

LUT UNIVERSITY
LUT School of Energy Systems
LUT Mechanical Engineering

Tuukka Harju

**DIGITAL TWIN METHODS FOR FEEDBACK CONTROL IN MULTI-ROBOT
WELDING CELLS**

**DIGITAALISEN KAKSOSEN TAKAISINKYTKENTÄ MENETELMÄT
ROBOTISOIDUSSA HITSAUSKENNOSSA**

Lappeenranta 27.3.2020

Tuukka Harju

Examiner: M.Sc.Sakari Penttilä

Supervisor: M.Sc. Sakari Penttilä

TIIVISTELMÄ

LUT-yliopisto
LUT Energiajärjestelmät
LUT Kone

Tuukka Harju

Digitaalisen kaksosen takaisinkytkentä menetelmät robotisoidussa hitsauskennossa

Kandidaatintyö

2020

42 sivua, 17 kuvaa and 2 taulukkoa

Tarkastaja: DI Sakari Penttilä

Hakusanat: Digitaalinen kaksosen, takaisinkytkentä, robottihitsaus

Tämän kandidaatintyön tavoitteena on tutustua digitaalisen kaksosen perusteisiin ja ominaisuuksiin sekä takaisinkytkentä menetelmiin, joita voisi soveltaa robottihitsaukseen. Digitaalinen kaksosen on kattava digitaalinen malli, joka peilaa fyysisen järjestelmän käyttäytymistä ja voi simuloida erilaisia skenaarioita, joita fyysinen järjestelmä voi kohdata. Digitaalisella kaksosella on valtava potentiaali monilla tekniikan osa-alueilla aina suunnittelusta elinkaarihallintaan.

Kandidaatintyössä suoritettiin laboratoriokoe, jossa kokeiltiin robottihitsaukseen soveltuvaa takaisinkytkentä menetelmää mittaamalla laser anturilla t-liitosta. Ensin mitattiin sauman paikoitus oletetulla oikealla paikalla, jonka jälkeen työkappaletta liikuteltiin satunnaisesti ja tehtiin mittaus uudelleen. Lasketut siirtymät ja siirtymäkulma sijoitettiin digitaalisen kaksosen ympäristöön peilaamaan fyysistä siirtymää.

Siirtymä peilattiin onnistuneesti digitaalisella kaksosella, raakadatasta lasketuilla arvoilla. Laboratoriokokeen perusteella, käytetyt menetelmät soveltuvat robottihitsaukseen ja niitä voitaisiin jatkossa kehittää käytettäväksi monimutkaisempien liikkeiden kanssa. Lisätutkimusta vaaditaan kokonaisvaltaisen takaisinkytkennän käyttöönottoa varten, jossa digitaalinen malli voisi palauttaa laskettuja arvoja takasin robottihitsausjärjestelmään.

ABSTRACT

LUT University
LUT School of Energy Systems
LUT Mechanical Engineering

Tuukka Harju

Digital twin methods for feedback control in multi-robot welding cells

Bachelor's thesis

2020

42 pages, 17 figures and 2 tables

Examiner: M.Sc., IWE Sakari Penttilä

Keywords: Digital twin, feedback, welding cell

The goal of this bachelor's thesis is to discover the principles and characteristics of a digital twin and the feedback methods available for use in a multi-robot welding cell. A digital twin is a comprehensive digital model that mirrors a physical systems behavior and can use its computational capabilities to simulate different scenarios that the physical system may encounter. Digital twin has tremendous potential in many aspects of engineering, from design to lifecycle management.

A laboratory experiment was conducted in which a feedback method that was determined to be suitable for use in a welding cell was tested by measuring the seam of a t-joint workpiece in its assumed correct position and then measuring the same workpiece again after apply a random offset. The scanned positional data was then applied to a digital twin environment to replicate the offset in a digital twin model of the workpiece.

The offset of the workpiece was successfully replicated by calculating the offset and offset angle values from the post-processed raw profile data of the scans. It was concluded that the methods used in the experiment were suitable for use in robot welding cells and could potentially be further refined for more complex movements. Further study is required to produce a full feedback loop where the digital twin model could return calculated values back to the system after self-correcting.

ACKNOWLEDGEMENTS

I would like to thank my supervisor Sakari Penttilä for his guidance throughout the writing of this thesis and Hannu Lund for his part in the experimental setup. A special thank you to my family who have supported me in my studies throughout the years with their encouragement.

The research work was completed during ENI CBC project Energy-efficient systems based on renewable energy for Arctic conditions “EFREA” as a part of developing digital twin welding cell.

Tuukka Harju

Lappeenranta

27.3.2020

TABLE OF CONTENTS

TIIVISTELMÄ

ABSTRACT

ACKNOWLEDGEMENTS

LIST OF SYMBOLS AND ABBREVIATIONS

1	INTRODUCTION	7
1.1	Background	7
1.2	Scope and Focus	8
1.3	Objectives and outline	8
1.4	Thesis structure	9
2	DIGITAL TWIN	10
2.1	Phases.....	11
2.2	Feedback	13
2.2.1	Sensing.....	14
2.3	Current applications	15
2.4	Future	16
3	MATERIALS AND METHODS	18
3.1	Setup	20
3.2	Software	25
4	RESULTS	29
5	ANALYSIS	34
6	DISCUSSION	36
7	CONCLUSIONS	39
	LIST OF REFERENCES	41

LIST OF SYMBOLS AND ABBREVIATIONS

DTE	Digital twin environment
DTI	Digital twin instance
DTMC	Digital twin manufacturing cell
DTP	Digital twin prototype
IoT 4.0	Internet of Things 4.0
MQTT	Message queuing telemetry transport
PLM	Product lifecycle management
WPS	Welding procedure specification

1 INTRODUCTION

During the industrial revolution of the late 18th to early 19th century the way products were manufactured completely changed. The emergence of mechanized factory systems using steam and waterpower revolutionized not only the way things were made but the way we thought. The emergence of automation and IoT 4.0 (Internet of Things 4.0) is similarly changing the way we think about both manufacturing and product development[1,2]. A trend towards digitized and automated manufacturing practices has fueled an ever-increasing desire for faster product development and more flexible manufacturing systems [3,4]. The capabilities of these manufacturing systems and design paradigms, in turn, fuels technological advancement and human ingenuity.

To help achieve this goal, concepts such as digital twins have been adopted. A digital twin is essentially a digital copy of a physical thing that is continuously updated throughout the physical thing's lifecycle [5]. With these things in mind, we will examine the capabilities and applications of a digital twin with regards to robot welding cells.

In product development, there is sometimes a disconnect between a customer wants and needs and the design teams' vision of the product. This is especially true as the system becomes more complex and novel. The problem often arises that it is difficult to describe a complex system, especially involving new technology, to a customer or from the customer's perspective to the design team[6]. To combat this, a more streamlined approach with which one can visually represent a concept or system is needed.

1.1 Background

Digital twin has been gaining traction and more widespread use over the last several years. It has been implemented in a wide range of industries and at many different levels and phases of a product's lifecycle. From a product design phase to its service phase, the digital twin provides an omnipresent data repository of information related to its physical twin. This information can be used to not only have a record of a physical twin's service history and current status but to simulate future events and not only predict but optimize behavior through simulations [7].

The concept of a digital twin was first introduced by Dr. Michael Grieves at a Society of Manufacturing Engineers conference in 2002 [5]. Digital twin was initially imagined as a lifecycle management tool. It was thought of as a dynamic system that would remain intertwined with its physical twin throughout creation, production, operation and disposal [5]. Throughout the years since its appearance it has gone by various names: from mirrored spaces model as it was known at the first PLM (Product lifecycle management) course at the University of Michigan to the information mirroring model as it was known until the name digital twin was attached to it in *Virtually Perfect: Driving Innovative and Lean Products through Product Lifecycle Management* [8].

1.2 Scope and Focus

This bachelors' thesis will focus on digital twin as a concept and how it can be applied in mechanical engineering applications, specifically in multi-robot welding cells. Digital twin is already used in many applications, most prominently in product development and lifecycle management; however, it has seen more limited use in welding. Of particular import are the control methods that can be used to gather data from the physical twin and more importantly what methods can currently be used at the laboratories in LUT University. Once an appropriate method has been identified; an experiment will be performed using the robot cell in the welding laboratory at LUT University. Based on these experiments a determination will be made about whether the method is successful and worth further study.

1.3 Objectives and outline

The purpose of this thesis is to determine what a digital twin is and to find control methods for digital twin as it relates to multi-robot welding cells and its related feedback methods. Furthermore, discovering the current applications and future applications will help provide a clear picture of the capabilities and advantages of digital twins. The research questions are as follows:

1. What is a digital twin?
2. What control methods are available
3. What is the best application for a robot welding cell?

Current manufacturing technology has reached a point where the next natural step is to implement an increasing amount of data-driven manufacturing and design. This requires not only the collection of large amounts of data but the efficient use of that data to optimize production and provide increase efficiency. Problem: Simulation results aren't accurately representing reality.

The research in this bachelor's thesis hopes to identify key features of digital twins that will further the goal of system interconnectivity and data-driven production. The research hypothesis is that digital twin concepts can be used in multi-robot welding cells.

1.4 Thesis structure

For the theoretical portion of this thesis, a literary review was used to provide the theoretical framework for the research. At the time of writing this thesis, there were no publications about digital twin with regards to multi-robot welding cells, the theoretical portion will focus on the general concept of digital twin with regards to manufacturing. Due to digital twin being a relatively new concept, there is a lack of specific information regarding its use in multi-robot welding cells. Therefore, the theoretical background will focus on digital twin usage in manufacturing in general and its current applications.

Since digital twin is in its infancy, comparatively speaking, in manufacturing, research papers with a focus on the practical implementation or execution of creating a digital twin is scarce compared to more established technology. Due to this limitation, the material used explores digital twin in terms of the possibilities and opportunities it provides as opposed to detailed examination of practical applications. However, in the context of this bachelor's thesis, this is not necessarily detrimental to its overall objectives. The identification of the advantages and capabilities will provide a basis for further research into the subject.

2 DIGITAL TWIN

According to Boschert and Rosen, “The vision of the Digital Twin itself refers to a comprehensive physical and functional description of a component, product or system, which includes more or less all information which could be useful in all—the current and subsequent— lifecycle phases.”[7]. A Digital Twin is a comprehensive digital model that can accurately represent its physical counterpart’s functions and attributes [1,9–11]. Ideally, all information obtainable from a physical component or system should be represented by its digital twin [5,7]. Over the course of a systems lifecycle, its digital twin will be continuously updated so that it remains an accurate representation of its physical counterpart. According to Grieves and Vickers, there are two types of digital twins: Digital Twin Prototype (DTP) and Digital Twin Instance (DTI) [5].

A DTP is a prototype that provides the information necessary to create a physical system based on the DTP or a digital copy of itself [5]. The digital twin usually contains a comprehensive 3D model, materials, processes, services, requirements and disposal [5]. Conversely, a DTI represents an existing physical product that it is linked to. Similarly, to a DTP a DTI includes a 3D representation of the product and its components, including processes and materials that were used. Additionally, a DTI includes a service record in which services, maintenance and operational states are described to give a broad picture of the system [5].

A Digital Twin Environment (DTE) is an application space where a digital twin is simulated [5]. A DTE is used as a predictive tool to gather data related to the future behavior of a product and its performance in the prototype stage while in the instance stage these are studied for more specific purposes where a component of the system is studied based on its history [5] pp.95.

Grieves and Vickers further explain that a DTE includes an interrogative purpose where the system is studied from a behavioral standpoint. In other words, this is the simulation of different settings and states the physical product may encounter but are not currently undergoing. Using multiple simulations of the product allows for the collection of data that allows for the facilitates the prediction of component failure and system errors when similar sensor readings are collected in the physical product [5]. In robot welding cells this

could be an important tool to anticipate pathing issues in order to reduce issues like workpiece geometries affecting workpiece positioning. Simulations can be run to ensure the welding parameters and robot range of motion do not clash in its environment.

2.1 Phases

A digital twin's usage can be roughly categorized into 4 categories according to Boschert & Rosen: Design phase, engineering phase, reuse operation and service phase. In each phase, the digital twin provides a distinct advantage versus conventional methods.

From the beginning of the development phase, the groundwork for the creation of a digital twin is laid. Models and data are created based on design specifications and requirements. These models must be continuously updated throughout the design phase to keep up to date with the current prototype [7]. The digital model grows continuously during this phase and more importantly creates an image of the interactions within the model that can be addressed easily.

As the complexity of the model increases the additional need to test functionality and verify existing features becomes more important. Interactions between different components of a system must be tested by different teams with different areas of expertise. Traditionally this is a sometimes cumbersome and expensive process that requires a great deal of effort just to coordinate with other teams and keep everyone up to date to the changes that are made. In this function, the digital twin can work as a depository of this information that can be presented in a convenient way. Teams can in theory work on the same model and test out different functions while taking into account other parts of the project that are also being updated. The collective efforts of the teams can be focused on not only their own component of the system but the overall compatibility of all the components within the system as a whole [7]. In this phase, it is important to note that the digital twin itself is not only a single model but rather a collection of components that can, to the degree allowed by the design phase, be used interchangeably according to changing specifications and requirements. If for example, the team finds that there are integration difficulties with a certain component, that component can be easily replaced with a more optimized solution. Furthermore, the simulation of different configurations to find the

optimal setting can be readily executed before further physical prototypes need to be created [12].

Since the digital twin is continuously updated from the start of its development to the end of its lifecycle, that data can be easily used during and after the start of the operation. Data collected during the design of the product and more importantly during the use of the product can be continuously integrated into new simulations that validate further changes or improvements to the product [7]. Data collection and management have traditionally relied on manual human labor and thus, the data isn't always available in real time[13]. However, that could change with a working digital twin that would integrate the data collection process into the design and lifecycle of the product [1]. This also adds additional utility to online monitoring systems by giving an additional data set through simulations using real-world data and not relying entirely on sensor data. Virtual sensing can be used to measure values that may not be physically realistic to measure. Comparing the simulated data to real data will allow for better detection of different failure conditions and more accurate prognostics. A digital twin in this phase will also help to create a point of contact for the design team as well as the teams operating the product or system where both can receive input and give suggestions to further optimize the existing system or further variations. Through these interactions a more comprehensive model will be created, allowing for more accurate lifecycle predictions and maintenance schedules. [7,14]

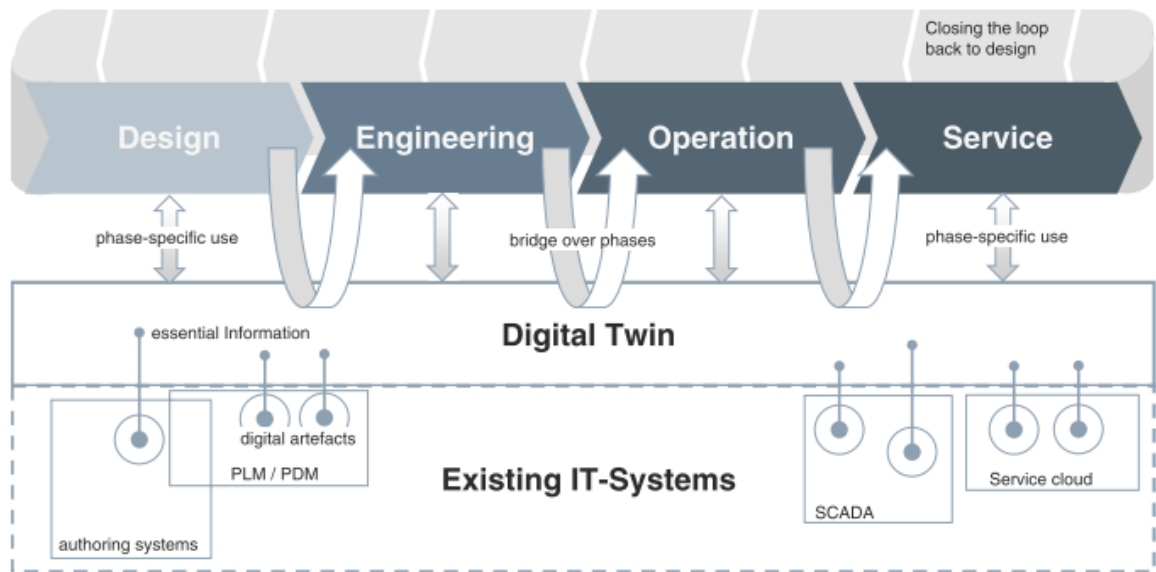


Figure 1. Conceptualization of a digital twins role as a mediator between different phases and the existing IT-Systems. [12]

2.2 Feedback

Traditionally when talking about industrial robots, teach and play robots have been used. These robots require a great deal of time to program and are susceptible to errors with even small deviations of the preprogrammed path or workpiece position. The labor-intensive work and inflexibility have led to the need for a more flexible solution that can be reprogrammed on the fly and ideally a solution that can self-correct. The question is then how can this be achieved? First of all, the use of sensor technology that enables a robot to identify its position and surroundings plays an important role in improving robot capabilities [15]. More importantly, these sensors are ideally able to transmit said data back into a computer for further processing with the goal of creating a feedback loop.

When talking about feedback loops in robot welding cells the three most important data points are naturally the welding parameters, the robot's position and the weld seam itself. Naturally, all these things need to be measured and transmitted back into the computer system. Welding parameters are obtained from a welding procedure specification (WPS) of the process. Directly related to the welding parameters is the actual welding seam itself. As previously mentioned, this can be obtained using seam tracking technology and an appropriate setup of sensors. Most importantly for this thesis however is position data related to the robot itself.

For a digital twin to work, a feedback loop must be established in order to keep the model up to date. Methods for this feedback are varied and depend largely on the system or application. In most cases, only the necessary data is collected with appropriate sensors. The sensor data is then carried to the digital twin through an IT infrastructure for processing. This data is then collected and used to update the instance of the physical twin in real-time and can be used for process optimization and simulations. These simulations are what allow the digital twin to differentiate itself by running parallel simulations that do not simply follow the physical twin actions but iteratively test different pathing and parameters that can both improve the process itself and the final product, in this case, the weld itself. Based on these simulations, incremental improvements can be relayed to the process itself in order to create the best result [1].

2.2.1 Sensing

In robotics, there are typically six different types of sensing used: tilt, rotation, acceleration, shock, vibration and proximity [16]. In addition to the aforementioned variables, the welding process itself must also be monitored. The welding parameters are selected based on the WPS specifications for a given process.

Laser triangulation is the process of conducting distance measurements with the help of laser beam illumination and a camera. A laser beam is aimed at the surface of the object to be measured and the camera captures the image from which the distances can be calculated.

In addition to the robot cell's position, the geometry of the weld is also of high importance. Getting a visual depiction of a weld seam is called seam tracking, which can be done by using, for example, a CCD camera and various other components [15].

The problem that often arises is that the welding process itself causes interference due to both the heat it produces as well as the bright nature of the arc [17]. In order to get an accurate picture, in addition to the camera, various filters should be used. However, the image must be further processed through algorithms in order to remove random noise[15].

2.3 Current applications

Currently, there are applications that, in part, implement digital twin, in their products and services. Comprehensive simulations are created for lifecycle analysis and maintenance prediction. Physics-based simulations of systems are created to train a test machine. There however are not yet any true real-time digital twin applications in existence.

Zhang et al. describe the principle of a DTMC (Digital twin manufacturing cell). In this description the digital twin is created from three parts: the physical model, virtual model and simulation model. The virtual model is created based on the input parameters that correspond with the physical robot cell (e.g. range, radius, position, etc). Then based on the virtual model a multidisciplinary simulation model is created to correspond to the virtual model. These three components are connected using MQTT (message queuing telemetry transport and publish-subscribe architecture). In this example, the physical model would automatically complete its work cycle and the data from the robot would be published to the virtual model and simulation model subscribed to it. The virtual model and simulation model would then optimize the process through simulations in real-time. In essence, the virtual model provides real-time data, the simulation model runs simulations based on that data and finally, the virtual model visualized the simulations. [18] A representation of the system is presented in figure 2.

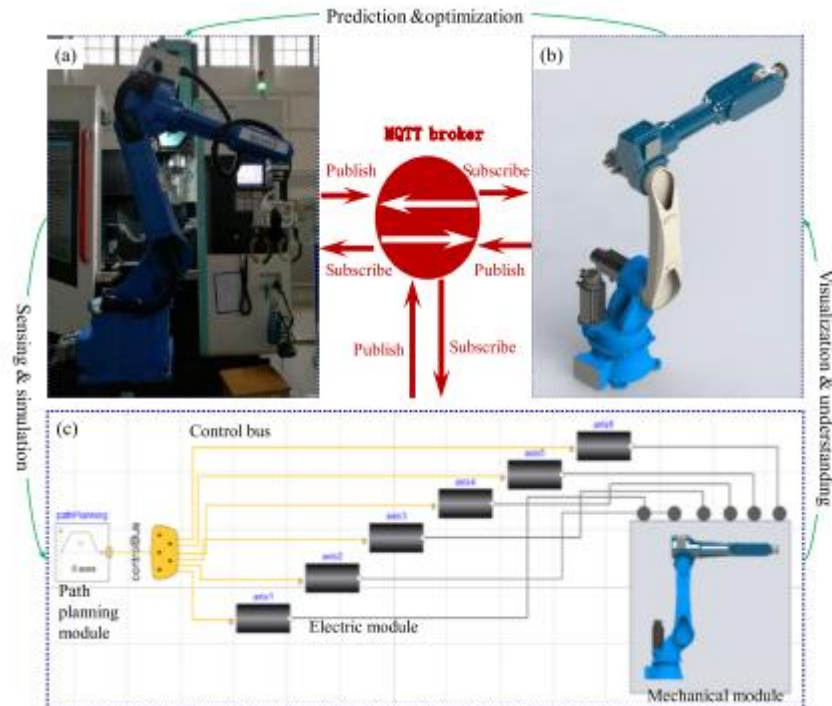


Figure 2. Physical model (a); virtual model (b); simulation model (c). [18]

Different simulation models can be created in accordance with the requirements of the production process. Path optimization in welding could be done by feeding the physical robots cells position data with which the simulation could optimize the path and correct the starting position, for example, with a point to point calculating strategy. [18]

2.4 Future

One of the main advantages of the use of a digital twin model is the intertwining of a comprehensive model with real-time simulations over a system's entire lifecycle. This allows for a reduction in the time-to-market in product development and allows for more flexibility throughout the design phase and perhaps more importantly allows users to maintain a clear picture of a system's individual attributes in service [12]. Users of a system that has been developed with a digital twin will be able to incorporate a predictive maintenance paradigm and through that increase a system's life-time viability when compared to more traditional reactive and preventative maintenance [1].

Information is key in product development and end-use alike, but the gathering and dissemination of this information is largely dependent on the people involved in the

development and end-use according to their organization's preferences. Currently, it is not always realistic for all the relevant information to make its way to different teams and organizations involved in the development and use of systems. Human error among other things and in some cases legal barriers can create lag time in this information being shared. A digital twin requires a new approach to be developed in order to overcome legal barriers and proprietary data. [12].

3 MATERIALS AND METHODS

The laboratory experiment is intended to provide a proof of concept for the creation of a digital twin that can mirror a welding process in real-time and update its parameters based on what is physically happening with said robot cell. The experiment hypothesis is that by using coordinate values from a multi-robot welding cell's (physical twin) programming along with scanning data during the welding process, a digital representation of the physical twin can be created. In other words, the experiment intends to create a rudimentary digital twin of the multi-robot welding cell. As mentioned earlier, there is no literature currently available for the creation of a digital twin in a welding cell. Therefore, the results can ideally be used to further develop a more sophisticated process for both obtaining the data and importing that data into a digital model/simulation. A table of the equipment and software used is presented in table 2.

Table 1. Table of equipment and software used in the experiment.

Robot welding cell	Motoman MA 1900
Rotating table	Motoman MT 1000
Laser sensor	Meta SLS 50 V1
Welding machine	Kemppi A7 Mig
Processing software	Matlab
Modeling software	Delfoi

In practice, the robot welding cell will move along a preprogrammed welding path while the laser scanner scans the seam during this movement. As the process moves forward, the measurement data will be collected for further processing. The model will be run using the python API within the Delfoi program. The scanning data is then used to create visual representations of the scan. Using the scanning data from several scans, the offset of the seam can be calculated. An overview of how the system is imagined to be connected is presented in figure 3.

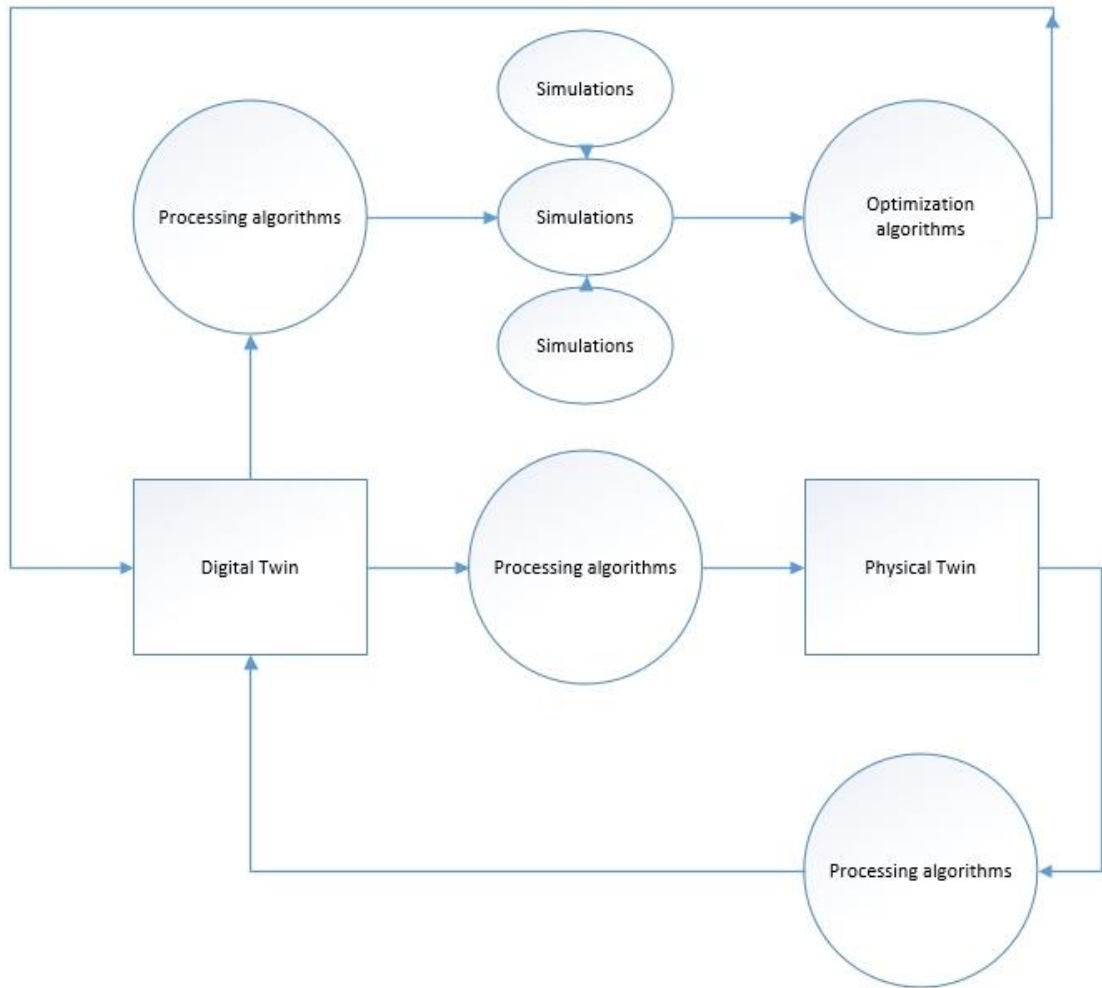


Figure 3. Visual representation of the DTE system.

The experiment consists of two scans, one with the workpiece in its ideal location and for the second scan, the workpiece is moved off-center. Using the two scanning datasets, the offset and offset angle, are calculated by hand.

3.1 Setup

The experiment was carried out using a Motoman industrial robot. The setup also included a Motoman ES 165 N robot that can be used to deliver workpieces to the MT 1000 rotating table but was not used in this experiment but could be incorporated into the system in the future. The main components of the experimental setup are pictured in figure 4.

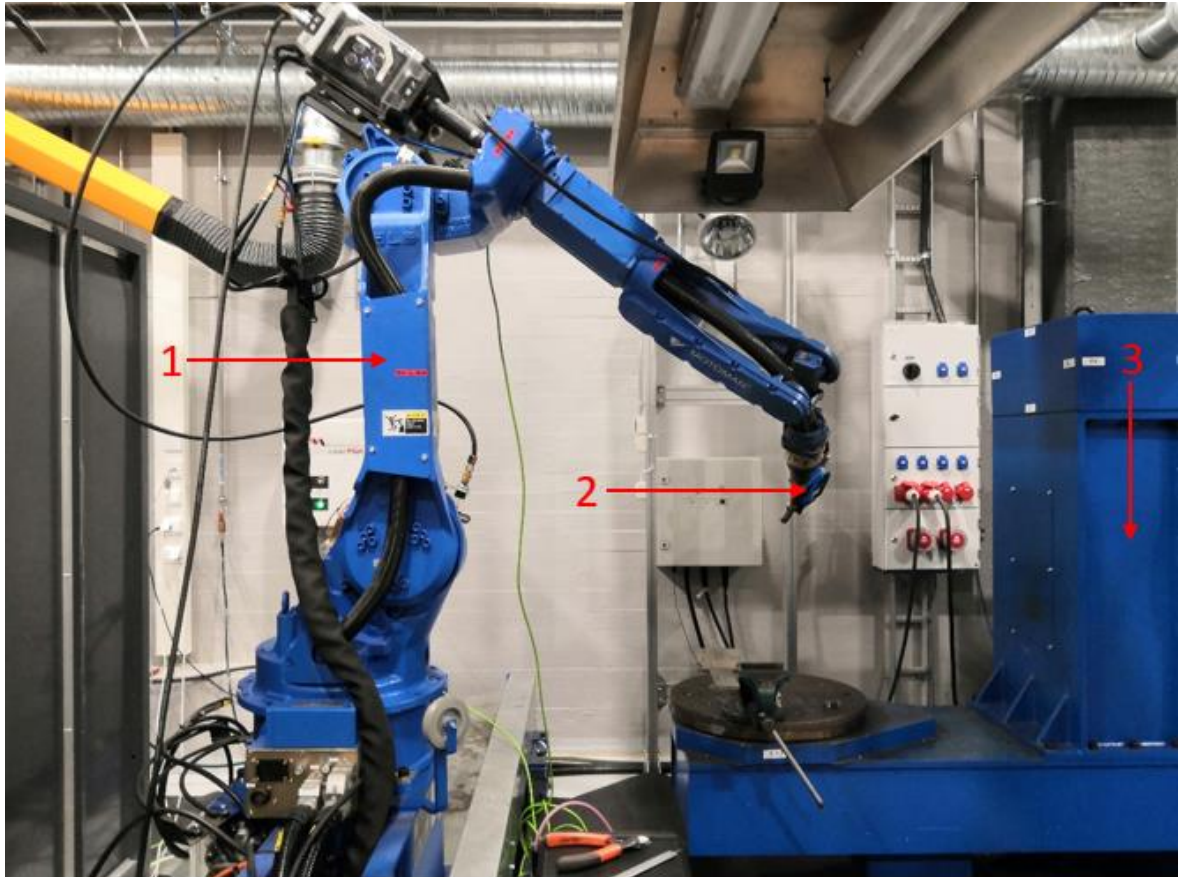


Figure 4. Main equipment in the experimental setup. 1. Motoman MA 1900. 2. Meta SLS 50 V1. 3. Motoman MT 1000.

A welding torch from a Kemppi A7 welding power source (**Figure 5**) was attached to the end of the actuator to provide visual cues to help position the laser sensor. While no welding was done during this experiment, it is important to present an example application for this process considering that MIG/MAG welding has many potential applications regarding the use of digital twin in manufacturing processes.



Figure 5. Kemppi A7 Mig.

A Meta SLS 50 V1 laser sensor was used in this experiment. The laser sensor was attached to the welding head using a 3D-printed bracket. The specifications for the Meta SLS 50 V1 can be seen in table 2 and in figure 6 the laser sensor and bracket attachment are shown.

Table 2. Meta SLS 50 V1 specifications.[19]

Field of view	50 mm
Nominal standoff distance	65 mm
Horizontal pixel resolution	0,05 mm
Tracking position accuracy: Horizontal	+/- 0,1 mm
Tracking position accuracy: Vertical	+/- 0,1 mm



Figure 6. Laser sensor and bracket attachment connected to the welding torch.

The seam of the workpiece was measured at 364 mm in length as seen in figure 8. The workpiece's other dimensions were not measured as they are not relevant to the experiment. The total length of the seam allowed for the calibration of the weld path, allowing the accurate measurement of the seams positional data. The material used was hot rolled structural steel. A t-joint weld was selected for the purposes of this experiment.



Figure 7. Measurement of the seam. Note that the ruler starts at 100 mm .

The starting of the laser sensor position was incrementally calibrated to centre the laser scanner at the mid-point of the weld with the help of a smart laser sensor remote shown in figure 8.



Figure 8. Robot controller used to set the starting position of the scan.

Figure 9 shows the Smart laser sensor remote which is used as a visual guide when calibrating the laser towards the centre of the seam. The monitor shows a visual and numerical value depicting how close to the centre of the seam the scanner is.

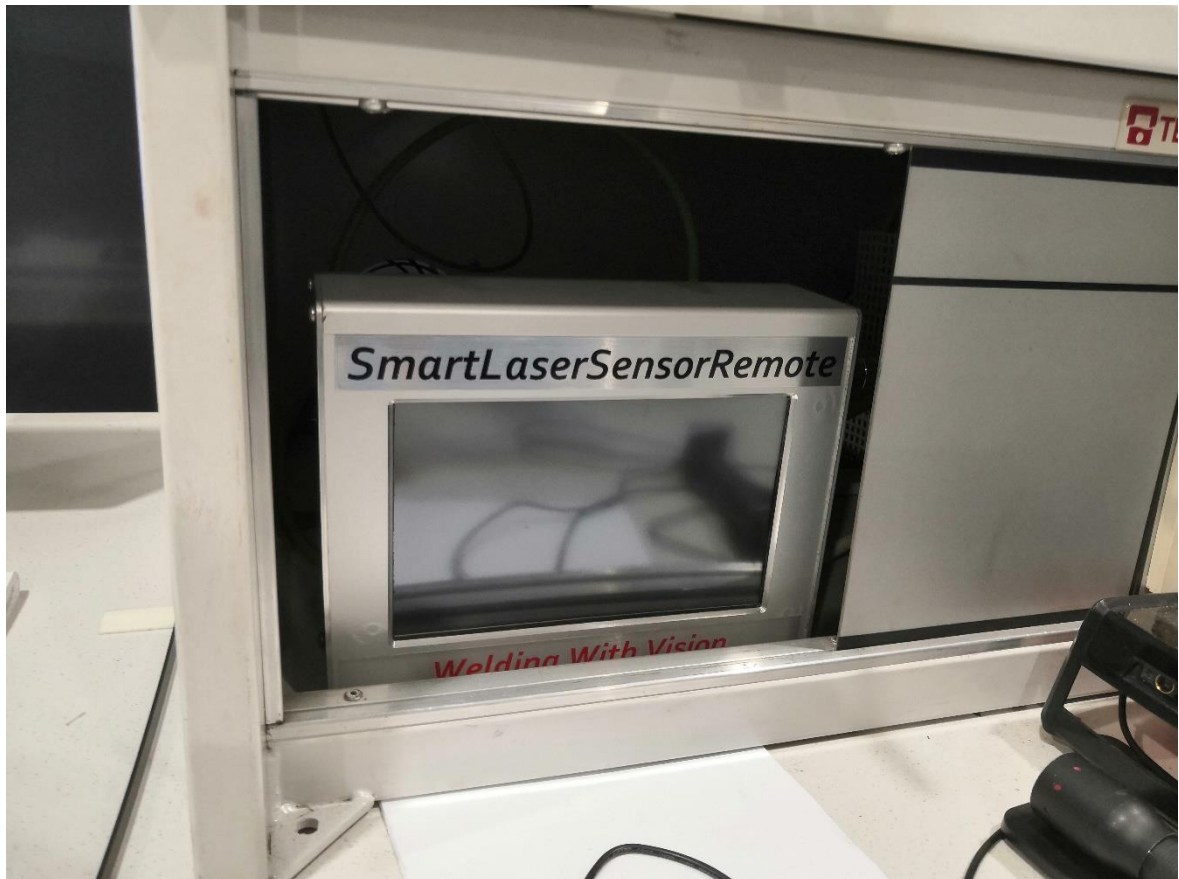


Figure 9. Smart laser sensor remote.

The sensor position centering process can be seen in figure 10. The process consisted of using the controller seen in figure 8 to manually move the laser according to the visual and numerical data displayed on the smart laser sensor remote monitor in figure 9.



Figure 10. Laser sensor position relative to the workpiece.

3.2 Software

The experiment was carried out using a pre-programmed welding path in which the welding head was first moved to the starting position at the end of the workpiece and then moved across the seam to the opposite end of the workpiece as depicted in figure 11. In other words, the workpiece was scanned at its assumed correct position. The position data during the scan was collected using Matlab code where it was processed for further examination. The code produced graphs from which the seam position during the scan can be examined. The code additionally produced topology figures for each scan that can be used as a visual reference for seam and workpiece geometry.

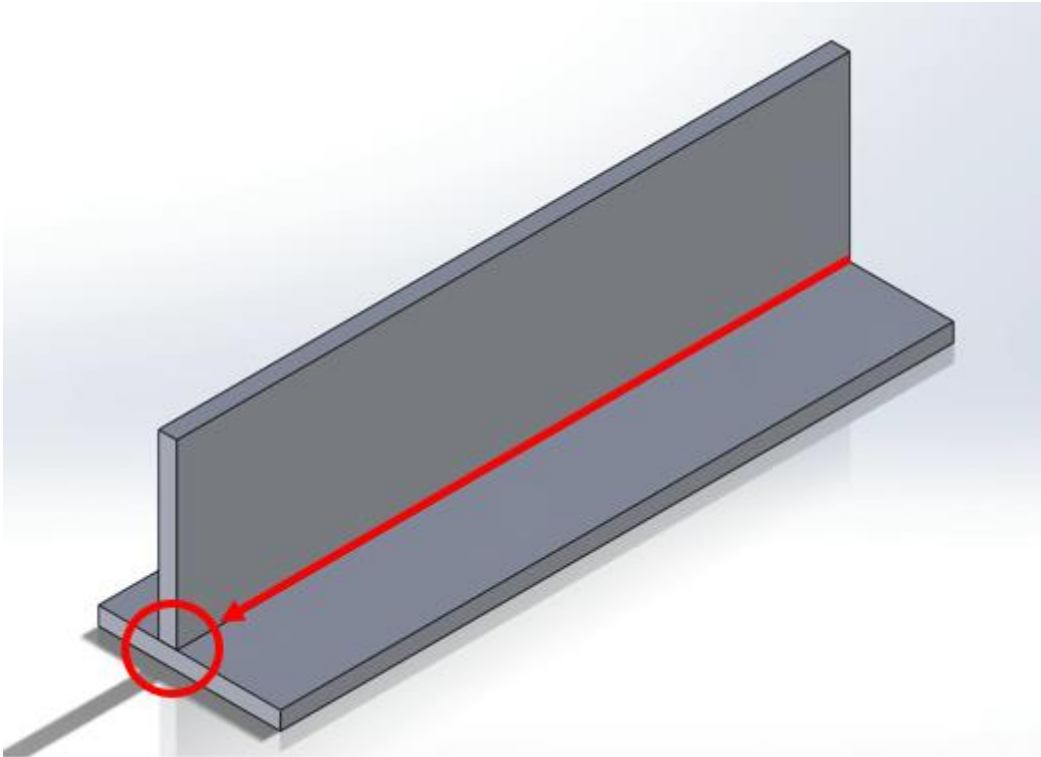


Figure 11. Scanning path of the measurement in the experiment.

To test the hypothesis that data obtained from this type of scan could be used to replicate the physical process in a digital environment, an identical workstation was created using Delphi. The Delphi model worked as a DTE for the purposes of this experiment and the data obtained using the Matlab code provided the positional data required to provide inputs for the Delphi model. For the model to correctly interpret the position data a custom python script was created to effectively “drive” the welding torch correctly. The basic principle of said code was that individual coordinates were manually fed into the script after which the welding torch would move to each coordinate individually. Chaining these coordinates together allows the system to follow an identical path to the physical system. After the desired path has been travelled the model is then reset and the torch moves back to its original position.

During the welding process, the laser scanner measures the deviation from the centre of the seam throughout the weld. This gives us data based on which the position can be corrected so that the weld can be modelled correctly in the DTE. The data produced from the scan is

in pixels, so before it can be implemented into the modelling software it must be converted to mm. According to the specifications presented in table 2, one pixel is equal to 0,05 mm,

Before the data can be used, the coordinates must be corrected so that they correlate with the coordinate system in Delfoi. Using the data points from the scan, the correction is calculated by hand or by using the software. To get the correction values we need to take the data from both scans and subtract them from each other. This gives us the difference in seam position relative to the centre point, which in this case is 0. With the new data obtained through subtraction, we can calculate the offset distance to the desired location as well as the angle of the offset. This data is then used to correct the positioning within the DTE (Figure 12) environment by inputting the corrected values. For the sake of efficiency, a code that calculates the difference and angle automatically can be made.

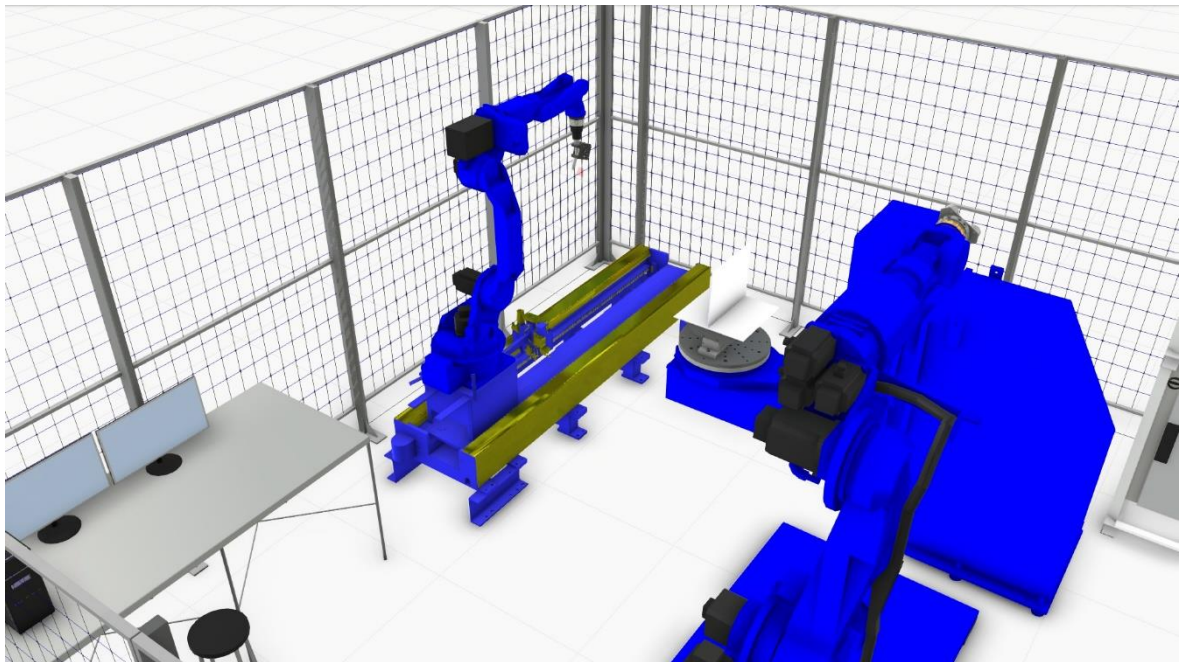


Figure 12. The DTE created using Delfoi.

The correction was made by inputting the values into a python script within the DTE. The script itself takes the movement values and moves the workpiece to the correct position. The script allows for quick corrections with the ability to reset the workpiece into its original position. Although during the time of writing, the code was created to replicate the basic movements of the experiment, in the future it can be built upon to accommodate more complex movements and applied to different DTEs.

The experiment will be done in the welding laboratory at LUT University using the equipment available. The welding robot used is a Motoman MA 1900 and the positional data will be taken from the robot program. The data will be manually fed into the model that has been created using Visual Components. The welding cell will be programmed for a preset welding path. The model will be made using Visual components in Delphi software. Within the software itself, the built-in python API will be used to write the required code.

4 RESULTS

This section will focus on the results from the measurements and later the implementation of said results into the Delfoi model of the system. With any success, the lab work and test setup will be able to represent a rudimentary digital twin system. The system, of course, isn't a real-time system but in practice, the experiment provides evidence that such a system could be created with a program using automatic telemetry transfer and data processing.

Two scans were done using the described setup to gather the data needed to process the code. The Matlab code processing the data provided several plots of the scanned seam. The plots provide a visual representation of the scanned seam as well as provide the data points needed to test the hypothesis in Delfoi.

The topology figures obtained from the code visualize the offset of the workpiece between the two scans. These figures consist of raw profile data from the scan using a two-dimensional median filter of 31 pixels. The topology of both scans is presented in figure 13, where the movements between the two scans was illustrated.

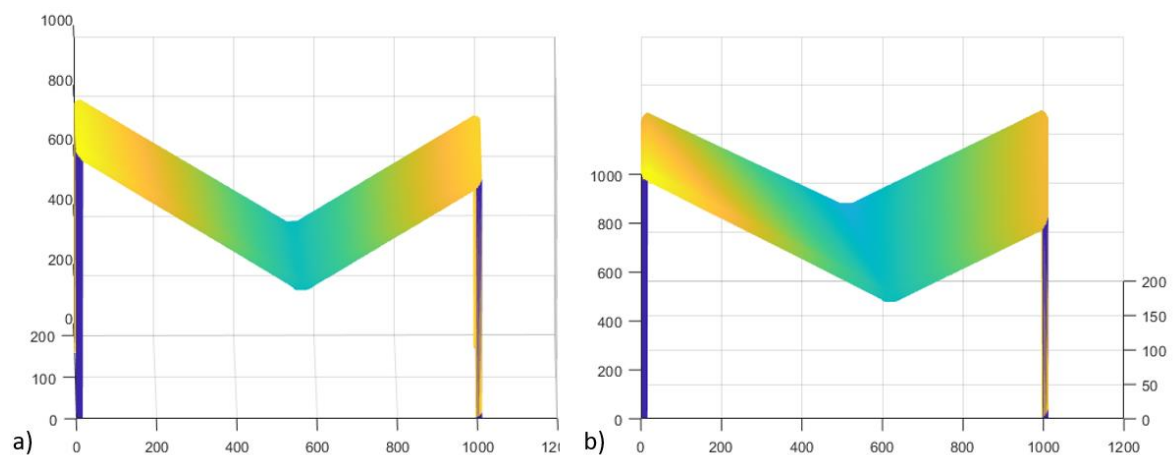


Figure 13. 3D mesh of the two scans. A: Mesh of the first scan. B: Mesh of the second scan. The data on both axes is presented as pixels.

As can be seen from figure 13, the second scan shows that the workpiece was moved out of position to represent an offset workpiece. The seam position of scan 1 and scan 2 as pixels

is presented in figure 14. A median filter was used to reduce to measurement spikes, as seen in figure 14, so that large spikes would not affect the results significantly.

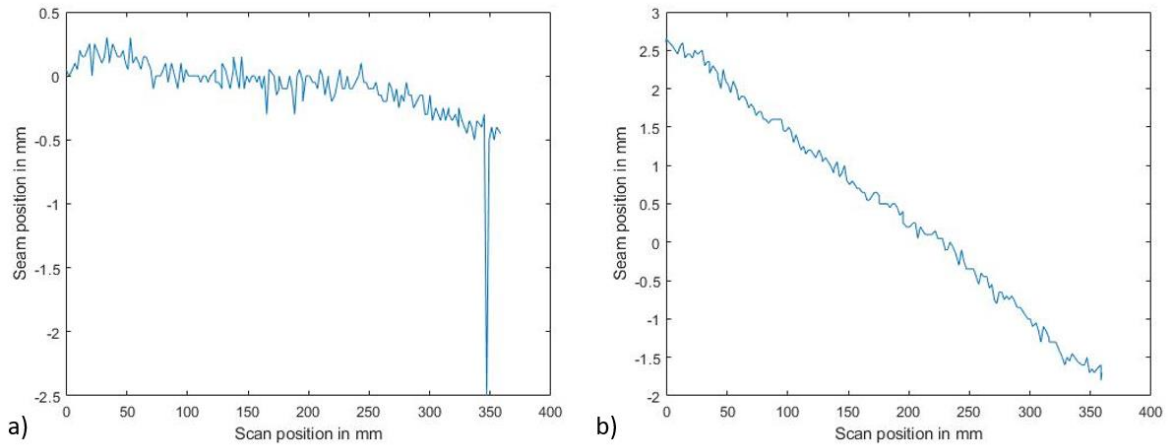


Figure 14. A: First scan. B: Second scan. X-axis: scan position in mm. Y-axis: Seam position in mm relative the starting position $x = 0$.

A plot was created that included a line fit for each scan. The values obtained from the end positions and centre point were converted to millimetres by multiplying the pixel value by the scanners horizontal pixel resolution presented in table 2. The line fit plot with values corresponding to the start and endpoints of the scan as well as the point of intersection are presented in figure 15.

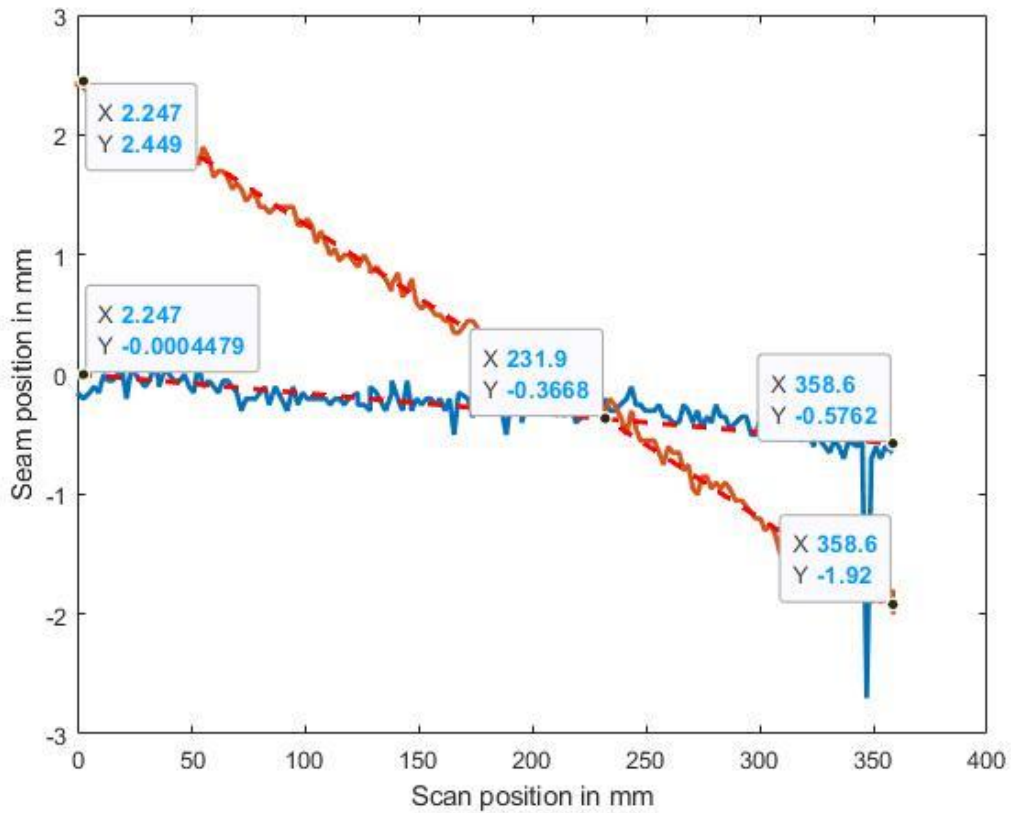


Figure 15. Polyfit plot of the two scans with data points used for calculations. The x-axis represents the location of the scan from its starting position in mm and the y-axis represents the offset from the starting position.

The offset at both ends of the workpiece were calculated by writing a code that subtracted the line fit equation from the first scan from the line fit equation of the second scan at scan positions $x = 2,247$ and $x = 358,6$. These line fit equations are presented for scan 1 and scan 2 in equations 1 and 2 respectively. To calculate the offset angle, we first calculated the length of the lines from $x = 2,247$ to $x = 231,9$ using the Pythagorean theorem after which the law of cosines (equation 3) was used to obtain the angle, where $a = 2,45$.

$$y = -0,001616 * x_1 + 0,0031831 \quad (1)$$

$$y = -0,012259 * x_2 + 2,4761 \quad (2)$$

$$\alpha = \arccos \left(\frac{b^2 + c^2 - a^2}{2 \cdot bc} \right) \quad (3)$$

The results from the Matlab calculations for the offset of the workpiece and the offset angle are presented in table 3. In figure 16 the offset related to the optimal position of the workpiece is presented.

Table 3. Calculated offset and offset angle of the workpiece after the second scan.

Offset at the starting point of the workpiece	2,48 mm
Offset at the end of the workpiece	-1,34 mm
Offset angle of the workpiece	1,2768° (Degrees)

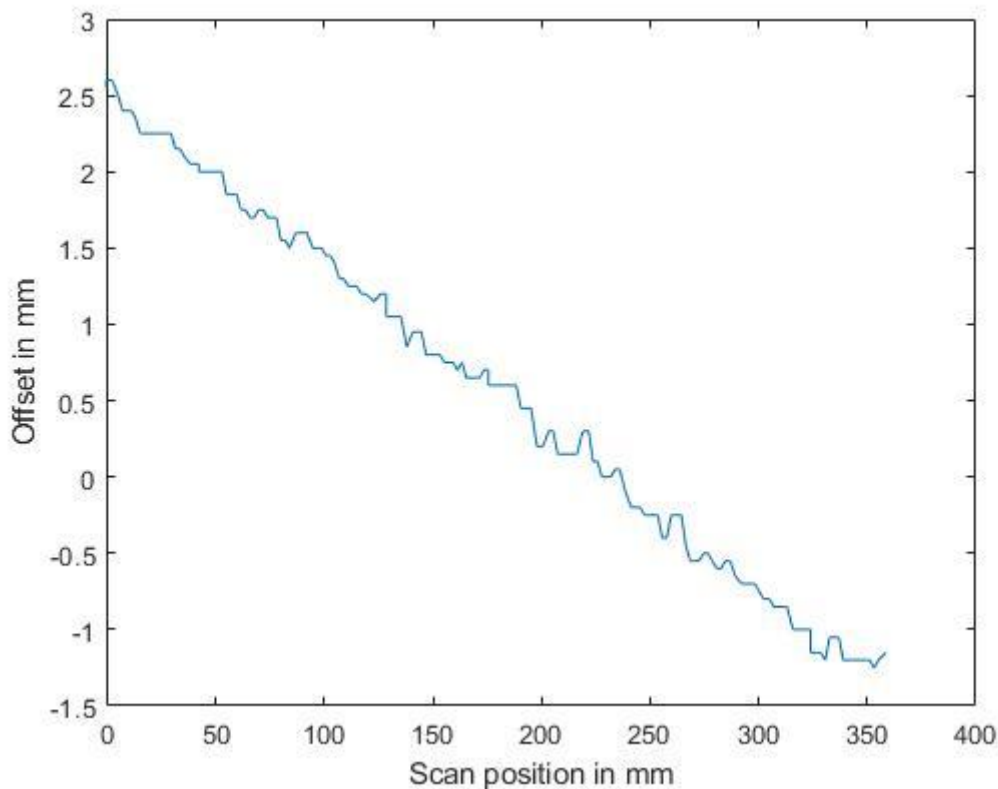


Figure 16. Offset of workpiece seam. Y-axis: offset in mm. X-axis: scan position in mm.

The presentation of the implementation into the Delfoi DTE is difficult to present in figures as the movements are more important in this instance. A visual depiction of the scanning process mid scan is presented in figure 17. The workpiece was set to the assumed correct position within the DTE. The calculated values were fed into the python script to replicate the offset. In this case with the use of coordinates corresponding to the offset compared to the reference plane.

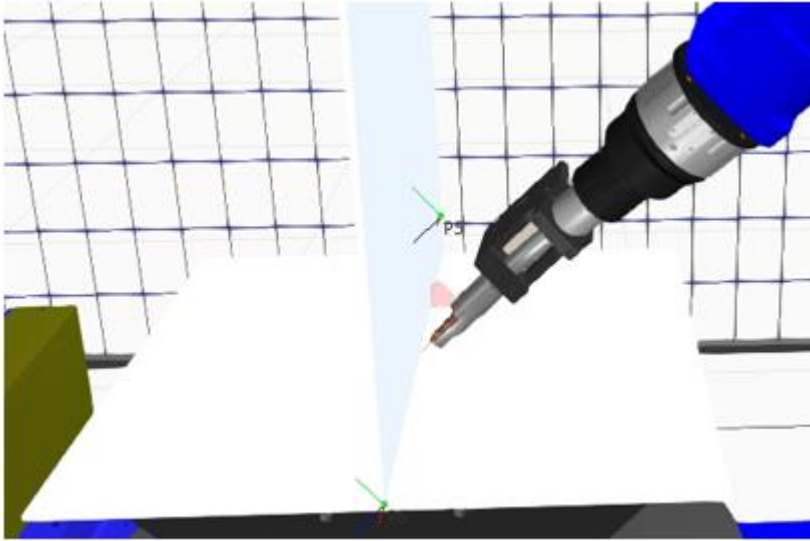


Figure 17. A mid-scan depiction of the DTE.

5 ANALYSIS

The simulation of the scanning process was successful, and the experiment was able to correctly visually represent the movement of the physical twin in both scans. The offset values were successfully used to reposition the rotated workpiece back to its optimal position. Using these same methods, it is possible to reproduce more complex movements and angles present in demanding welding positions. However, the complexity of the workpiece and especially its positioning naturally increases the complexity of the model.

In some cases, such as figure 14, the use of more filtering is desirable to prevent large spikes in the graph. The spike measurements were, however, low in this instance, appearing only once in both scans. These kinds of spikes are likely caused by the metallic surface reflecting light from the surface of the material, which causes a measurement error. However, a single spike does not affect the outcome of the calculations by much but could be a problem in an even more reflective material. Ideally, a material being scanned should be as non-reflective as possible. However, in the case of welding this is not possible as the surface material cannot be coated and must be clean to minimize the risk of imperfections.

In the future, the code should be written in a way that automatically converts the pixel data to mm (millimeters) to reduce the amount of post-processing work needed. This would help to create more easily readable figures and graphs as well as facilitate data input into a digital twin model where the feedback loop can give direct values to guide the placement of the workpiece.

The biggest difficulty in implementing the data into the digital twin model was setting the values for both scans. At this time there was no automatic script written for this process but could be implemented in the future with more time and coding. It is possible to do this in the software used for this experiment (Delfoi). The programs used are very flexible and customizable when it comes to experimentation with different functions and variables needed to produce a digital twin-like system. The most limiting factors are learning to implement proposed solutions into a seamless and automatic feedback loop that can do all the steps from measurement to model creation on its own.

The data shows that by using these programs it is possible to run a digital twin if the position data is readily available. This, however, can present its own challenges. The position data can be rather difficult and sometimes outright impossible to attain directly from the machine itself. To combat this a reliable way to scan the position is required, in this case, a laser scanner to measure the seam is enough, but in some applications, this may not be possible. In this was welding is an excellent application for a digital twin as the seam itself and the welding parameters give data points that can be used to extrapolate position data prior, during and after welding. Furthermore, in the case of welding, the same data serves a dual purpose as it can simultaneously be used to monitor the weld itself and provide a multifaceted overview of the process. The data can then be stored and reused for both optimization and as a guideline for similar welds in the future.

6 DISCUSSION

Literature pertaining to the implementation of digital twins in robot welding cells, as mentioned previously, is not readily available at the time of writing this thesis. However, the available material was nonetheless helpful in providing an overview of the topic of digital twins. The advantage of the scarce material, however, was that many of the papers on the subject were recently published. While writing this theses, new research papers on the process continued to become available and continued to provide additional information and viewpoints on the subject. Digital twin as a research subject is, in some regards, at a stage of study where a deluge of new papers continues to appear.

The European Centre for International Political Economy suggests in its 2018 study that commercial cyber espionage risks up to €60 bn in potential economic growth and up to 289000 jobs [20]. Security concerns will certainly become relevant as digital twins start to become a reality. Certain concerns related to the models and simulations that are essentially always online in one way or another pose several risks. While intellectual property theft is present through corporate espionage, a digital model that doesn't contain only a single iteration but all iterations and simulations including real-time data over the systems lifetime is an order of magnitude more costly to lose to competitors. A free flow of data the is created with a digital twin system can also make it easier for a single employee to leak data related to a system both intentionally and unintentionally.

This presents a challenge that is not easily solved because limiting access to the system defeats the purpose of its implementation. A culture of trust is always necessary for teamwork in engineering, but even more so when everything related to a project or product is readily available in one location. While digital twin provides additional possibilities for customer interaction and participation in the development process, this again adds an additional failure point in the security process where the data is vulnerable to 3rd party actors, through carelessness or malicious intent. the digital twin can create multiple vulnerabilities to the integrity of the design process and data management of a system. System integrity must also be considered to prevent instances of intentional sabotage. These issues must be addressed with care to reduce the risks associated with its implementation and allow its users to fully benefit from its potential.

The current effort in moving towards digitalization in all aspects of design and manufacturing presents an excellent opportunity for the implementation of digital twin. Digital twin can help bridge the gap that is often seen between manufacturing and design. With digitized manufacturing and design, these two engineering disciplines can find a common interface in digital twin with which they can communicate their requirements and suggestions. If both teams can see what the other is doing and thinking, implementing modifications can be streamlined to provide an efficient workflow that can lead to increased productivity and innovation.

The end goal of digitalization is the creation of cyber-physical production systems that integrate computer systems and physical systems. A digital twin can play a key role in these systems by creating a connection and working as a platform through which to run the systems, simulations, monitoring and act as a data repository for all the data. An entire assembly line could be created in a DTE in which all the parts and components of the system are present, providing a visual interface with which to interact. The possibilities are immense, albeit not an easy task to achieve, and the rewards can be seen in many facets including safety. The safety aspect can be especially pronounced when the requirement for human interaction around dangerous machinery is reduced.

The application for robot welding cells is a great example where digital twin strengths mesh well with the application. Welding requires accurate positioning of the workpiece to produce the best results. With the implementation of a digital twin, the system can, with the help of sensors, ideally measure the position with great accuracy and self-correct if the workpiece is misaligned. Instead of simply following a set procedure, the system, with the help of a digital twin, provides feedback through simulations run by using the data collected during the scanning process.

The current wave of manufacturing advancements and increased automation will be capable of bringing a new era of manufacturing and the companies that are able to implement these concepts into their businesses will have an enormous competitive advantage over companies that do not adopt the most current technologies. Using digital twin for geometry assurance as suggested by Söderberg et al. in their paper titled “Toward a Digital Twin for real-time geometry assurance in individualized production”, can be used

to create highly efficient production lines that allow for fast distribution of manufacturing data where needed [21].

7 CONCLUSIONS

This thesis set out to discover the principles of digital twin, its feedback methods and applicability in welding applications. This thesis was able to provide an overview of the basic principles of a digital twin. The feedback methods available for such a system are numerous but at the time of writing, there is no standard operating procedure for how this should be done. The method tested in this thesis' experimentation proved successful in providing the digital model the correct input to mirror the physical twin, although the next step in creating a feedback loop back to the physical system will require further study.

From the results it can be concluded that the test was a success. The results show that using this method is compatible with the welding of tee joints. The process allows for the workpiece to be scanned during the welding process and that data can be used in conjunction with a code that calculates the offset of the seam and corrects it for implementation into a digital twin model. With more research and testing there is little doubt that the implementation of fully fleshed-out digital twin models in welding is an exciting development. Digital twin as a concept goes hand in hand with increased automation and allows for a higher level of control and prognostic capabilities.

The benefits gained from the implementation of a digital twin are undeniable in all aspects of the lifecycle of the product. It is much more than a quality of life and efficiency tool. It can provide a robust toolset that streamlines the design process, allows customers to take a more active role in product development and increase lifecycle management through a prognostic approach that can help predict a system's status under various conditions. The ability to inspect a system's history without physical inspection and mountains of documents provides an opportunity to further automate a system to free up human labor for the most critical applications.

Further study into the digital twin applications in welding could most certainly pay off. Focusing on the creation of a feedback loop with which the digital twin and physical twin could effectively communicate is an important next step in the process of bringing cyber-physical systems into reality. Once a fluid connection can be established it is only a matter of time and effort until entire systems can be connected into a single network from which

all operations could be interconnected and simultaneously controlled in a dynamic environment where geometries and tolerances need to be modified to match the ever-increasing demands of industrial manufacturing. In the future, digital twin will hopefully go from being an interesting idea with great potential, to something that is simply taken for granted like electricity is every day, regardless of the immeasurable impact that it has on our lives. An unseen entity that despite our lack of conscious recognition, quietly works away in the background as we continue to bear the fruits of its labor.

LIST OF REFERENCES

- [1] M.J. Kaur, V.P. Mishra, P. Maheshwari, The Convergence of Digital Twin, IoT, and Machine Learning: Transforming Data into Action, in: 2020: pp. 3–17. https://doi.org/10.1007/978-3-030-18732-3_1.
- [2] S. Haag, R. Anderl, Digital twin – Proof of concept, *Manuf. Lett.* 15 (2018) 64–66. <https://doi.org/10.1016/j.mfglet.2018.02.006>.
- [3] B. Schleich, N. Anwer, L. Mathieu, S. Wartzack, Shaping the digital twin for design and production engineering, *CIRP Ann. - Manuf. Technol.* 66 (2017) 141–144. <https://doi.org/10.1016/j.cirp.2017.04.040>.
- [4] R. Rosen, G. Von Wichert, G. Lo, K.D. Bettenhausen, About the importance of autonomy and digital twins for the future of manufacturing, in: *IFAC-PapersOnLine*, Elsevier, 2015: pp. 567–572. <https://doi.org/10.1016/j.ifacol.2015.06.141>.
- [5] M. Grieves, J. Vickers, Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems, in: F.-J. Kahlen, S. Flumerfelt, A. Alves (Eds.), *Transdiscipl. Perspect. Complex Syst. New Find. Approaches*, Springer International Publishing, Cham, 2017: pp. 85–113. https://doi.org/10.1007/978-3-319-38756-7_4.
- [6] N. Alaei, A. Rouvinen, A. Mikkola, R. Nikkilä, Commercial Vehicle Technology 2018, (2018) 187–194. <https://doi.org/10.1007/978-3-658-21300-8>.
- [7] S. Boschert, R. Rosen, Digital Twin---The Simulation Aspect, in: P. Hehenberger, D. Bradley (Eds.), *Mechatron. Futur. Challenges Solut. Mechatron. Syst. Their Des.*, Springer International Publishing, Cham, 2016: pp. 59–74. https://doi.org/10.1007/978-3-319-32156-1_5.
- [8] M. Grieves, *Virtually Perfect: Driving Innovative and Lean Products through Product Lifecycle Management*, 2011.
- [9] E.H. Glaessgen, D.S. Stargel, The digital twin paradigm for future NASA and U.S. Air force vehicles, in: *Collect. Tech. Pap. - AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, 2012. <https://ntrs.nasa.gov/search.jsp?R=20120008178>.
- [10] J. Liu, H. Zhou, G. Tian, X. Liu, X. Jing, Digital twin-based process reuse and evaluation approach for smart process planning, *Int. J. Adv. Manuf. Technol.* 100 (2019) 1619–1634. <https://doi.org/10.1007/s00170-018-2748-5>.
- [11] A.A. Malik, A. Bilberg, Digital twins of human robot collaboration in a production

- setting, *Procedia Manuf.* 17 (2018) 278–285.
<https://doi.org/10.1016/j.promfg.2018.10.047>.
- [12] P. Hehenberger, D. Bradley, Mechatronic futures: Challenges and solutions for mechatronic systems and their designers, *Mechatron. Futur. Challenges Solut. Mechatron. Syst. Their Des.* (2016) 1–259. <https://doi.org/10.1007/978-3-319-32156-1>.
- [13] Q. Zhang, X. Zhang, W. Xu, A. Liu, Z. Zhou, D.T. Pham, Modeling of digital twin workshop based on perception data, in: *Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, Springer, Cham, 2017: pp. 3–14. https://doi.org/10.1007/978-3-319-65298-6_1.
- [14] F. Tao, F. Sui, A. Liu, Q. Qi, M. Zhang, B. Song, Z. Guo, S.C.-Y. Lu, A.Y.C. Nee, Digital twin-driven product design framework, *Int. J. Prod. Res.* 57 (2019) 3935–3953. <https://doi.org/10.1080/00207543.2018.1443229>.
- [15] Y. Xu, H. Yu, J. Zhong, T. Lin, S. Chen, Real-time seam tracking control technology during welding robot GTAW process based on passive vision sensor, *J. Mater. Process. Technol.* 212 (2012) 1654–1662. <https://doi.org/10.1016/j.jmatprotec.2012.03.007>.
- [16] B. Giovino, Robots Assume the Position with Sensors, *Mouser Electron.* (2019). <https://www.mouser.fi/applications/robotics-position-sensors/> (accessed November 25, 2019).
- [17] S. Penttilä, Master of Science: Junior researcher, LUT University. Interview 27.11.2019. Interviewer Tuukka Harju Bachelor's of Science student. Notes are occupied by the interviewer, (2019).
- [18] C. Zhang, G. Zhou, J. He, Z. Li, W. Cheng, A data- and knowledge-driven framework for digital twin manufacturing cell, *Procedia CIRP.* 83 (2019) 345–350. <https://doi.org/10.1016/j.procir.2019.04.084>.
- [19] P.T. Information, S. Laser, S. Integration, Smart Laser Sensor SLS-050 Preliminary Specifications SLS-050, (2009).
- [20] P. Advisory, E.U. Services, The scale and impact of industrial espionage and theft of trade secrets through cyber Executive summary, (2018).
- [21] R. Söderberg, K. Wärmefjord, J.S. Carlson, L. Lindkvist, Toward a Digital Twin for real-time geometry assurance in individualized production, *CIRP Ann. - Manuf. Technol.* 66 (2017) 137–140. <https://doi.org/10.1016/j.cirp.2017.04.038>.