6	OK	OK	TP	98
Part 7	NOK	NOK	TN	84
Part 8	OK	OK	TP	94
Part 9	OK	OK	TP	90
Part 10	NOK	OK	FP	94
Part 11	NOK	NOK	TN	85

Table B.50: Weld 8 confusion matrix components method B, threshold = 80.

True Positive	9	100%
False Negative	0	0%
False Positive	1	50%
True Negative	1	50%

Table B.51: Weld 9 confusion matrix values method B, threshold = 80.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	97
Part 2	OK	OK	TP	92
Part 3	NOK	NOK	TN	84
Part 4	OK	OK	TP	90
Part 5	OK	OK	TP	94
Part 6	OK	OK	TP	95
Part 7	OK	OK	TP	92
Part 8	OK	OK	TP	95
Part 9	OK	OK	TP	89
Part 10	NOK	NOK	TN	94
Part 11	NOK	NOK	TN	91

Table B.52: Weld 9 confusion matrix components method B, threshold = 80.

True Positive	8	100%
False Negative	0	0%
False Positive	0	0%
True Negative	3	100%

Table B.53: Weld 10 confusion matrix values method B, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	99
Part 2	OK	OK	TP	96
Part 3	OK	NOK	FN	95
Part 4	OK	OK	TP	92
Part 5	OK	NOK	TP	97
Part 6	OK	OK	TP	94
Part 7	OK	OK	TP	97
Part 8	OK	OK	TP	93
Part 9	OK	OK	TP	100
Part 10	OK	OK	TN	89
Part 11	NOK	NOK	TN	94

Table B.54: Weld 10 confusion matrix components method B, threshold = 85.

True Positive	8	88.89%
False Negative	1	11.11%
False Positive	0	0%
True Negative	2	100%

Table B.55: Weld 11 confusion matrix values method B, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	100
Part 2	OK	OK	TP	100
Part 3	NOK	NOK	TN	98
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	100
Part 6	OK	OK	TP	100
Part 7	OK	OK	TP	100
Part 8	OK	OK	TP	100
Part 9	OK	OK	TP	100
Part 10	OK	OK	TP	100
Part 11	NOK	NOK	TN	100

Table B.56: Weld 11 confusion matrix components method B, threshold = 85.

True Positive	9	100%
False Negative	0	0%
False Positive	0	0%
True Negative	2	100%

Table B.57: Weld 12 confusion matrix values method B, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	99
Part 2	OK	OK	TP	96
Part 3	NOK	OK	FP	92
Part 4	OK	OK	TP	100
Part 5	OK	OK	TP	96
Part 6	OK	OK	TP	98
Part 7	OK	OK	TP	95
Part 8	OK	OK	TP	99
Part 9	OK	OK	TP	89
Part 10	NOK	OK	FP	80
Part 11	NOK	NOK	TN	92

Table B.58: Weld 12 confusion matrix components method B, threshold = 85.

True Positive	8	100%
False Negative	0	0%
False Positive	2	66.66%
True Negative	1	33.33%

Table B.59: Weld 13 confusion matrix values method B, threshold = 60.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	90
Part 2	OK	OK	TP	79
Part 3	OK	OK	TP	61
Part 4	OK	OK	TP	68
Part 5	OK	OK	TP	74
Part 6	OK	OK	TP	81
Part 7	OK	OK	TP	69
Part 8	OK	OK	TP	75
Part 9	OK	OK	TP	77
Part 10	OK	OK	TP	91
Part 11	NOK	NOK	TN	85

Table B.60: Weld 13 confusion matrix components method B, threshold = 60.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.61: Weld 14 confusion matrix values method B, threshold = 75.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	98
Part 2	OK	OK	TP	79
Part 3	NOK	OK	TN	70
Part 4	OK	OK	TP	84
Part 5	OK	OK	TP	76
Part 6	OK	OK	TP	86
Part 7	OK	OK	TP	89
Part 8	OK	OK	TP	78
Part 9	OK	OK	TP	75
Part 10	OK	OK	TP	90
Part 11	NOK	NOK	TN	83

Table B.62: Weld 14 confusion matrix components method B, threshold = 75.

True Positive	9	100%
False Negative	0	0%
False Positive	0	0%
True Negative	2	100%

Table B.63: Weld 15 confusion matrix values method B, threshold = 85.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	99
Part 2	OK	OK	TP	97
Part 3	OK	OK	TP	98
Part 4	OK	OK	TP	96
Part 5	OK	OK	TP	98
Part 6	OK	OK	TP	94
Part 7	OK	OK	TP	95
Part 8	OK	OK	TP	93
Part 9	OK	OK	TP	87
Part 10	OK	OK	TP	93
Part 11	NOK	NOK	TN	90

Table B.64: Weld 15 confusion matrix components method B, threshold = 85.

True Positive	10	100%
False Negative	0	0%
False Positive	0	0%
True Negative	1	100%

Table B.65: Weld 16 confusion matrix values method B, threshold = 80.

	Real	Prediction	AI term	Score
Part 1	OK	OK	TP	81
Part 2	OK	NOK	TP	82
Part 3	OK	OK	TP	84
Part 4	OK	OK	FN	75
Part 5	OK	OK	TP	80
Part 6	OK	OK	FN	78
Part 7	OK	OK	FN	79
Part 8	OK	OK	TP	84
Part 9	OK	OK	TP	86
Part 10	OK	OK	TP	87
Part 11	NOK	OK	TN	89

Table B.66: Weld 16 confusion matrix components method B, threshold = 80.

True Positive	7	70%
False Negative	3	30%
False Positive	0	0%
True Negative	1	100%

Table B.67: Weld 17 confusion matrix values method B, threshold = 75.

	Real	Prediction	AI term	Score
Part 1	OK	NOK	FN	88
Part 2	OK	OK	TP	81
Part 3	NOK	OK	FP	85
Part 4	OK	OK	TP	86
Part 5	OK	OK	TP	87
Part 6	OK	OK	TP	84
Part 7	OK	OK	TP	85
Part 8	OK	OK	TP	90
Part 9	OK	OK	TP	86
Part 10	OK	OK	TP	88
Part 11	NOK	NOK	TN	85

Table B.68: Weld 17 confusion matrix components method B, threshold = 75.

True Positive	8	88.89%
False Negative	1	11.11%
False Positive	1	50%
True Negative	1	50%

Table B.69: Gage R&R study values, Weld 1.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	100	100	100	100	100	100	99	99	99
2	100	100	100	100	100	100	99	99	99
3	88	88	88	88	88	88	87	87	87
4	90	90	90	91	91	91	89	89	89
5	92	92	92	93	93	93	90	90	90
6	94	94	94	95	95	95	93	93	93
7	96	96	96	96	96	96	98	98	98
8	95	95	95	97	97	97	96	96	96
9	97	97	97	98	98	98	99	99	99
10	98	98	98	97	97	97	95	95	95
Scenario A average: 95				Scenario B average: 95.5			Operator A Average: 94.5		
Scenario A range: 0				Scenario C range: 0			Scenario C range: 0		

Table B.70: Gage R&R study values, Weld 2.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	99	99	99	100	100	100	92	92	92
2	99	99	99	100	100	100	99	99	99
3	95	95	95	96	96	96	96	96	96
4	100	100	100	100	100	100	100	100	100
5	100	100	100	100	100	100	100	100	100
6	99	99	99	100	100	100	100	100	100
7	100	100	100	100	100	100	100	100	100
8	100	100	100	99	99	99	100	100	100
9	99	99	99	100	100	100	98	98	98
10	100	100	100	98	98	98	99	99	99
Scenario A average: 99.1				Scenario B average: 99.3			Operator A Average: 98.4		
Scenario A range: 0				Scenario C range: 0			Scenario C range: 0		

Table B.71: Gage R&R study values, Weld 3.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	68	68	68	70	70	70	75	75	75
2	93	93	93	94	94	94	97	97	97
3	66	66	66	68	68	68	72	72	72
4	63	63	63	64	64	64	68	68	68
5	70	70	70	73	73	73	75	75	75
6	79	79	79	79	79	79	82	82	82
7	93	93	93	95	95	95	96	96	96
8	95	95	95	96	96	96	97	97	97
9	90	90	90	91	91	91	94	94	94
10	98	98	98	99	99	99	98	98	98
Scenario A average: 81.5				Scenario B average: 82.9			Operator A Average: 85.4		
Scenario A range: 0				Scenario C range: 0			Scenario C range: 0		

Table B.72: Gage R&R study values, Weld 4.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	99	99	99	98	98	98	98	98	98
2	97	97	97	97	97	97	99	99	99
3	98	98	98	99	99	99	99	99	99
4	60	60	60	64	64	64	74	74	74
5	89	89	89	90	90	90	93	93	93
6	95	95	95	96	96	96	98	98	98
7	90	90	90	89	89	89	92	92	92
8	98	98	98	98	98	98	96	96	96
9	95	95	95	99	99	99	99	99	99
10	93	93	93	99	99	99	100	100	100
Scenario A average: 91.4				Scenario B average: 92.9			Operator A Average: 94.8		
Scenario A range: 0				Scenario C range: 0			Scenario C range: 0		

Table B.73: Gage R&R study values, Weld 5.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	100	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100	100	100	100
3	100	100	100	100	100	100	100	100	100
4	98	98	98	100	100	100	100	100	100
5	100	100	100	100	100	100	100	100	100
6	99	99	99	100	100	100	100	100	100
7	100	100	100	100	100	100	100	100	100
8	100	100	100	100	100	100	99	99	99
9	100	100	100	100	100	100	100	100	100
10	93	93	93	96	96	96	97	97	97
Scenario A average: 99.2				Scenario B average: 99.6			Operator A Average: 99.6		
Scenario A range: 0				Scenario C range: 0			Scenario C range: 0		

Table B.74: Gage R&R study values, Weld 6.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	96	96	96	99	99	99	98	98	98
2	98	98	98	99	99	99	98	98	98
3	97	97	97	97	97	97	97	97	97
4	98	98	98	99	99	99	99	99	99
5	98	98	98	99	99	99	99	99	99
6	97	97	97	99	99	99	98	98	98
7	99	99	99	99	99	99	99	99	99
8	97	97	97	99	99	99	100	100	100
9	98	98	98	100	100	100	100	100	100
10	99	99	99	99	99	99	100	100	100
Scenario A average: 97.7				Scenario B average: 98.9			Scenario C average: 98.8		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.75: Gage R&R study values, Weld 7.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	94	94	94	96	96	96	92	92	92
2	98	98	98	98	98	98	98	98	98
3	97	97	97	97	97	97	98	98	98
4	98	98	98	98	98	98	98	98	98
5	98	98	98	99	99	99	99	99	99
6	97	97	97	98	98	98	97	97	97
7	92	92	92	96	96	96	99	99	99
8	94	94	94	98	98	98	98	98	98
9	96	96	96	98	98	98	96	96	96
10	97	97	97	99	99	99	99	99	99
Scenario A average: 96.1				Scenario B average: 97.7			Scenario C average: 97.4		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.76: Gage R&R study values, Weld 8.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	99	99	99	100	100	100	100	100	100
2	100	100	100	100	100	100	100	100	100
3	98	98	98	98	98	98	99	99	99
4	99	99	99	99	99	99	99	99	99
5	98	98	98	100	100	100	100	100	100
6	99	99	99	100	100	100	100	100	100
7	79	79	79	84	84	84	91	91	91
8	93	93	93	95	95	95	96	96	96
9	96	96	96	98	98	98	98	98	98
10	86	86	86	88	88	88	90	90	90
Scenario A average: 94.7				Scenario B average: 96.2			Scenario C average: 97.3		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.77: Gage R&R study values, Weld 9.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	100	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100	100	100	100
3	99	99	99	100	100	100	100	100	100
4	100	100	100	100	100	100	100	100	100
5	100	100	100	100	100	100	100	100	100
6	100	100	100	100	100	100	100	100	100
7	100	100	100	100	100	100	100	100	100
8	100	100	100	100	100	100	100	100	100
9	99	99	99	100	100	100	100	100	100
10	97	97	97	98	98	98	99	99	99
Scenario A average: 99.5				Scenario B average: 99.8			Scenario C average: 99.9		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.78: Gage R&R study values, Weld 10.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	100	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100	100	100	100
3	100	100	100	100	100	100	100	100	100
4	99	99	99	100	100	100	100	100	100
5	100	100	100	100	100	100	100	100	100
6	98	98	98	100	100	100	100	100	100
7	93	93	93	95	95	95	97	97	97
8	100	100	100	100	100	100	100	100	100
9	99	99	99	100	100	100	100	100	100
10	96	96	96	99	99	99	100	100	100
Scenario A average: 98.5				Scenario B average: 99.4			Scenario C average: 99.7		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.79: Gage R&R study values, Weld 11.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	100	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100	100	100	100
3	98	98	98	98	98	98	99	99	99
4	100	100	100	100	100	100	100	100	100
5	100	100	100	100	100	100	100	100	100
6	100	100	100	100	100	100	100	100	100
7	99	99	99	100	100	100	100	100	100
8	100	100	100	100	100	100	99	99	99
9	99	99	99	100	100	100	100	100	100
10	98	98	98	100	100	100	100	100	100
Scenario A average: 99.4				Scenario B average: 99.8			Scenario C average: 99.8		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.80: Gage R&R study values, Weld 12.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	100	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100	100	100	100
3	82	82	82	82	82	82	76	76	76
4	99	99	99	100	100	100	100	100	100
5	100	100	100	100	100	100	100	100	100
6	100	100	100	100	100	100	100	100	100
7	98	98	98	100	100	100	99	99	99
8	100	100	100	100	100	100	100	100	100
9	100	100	100	100	100	100	97	97	97
10	73	73	73	75	75	75	80	80	80
Scenario A average: 95.2				Scenario B average: 95.7			Scenario C average: 95.2		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.81: Gage R&R study values, Weld 13.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	87	87	87	92	92	92	89	89	89
2	90	90	90	90	90	90	88	88	88
3	87	87	87	90	90	90	88	88	88
4	86	86	86	86	86	86	88	88	88
5	86	86	86	86	86	86	88	88	88
6	90	90	90	93	93	93	96	96	96
7	95	95	95	94	94	94	94	94	94
8	90	90	90	90	90	90	91	91	91
9	75	75	75	76	76	76	79	79	79
10	97	97	97	98	98	98	97	97	97
Scenario A average: 88.3				Scenario B average: 89.5			Scenario C average: 89.8		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.82: Gage R&R study values, Weld 14.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	98	98	98	98	98	98	97	97	97
2	94	94	94	95	95	95	94	94	94
3	79	79	79	78	78	78	75	75	75
4	98	98	98	100	100	100	97	97	97
5	97	97	97	98	98	98	98	98	98
6	97	97	97	98	98	98	99	99	99
7	98	98	98	97	97	97	96	96	96
8	95	95	95	95	95	95	96	96	96
9	97	97	97	98	98	98	97	97	97
10	94	94	94	97	97	97	99	99	99
Scenario A average: 94.7				Scenario B average: 95.4			Scenario C average: 94.8		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.83: Gage R&R study values, Weld 15.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	95	95	95	96	96	96	95	95	95
2	97	97	97	99	99	99	96	96	96
3	97	97	97	98	98	98	98	98	98
4	94	94	94	95	95	95	93	93	93
5	94	94	94	96	96	96	96	96	96
6	95	95	95	95	95	95	96	96	96
7	96	96	96	97	97	97	97	97	97
8	94	94	94	98	98	98	99	99	99
9	98	98	98	99	99	99	98	98	98
10	97	97	97	99	99	99	100	100	100
Scenario A average: 95.7				Scenario B average: 97.2			Scenario C average: 96.8		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.84: Gage R&R study values, Weld 16.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	91	91	91	92	92	92	90	90	90
2	94	94	94	94	94	94	96	96	96
3	86	86	86	88	88	88	88	88	88
4	93	93	93	94	94	94	94	94	94
5	93	93	93	96	96	96	97	97	97
6	97	97	97	98	98	98	97	97	97
7	99	99	99	97	97	97	98	98	98
8	90	90	90	89	89	89	90	90	90
9	92	92	92	94	94	94	96	96	96
10	91	91	91	95	95	95	94	94	94
Scenario A average: 92.6				Scenario B average: 93.7			Scenario C average: 94.0		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

Table B.85: Gage R&R study values, Weld 17.

Parts	Scenario A			Scenario B			Scenario C		
	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3	Meas1	Meas2	Meas3
1	98	98	98	97	97	97	95	95	95
2	97	97	97	96	96	96	98	98	98
3	74	74	74	73	73	73	69	69	69
4	95	95	95	95	95	95	96	96	96
5	92	92	92	96	96	96	97	97	97
6	93	93	93	94	94	94	95	95	95
7	90	90	90	93	93	93	95	95	95
8	96	96	96	97	97	97	98	98	98
9	94	94	94	96	96	96	96	96	96
10	93	93	93	95	95	95	97	97	97
Scenario A average: 92.2				Scenario B average: 93.2			Scenario C average: 93.6		
Scenario A range: 0				Scenario B range: 0			Scenario C range: 0		

References

- [1] Forvia - inspiring mobility. Available at <https://www.forvia.com/>, Accessed last time in March 2023, 2022.
- [2] Dinbandhu, Vishalkumar Prajapati, Jay J. Vora, and Kumar Abhishek. *Advanced Welding and Deforming*. Elsevier, 2021.
- [3] Karim Tout, Anis Meguenani, Jean-Philippe Urban, and Christophe Cudel. Automated vision system for magnetic particle inspection of crankshafts using convolutional neural networks. *The International Journal of Advanced Manufacturing Technology*, pages 3307–3326, February 2021.
- [4] Adrian P. Mouritz. *Introduction to Aerospace Materials*. Woodhead Publishing, 2012.
- [5] Universal Robots. The ur10. Available at <https://www.universal-robots.com/products/ur10-robot/>, Accessed last time in May 2023.
- [6] Cognex. In-sight 2800 vision system. Available at <https://www.cognex.com/products/machine-vision/2d-machine-vision-systems/in-sight-2800>, Accessed last time in May 2023.
- [7] Keyence. Vision sensor with built-in ai, iv2 series. Available at <https://www.keyence.com/products/vision/vision-sensor/iv2/>, Accessed last time in May 2023.
- [8] Markforged. Mark two. Available at https://markforged.com/3d-printers/mark-two?mwg_rnd=7944055, Accessed last time in May 2023.
- [9] Beckhoff New Automation Technology. Cu2008 I infrastructure, 8-port switch, ethernet, 100 mbit/s, 24 v dc, rj45. Available at <https://www.beckhoff.com/en-en/products/i-o/infrastructure-components/cuxxxx-epxxx-ethernet-switches-and-components/cu2008.html>, Accessed last time in May 2023.
- [10] Nafaa Nacereddinea, Aicha Baya Goumeidanea, and Djemel Ziou. Unsupervised weld defect classification in radiographic images using multivariate generalized gaussian mixture model with exact computation of mean and shape parameters. *Computers in industry 108*, pages 132–149, March 2019.
- [11] FORVIA Seating. *Standard MAG welding control plan. Unpublished internal company document*. 2022.
- [12] J.R. Deepak, V.K. Bupesh Raja, D. Srikanth, H. Surendran, and M.M. Nickolas. Non-destructive testing (ndt) techniques for low carbon steel welded joints: A review and experimental study. *Materials Today: Proceedings 44*, pages 3732–3737, January 2021.

- [13] Paul Kah. *Advancements in Intelligent Gas Metal Arc Welding Systems*. Elsevier, 2021.
- [14] Baldev Raj, C. V. Subramanian, and T. Jayakumar. *Non-destructive testing of welds*. Alpha science, 2000.
- [15] Hernan Ratto. *Visualisation study of metal transfer in gas metal arc welding (GMAW)*. PhD thesis, University of Wollongong, 1996.
- [16] Nuraini A. A. and Zainal Abiddin Shah. The effects of welding parameters on butt joints using robotic gas metal arc welding. *Journal of mechanical engineering and sciences*, pages 988–994, June 2014.
- [17] Faurecia. *Gas metal arc welding process standard*. Unpublished internal company document. 2007.
- [18] ISO 6520-1:2007. *Welding and allied processes - Classification of geometric imperfections in metallic materials*.
- [19] R.J. Ditchburn, S.K. Burke, and C.M. Scala. Ndt of welds: state of the art. *NDTE International: Vol. 29*, pages 111–117, January 1996.
- [20] Seifollah Nasrazadani and Shokrollah Hassani. *Handbook of Materials Failure Analysis with Case Studies from the Oil and Gas Industry*. Butterworth-Heinemann, 2016.
- [21] B. BIDANDA, J. RUBINOVITZ, and S. RAMAN. Development of a spatter index for automated welding inspection using computer vision. *Computers ind. Engng Vol. 16, No. 2*, pages 215–224, May 1988.
- [22] A. C. Guu and S. I. Rokhlin. Weld penetration control with radiographic feedback on weld pool depression. *Review of Progress in Quantitative Nondestructive Evaluation, Vol. 9*.
- [23] H.I. Shafeek, E.S. Gadelmawla, A.A. Abdel-Shafy, and I.M. Elewa. Automatic inspection of gas pipeline welding defects using an expert vision system. *NDTE International 37*, pages 301–307, October 2003.
- [24] J.F. Wang, W.Y. Wang, and S.B. Chen. Inspection of welding pool height from shading in pulsed gtaw with wire filler. *Industrial Robot: An International Journal*, pages 270–276, March 2009.
- [25] D. Lévesque, Y. Asaumi, M. Lord, C. Bescond, H. Hatanaka, M. Tagami, and J.-P. Monchalain. Inspection of thick welded joints using laser-ultrasonic soft. *Ultrasonics 69*, pages 236–242, July 2016.
- [26] Laser vision based detection of weld penetration in gtaw: An inspection method was proposed to monitor weld penetration for investigating the control of weld defects. *Welding journal Vol.96*, pages 163–172, May 2017.
- [27] Ahmed Mazloun, Ahmed Mahrous, Alber Alphonse Sadek, and Abd ElRahman Mohamed Moussa. Characterization of welding discontinuities by combined phased array ultrasonic and artificial neural network. *Engineering Research Journal 163*, pages M1–M19, September 2019.
- [28] Yan Zeng, Xiaokai Wang, Xunpeng Qin, Lin Hua, Guocheng Liu, and Shanyue Guan. Laser ultrasonic inspection of defects in wire arc additive manufactured samples with different surface profiles. *Measurement 188*, 2022.

- [29] Markforged. Onyx. Available at <https://markforged.com/materials/plastics/onyx>, Accessed last time in May 2023.
- [30] Douglas E. Comer. *Internetworking with TCP/IP Vol.I*. Alan Apt, fourth edition, 2000.
- [31] António Pessoa de Magalhães. *Redes Industriais [PowerPointSlides]*. 2022.
- [32] Lydia Parziale, David T. Britt, Chuck Davis, Jason Forrester, Wei Liu, Carolyn Matthews, and Nicolas Rosselot. *TCP/IP Tutorial and Technical Overview*. International Technical Support Organization, eighth edition, 2006.
- [33] Ievgen Redko, Amaury Habrard, Emilie Morvant, Marc Sebban, and Younès Bennani. *Advances in Domain Adaptation Theory*. Elsevier, 2019.
- [34] Jason Brownlee. 4 types of classification tasks in machine learning. Available at <https://machinelearningmastery.com/types-of-classification-in-machine-learning/>, August 2020.
- [35] W. Richard Stevens. *TCP/IP Illustrated, Vol. 1: The Protocols*. Wesley Professional Computing Serie, 1994.
- [36] Ajay Kulkarni, Deri Chong, and Feras A. Batarseh. *Data Democracy, Chapter 5 - Foundations of data imbalance and solutions for a data democracy*. Academic Press, 2020.