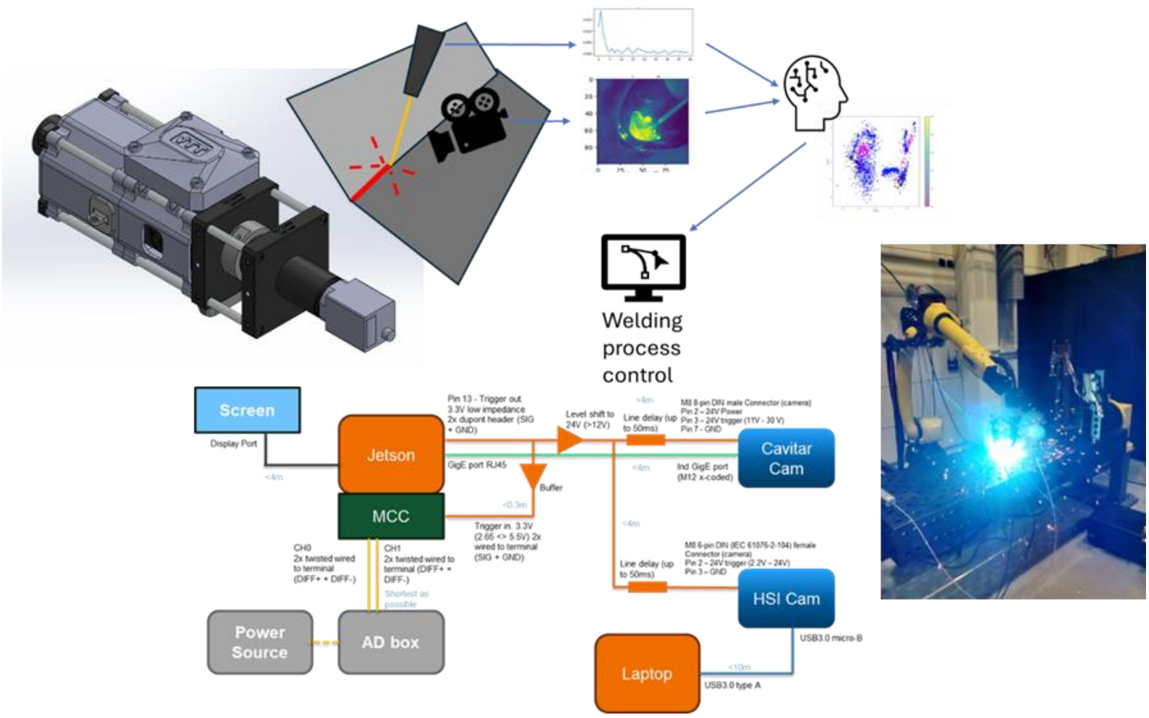
PROJECT FINAL REPORT




# AI toolbox for Lot-Size-One robot welding - AITOOLS1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beyond the obvious

# Contents

# 1. AITOOLS1 Introduction

The AI toolbox for Lot-Size-One robot welding (AITOOLS1) project deals with new applications of novel AI technologies for robot welding, such as AI tools for process control of complex multi-parameter dependent systems, as well as manufacturing quality control. Specific implementations include improving the weld quality by introducing ML models capable of dynamically optimising the robot welding processes.

However, in industrial applications the problem with data-based AI is the acquisition of large and reliable dataset(s). In several manufacturing applications, the size of the dataset is small, which is a major limitation for the use of traditional AI methods. The data scarcity problem is particularly evident in small series and Lot-Size-One (LS1) production. Hybrid modelling involving measurement data but also other form of knowledge capable of capturing physical phenomena and know-how is a solution to these challenges. These developments apply to other manufacturing methods, eg. Laser Welding or Additive Manufacturing AM, too.

For the participating companies, the key project topic is the effect of robot welding procedure on resulting weld quality and process productivity. The AI model teaching data include, eg. welding parameters, measured geometrical weld characteristics and global dimensional accuracy. The final company project goal is an AI based autonomous online process and quality control system for automated Lot-Size-One welding production.

AI based production and quality control processes in manufacturing also enable full product traceability through the whole production chain and provides possibilities for extension over the whole lifecycle for eg. optimising the service and maintenance operations. For the Original Equipment Manufacturers (OEM) the main project impact is the improved market position due to productivity increases and enhanced quality and consistency, leading into reliable long-term service properties.

## 1.1 Background

The manufacturing industry is going through a change of paradigm towards digitalisation of the product and production development and control. This is strongly accompanied by the increasing amount of data collected during the whole product lifecycle. This mass of data is utilised with the aid of increasingly intelligent production machinery, connected and operating together through cloud services, ie. internet of things IoT.

The current engineering design tools, ie. 3D CAD systems, have enabled the handling of complete product design data in digital form. AI technologies can boost productivity by analysing and extracting valuable information from large engineering datasets, automating complex engineering tasks and controlling and adjusting demanding manufacturing operations. The AITOOLS1 project deals with new applications of novel AI technologies for manufacturing industries, such as AI tools for product design, process control of complex multi-parameter dependent systems, as well as manufacturing quality control and requirement engineering. Specific implementations include improving the production quality by developing and introducing ML models capable of dynamically optimising the manufacturing processes.

In several manufacturing applications, the size of the dataset is small, which is a major limitation for the use of traditional AI methods. The data scarcity problem is particularly evident in small series and even Lot-Size-One (LS1) production of the majority of the Finnish manufacturing inudustries, including the current project industrial partners.

The utilisation of modern advanced data analytics and AI technologies for manufacturing quality prediction and control can be divided in three major phases, as seen in Figure 1 and summarized below.

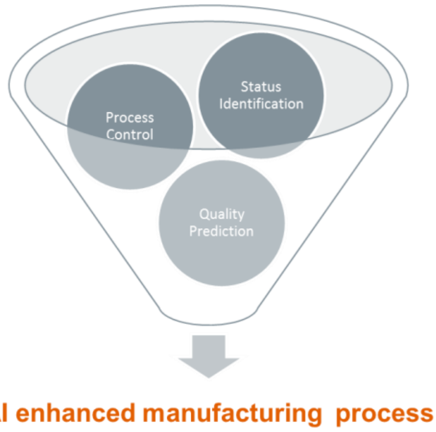


*Figure 1. A sketch of AI application in manufacturing process control.*

- **Phase 1:** Initial status identification: determination of the component or subassembly condition before the particular manufacturing phase.
- **Phase 2:** Manufacturing process control: utilising the production machinery internal numerical or digital control procedures and algorithms and simultaneously collecting processing data that enable on-line process adjustment and eventually adaptive process control based on AI algorithms.
- **Phase 3:** End product quality prediction: an intelligent, AI based procedure and relevant algorithms that are able to
  - Draw conclusions from the status identification and process control steps for predicting the quality of the final product
  - Decide whether the quality indicators are within the pre-set acceptance limits
  - Take the required corrective actions

For the participating companies, the key project topic is the effect of robot welding procedure on resulting weld quality and process productivity. The AI model teaching input data include, eg. welding parameters, geometrical weld characteristics and global dimensional accuracy. The final company project goal is an AI based autonomous online process and quality control system for automated Lot-Size-One welding production.

## 1.2 Partners

The AITOOLS1 project was carried out in co-operation with two research institutes, VTT Technical Research Centre of Finland Ltd and Tampere University, Mechanical Engineering and Industrial Systems (TAU). Additionally, the RTO´s are strongly supported by and work in integral co-operation with the following companies´ own Business Finland R&D projects:

**Kemppi** aims at successful implementation of Machine Learning features into their current digital welding production management platform WeldEye would (i) make a significant impact on the productivity of welding shops, (ii) increase the use of WeldEye considerably in mechanised welding solutions, making it almost a de-facto standard, and (iii) increase the attractiveness of Kemppi power sources, since the developed real-time problem detection and advanced automated corrections require Kemppi machines or plug-in/edge technologies to achieve the full productivity benefits.

**HT Laser**´s high-level goal was to increase welding automation in their plants to improve the productivity and overcome the worsening shortage of skilled welding personnel. An essential aim is to speed up offline programming for cost savings by cutting the amount unproductive working hours. Improvements in the real-time welding parameter control results in reduced reclamation and quality costs and is another spearhead in their development work. Together with their partners and customers, this helps to reach common goals as a final product contract manufacturer. An inherent HT Laser target is to improve the welding automation expertise level among HT Laser Group personnel. Finally, based on HT Laser offering an interesting AITOOLS1 topic is the adaptation of robot arc welding AI applications in laser welding and Additive Manufacturing, particularly PBF.

**Visual Components** outcome in this project is to develop an intelligent offline programming (OLP) software that will utilize the 3D CAD data, annotations and manufacturing metadata for automatic robot programme generation. The OLP software will map the correct welding parameters from WeldEye to a product design with dimensions, material characteristics and welding positions. It retrieves welding sequencing and directions information from an external FE analysis software of Wärtsilä. The software will learn from the real-world measurement input and adapt itself each time to the changed values of a real welded object.

**Cavitar** solutions for image collection and analysis is essential for data collection and training of the AI algorithms and also for online process control. The aim is to strengthen the capabilities of their own Welding Camera solution and integrate their products into an advanced system which integrates off-line programming and welding power source. Another essential topic is the development of the camera data analysis procedures and techniques.

**Wärtsilä** business case is to take robot welding to the next level by developing imaging for the robot as the first step. Second and long-term target is that with AI the imaging can even be discarded and welding quality is ensured through artificial intelligence used for welding data. Third target is to utilize design model from simulation automatically, ie. develop welding from design to finalized product as automated as possible. Wärtsilä is a self-funded partner, ie. they are not applying for BF funding.

## 1.3 Workplan

The project core is the ***selection of AI models used with different amounts of*** initial or pre-existing teaching ***data*** available: the starting point should be scarce or even non-existing measured and/or experimental data. The models need to be ***easily modifiable and adaptable as*** the amount of true or artificial, eg. simulated physics-based, ***datasets become available***.

***The AI models are trained, tested, validated and demonstrated in the company projects´ robot welding environment***. The eventual platform commercialisation will be carried out in company-driven follow-up actions and projects.

The close connection and company collaboration yield ***industrial relevance*** for the research results of all the partners, while still enabling the development of generic knowledge and AI models and algorithms based on the experimental work results. For the partner companies the project key scientific and technical goals are:

- Make a ***productivity leap in Lot-Size-One welding*** production by decreasing the need for finishing work through increased the automation rate
- The development of procedures to ***meet the robot welding quality requirements.***
- ***Reduce the overall working time*** for manufacturing of one-off or LS1 components, particularly the robot programming-related tasks.
- To improve capabilities to respond to the end user product demand by ***enhancing the product quality and consistency***, and hence reliability.

The AITOOLS1 project consists of six technical workpackages WP1 to 6 and a supporting one WP7. The workpackages, their sequencing and interactions are presented in Figure 2. Due to the variance in partners´ project durations between 24 and 36 months, the WP´s with durations exceeding 24 mths are indicated in lighter orange.

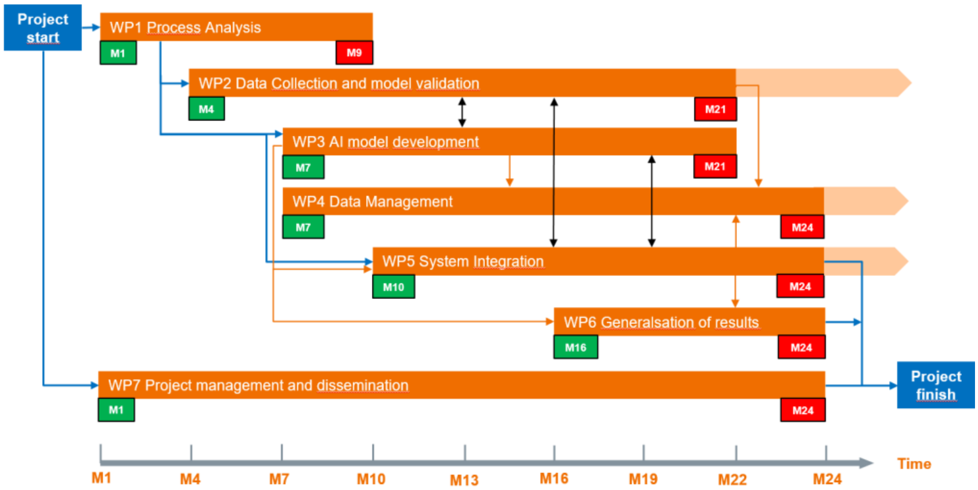


*Figure 2. A PERT presentation of AITOOLS1 workpackages.*

The project workpackages together with their respective tasks, work allocation in person-months (PM) and planned duration (start and end project months) after the project change request approved on 8.10.2024, are presented in Table 1.

*Table 1. AITOOLS1 work packages and their tasks, planned work allocations and durations.*

| Work package/ Task | Title | PM | Duration $M_{start}$ | $M_{end}$ |
|---|---|---|---|---|
| **WP1 Process Analysis** | | **2.5** | 1 | 9 |
| T1.1 | Collection of pre-existing data | | | |
| T1.2 | Definition of Key process indicators and enablers | | | |
| T1.3 | Vision techniques for pre- & post-welding quality assessment | | | |
| T1.4 | Screening of AI techniques | | | |
| T1.5 | Definition of benchmark cases | | | |
| **WP2 Data Collection and validation of models** | | **4** | 4 | 21 |
| T2.1 | Planning of experimental data collection | | | |
| T2.2 | Experimental work to collect data for model training | | | |
| T2.3 | Evaluation of weld quality using developed AI methods | | | |
| **WP3 AI model development** | | **7** | 7 | 21 |
| T3.1 | Parsimonious and explainable AI methods for welding | | | |
| T3.2 | AI for welding process control | | | |
| T3.3 | AI model integration for welding | | | |
| **WP4 Data Management** | | **3** | 7 | 24 |
| T4.1 | Data homogenization for AI | | | |
| T4.2 | Communication and data exchange | | | |
| T4.3 | Data warehousing | | | |
| **WP5 System Integration** | | **3.5** | 10 | 24 |
| T5.1 | WeldEye, DelfoiArc, WeldingCamera and Robot integration | | | |
| T5.2 | Hardware framework to implement AI control algorithms | | | |
| **WP6 Generalization of results** | | **3.5** | 16 | 24 |
| T6.1 | Methodology Applicability | | | |
| T6.2 | Viability demonstration for Laser Welding | | | |
| T6.3 | Viability demonstration for Additive Manufacturing | | | |
| **WP7 Dissemination and project management** | | **3** | 1 | 24 |
| T7.1 | Dissemination | | | |
| T7.2 | Project management | | | |
| ***TOTAL*** | | ***26.5*** | | |

# 2. Welding experiments for data collection

Existing published data on intelligent robot welding systems was searched from various sources to achieve a proper starting point for the AITOOLS1 project data acquisition activities in WP2. In addition to studying various solutions for implementing sensor fusion and for AI-based process control procedures and systems in robot welding, experimental welding data was collected for the basis of project welding experiments to supplement the partners´ own existing practical experience.

## 2.1 Collection of pre-existing data

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into welding technologies has revolutionized traditional welding practices, leading to the development of Intelligent Welding Systems (IWS). With the advent of IWS, the possibility of producing products in small batches has become a reality. Welding technologies have evolved significantly, transforming from manual processes into highly automated and intelligent systems. The core components of an IWS include sensors, data collection systems, signal processing algorithms, and AI-driven decision-making models. When these components work together, they collect data from the welding process, control welding parameters, and ensure high-quality welds.

### 2.1.1 Sensors and Sensing Techniques

Sensors play a crucial role in intelligent welding, providing real-time data on various aspects of the welding process, such as temperature, current, and the weld pool. Wang et al. [1] discussed multi-sensor fusion as a means of enhancing the monitoring and control of the welding process. They also mentioned commercially available data collection systems in welding.

Xu et al. [2] conducted a comprehensive review of the application of different sensing technologies in welding. They illustrated the different stages of welding, the monitoring objectives, and the sensing signals that can be utilized to achieve these objectives in a table. The data collected from sensors often contains noise and irrelevant information. Signal processing techniques filter and refine this data, while feature extraction methods identify the most relevant aspects that correlate with weld quality. These refined data inputs are critical for AI models that predict welding outcomes or dynamically adjust parameters [3].

### 2.1.2 Applications of AI in Welding

AI application in welding extends across several domains, significantly improving process control, quality monitoring, and defect detection. Bose et al. [4] used artificial neural networks (ANN) in bi-directional modeling of robotic wire arc additive manufacturing (WAAM). The study developed hybridized ANN models for forward and backward mappings, using algorithms like gradient descent with momentum and grey wolf optimization. The research aimed to improve the modeling of robotic WAAM processes for better efficiency in manufacturing.

Another study [5] developed an adaptive AI-based gas metal arc welding control system using artificial neural networks (ANN) and machine vision to optimize welding parameters based on seam profile data. The results showed successful control of the welding process for consistent quality and suggest cost-efficient, high-quality welding applications.

Xiong et al. [6] developed a model to predict bead geometry in robotic gas metal arc welding using a neural network and second-order regression analysis. The results showed that the neural network model performs better than the regression model in predicting bead width and height. The authors [7] evaluated the impact of parameters like voltage, welding speed, and wire feeding rate on weld bead geometry. An Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to create a model to predict weld bead geometry based on these input parameters. The results showed a good correlation with experimental data, demonstrating its ability to predict welding geometry accurately.

The article by Chen et al. [8] discusses predicting weld bead geometry in MAG welding using the XGBoost algorithm. The study aims at assessing welding joint quality in real-time for chassis parts in robotic gas-shielded welding. The relationship between welding current, speed, energy input, and bead geometry are investigated. The approach [9] in utilized image processing techniques to classify and accurately locate defects like cracks, non-welded areas, pores, and solid inclusions in welded joints. The method used convolutional neural networks (CNN) and support vector machines for detecting weld defects.

The study [10] focused on using MATLAB to predict the weld bead shape of AA5052 using the cold metal transfer (CMT) welding process. The application uses multiple regression analysis (MRA) and an adaptive neuro-fuzzy inference system (ANFIS) to predict the weld bead profile based on welding current and speed inputs.

The research [11] aimed to show the feasibility of intelligent computer vision systems in defect monitoring for WAAM processes. The YOLOv3 algorithm is explained in detail, showing its improvements for object detection tasks. The study tested different models using YOLOv3 for defect detection in WAAM, showing promising results.

Li et al. [12] developed an algorithm based on a convolutional neural network (CNN) for the gas metal arc welding (GMAW) process to predict welding quality. The algorithm uses molten pool images to train the model. Various welding defects such as burn-through, lack of fusion, slag, and surface pores are accurately detected in real-time, improving welding quality.

In robotic welding, AI is used to optimize welding paths and sequences, particularly in complex assemblies. For instance, [13] used reinforcement learning to determine the most efficient path, minimizing welding time while ensuring quality. Duan et al. [14] developed path planning algorithms based on genetic algorithms for the robotic welding process.

### 2.1.3 Pre-existing data references

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## 2.2 Planning of experimental data collection

The welded Wärtsilä mock-up was used as the basis to extract simpler subcases, ie. typical mock-up welds, whose primary use is to produce true welding data for the AI development work. They were also used as development benchmarks within the project. The mock-up dimensions were approximately 1200 mm × 820 mm × 615 mm (L×W×H). In the mock-up there are two main weld types welded in several positions and containing different types of artificial defect sources, eg. air gaps and tack welds. The original mock-up design is presented in Figure 3: it should be noted that several revisions were made in the design after each mock-up as the robot welding experiments of the total six mock-ups progressed.

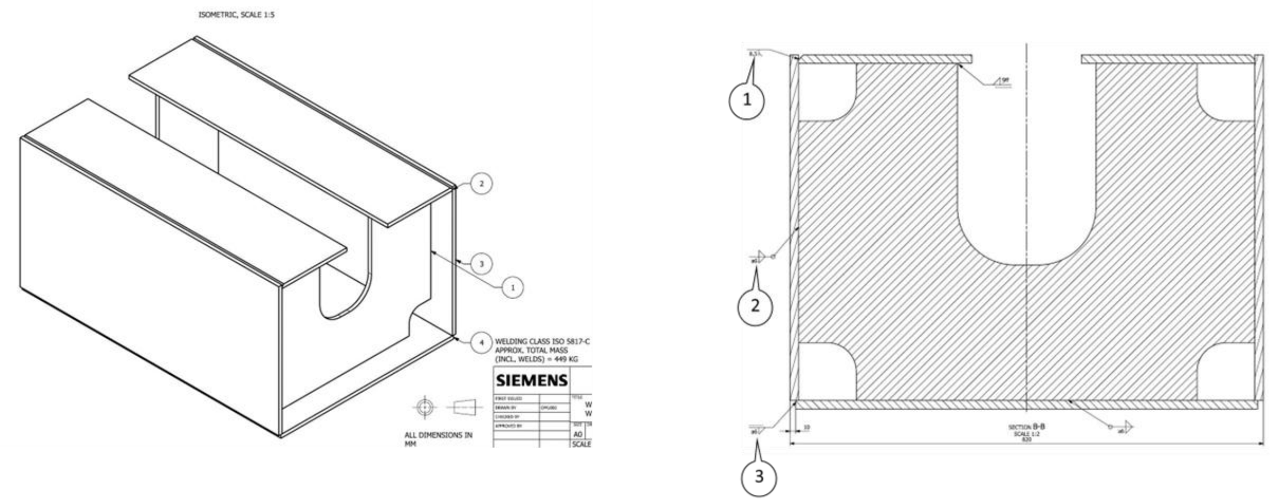


*Figure 3. The original Wärtsilä baseframe mock-up designed for AITOOLS1 project demonstrator experiments.*

Two common weld types were selected for the small-scale specimens, indicated with numbers 0 and 1 in Figure 4. These were produced in 15 mm S355 plates in optimal conditions ("defect free") and with air gaps and tack welds to introduce defects in the welds for AI model teaching purposes. The third weld type no. 2 was rejected because it is essentially similar fillet weld as the 0 one. Furthermore, a provision was made to test welding around the plate end (type 3) but in the end, the procedure for robot welding such around the corner welds was developed using actual mock-ups or sections of those.

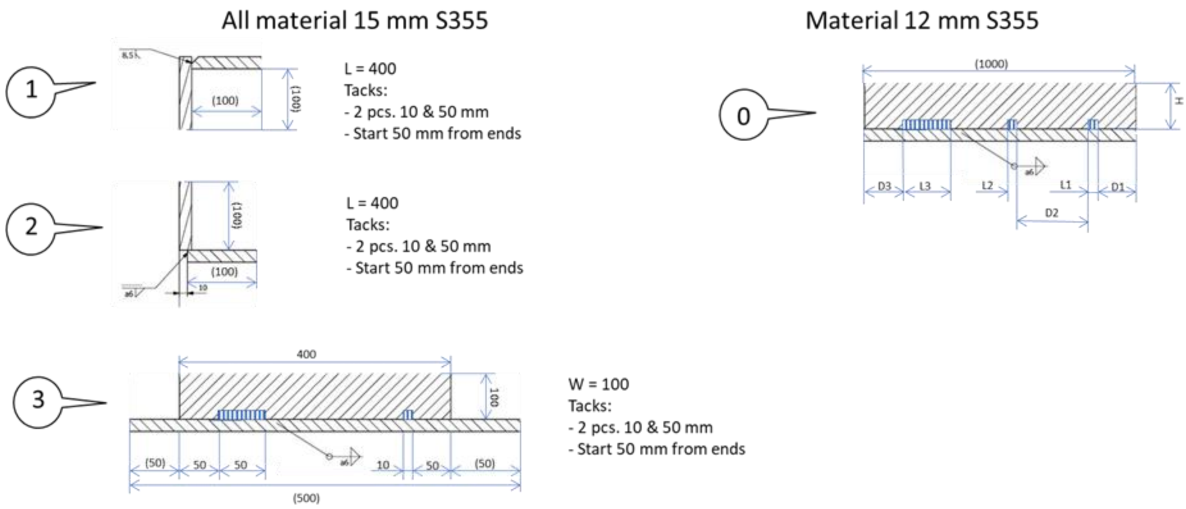


*Figure 4. Small-scale specimen types for welding data collection. Air gaps and tack welds were included as artificial defect sources in some experimental series as well.*

The welding parameters were recorded using Kemppi´s power source built-in WeldEye welding management system, complemented by an in-house built custom AD box, capable of sampling frequencies up to 100 kHz range (WeldEye max. 100 Hz). The welding tests were also monitored using Kemppi´s Cavitar Welding Camera C300. Cavitar also participated in the first tests with their own prototype camera that can use the dark light mode that Kemppi is not capable of recording. All this data was available for AI model development work.

# 3. Hyperspectral Imaging (HSI)

**Hyperspectral imaging** collects and processes information from across the electromagnetic spectrum[1]. The goal of hyperspectral imaging is to obtain the spectrum for each pixel in the image of a scene, with the purpose of finding objects, identifying materials, or detecting processes. There are three general types of spectral imagers. Push broom scanners and the related whisk broom scanners (spatial scanning), which read images over time, band sequential scanners (spectral scanning), which acquire images of an area at different wavelengths, and snapshot hyperspectral imagers, which uses a staring array to generate an image in an instant.

Spectral imaging divides the spectrum into several bands that can be extended beyond the human eye visible spectrum. In hyperspectral imaging, the recorded spectra have fine wavelength resolution and cover a wide range of wavelengths. Hyperspectral imaging measures continuous spectral bands, as opposed to multiband imaging which measures spaced spectral bands.

## 3.1 Hyperspectral Imaging HSI for process monitoring and control

VTT developed and manufactured a new Hyperspectral Imager HSI in Eureka! SMART TANDEM project for monitoring of molten metal processes, such as laser-based Powder Bed Fusion (L-PBF) and Directed Energy Deposition (L-DED), as well as robot arc welding. AITOOLS1 and TANDEM agreed of co-operation between the projects, and the use of HSI technology in welding applications was one the main collaboration topics.

The HSI camera was developed as a monitoring tool for welding and allied processes. It captures melt pool shape and specific emissions from alloy elements and provides relative comparisons between wavelengths to estimate temperatures. The motivation of the new camera development and build was to improve the performance of the previously existing prototype camera used in initial PoC testing, to better suit project needs – the prototype was not designed for dynamic high-temperature processes such as welding. The acquisition of meaningful data was difficult as the dynamic range of the signal recorded is quite high. In addition, the hardware used for data acquisition was developed for static applications and was not well suited for collection of data in highly dynamic processes such as welding and DED. For this purpose, a new imager system was developed that is better suited for the processes studied in both TANDEM and AITOOLS1 projects, Figure 5.

[1] https://en.wikipedia.org/wiki/Hyperspectral_imaging. Quoted on 17.11.2025

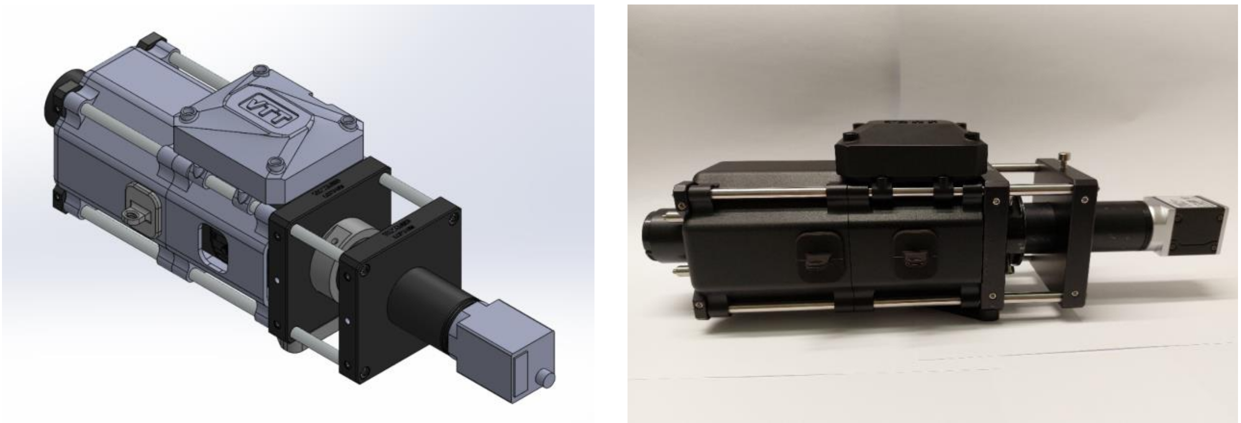

*Figure 5. VTT´s HSI camera newbuild.*

The HSI camera structure is very simple: the main components are a VTT FPI (Fabry–Pérot interferometer or etalon) module in front of a commercial lens and a commercial camera module. An additional tube extension with extra lens elements have been added between the commercial zoom lens and the camera module to increase the magnification on the melt pool area.

The new camera features higher frame rate and better magnification for melt pool analysis. It is controlled by a set of libraries that allow for integration with more general hardware platforms running Windows and Linux operating systems (as the NVIDIA Jetson device used for real-time AI inference in AITOOLS1 project). During AITOOLS1, experimental data of the robot GMAW (Gas-Metal Arc Welding, aka. MIG/MAG) process was collected using the HSI at TAU facilities to start with. After the initial tests, the experiments were continued in Kemppi robot welding laboratory in connection to welding data collection campaign for AI model and procedure development. The key characteristics of the new HSI system are collected in Table 2.

*Table 2. Summary of new HSI technical characteristics*

| | |
|---|---|
| Image size | 2600 × 2160 |
| Interface | USB3 |
| FOV | 3.1° × 4.0° |
| Spectral range | 450 – 750 nm |
| Sensor speed | 64 FPS full frame<br>Up to 700 FPS with a small ROI |
| Size (estimate) | 10 cm × 10 cm × 30 cm ( H x W x L ) |

The HSI technology can be used for at least three different purposes in welding process control:

- Melt pool shape: capturing direct images of the melt pool at different frequencies
- Plasma emissions: capturing possible emissions from the plasma indicating changes in the process
- Temperature profile: comparing the emissions at different wavelengths and comparing them to the black body emission curve

Other applications in DED and AM monitoring in general will be actively searched for in future projects. As part of AITOOLS1 work HSI can be used to complement the Cavitar welding monitoring camera for data collection during the development phase.

## 3.2 HSI experimental work

The VTT hyperspectral camera experiments focused on using the new HSI version to record data from welding processes, specifically the AITOOLS1 fillet welding experiments. The work followed a Design of Experiments (DoE) approach constructed by Jari Kuosmanen at TAU with nine different experimental runs, varying the wire feed rate, travel speed and torch angle at three different levels.

Data was collected using the Kemppi WeldEye, including power source data, and TAU developed DCS (Data Collection System) covering Cavitar welding camera data and HSI data, collected independently from DCS. The initial data collection was done for setpoint fifty-two to match the wavelength collected by the Cavitar camera. One of the main challenges was being able to handle the dynamic range of the images, as high gain/long exposure times would allow analysis of the area surrounding the melt pool area but produce oversaturation of the melt-pool itself; and vice versa, proper exposition of the melt pool area would correspond to an underexposed surrounding area. To address this, a calibration approach was used to find the set of gain and exposure values that would correspond to the best compromise between melt pool and surrounding area analysis.

The goal is to automate the selection of exposure and gain values during data collection. An initial script for this automation is ready but needs further testing. More experiments were carried out to collect data for different setpoints and the DoE matrix was completed in late 2024. After the DoE completion, the HSI work focused on development and realization of an integrated data collection system PoC with and at Kemppi, cf. Chapter 5.

# 4. AI development and application for welding process control

The AI technology work in AITOOLS1 project at VTT focussed on developing self-learning control models and algorithms that could detect any abnormal anomalities during welding that indicate later formation of weld defects. The detection should take place at an early enough stage to allow corrections in process parameters – including robot trajectory and poses – to avoid defect formation. In other words, at certain level the AI control system should be able to predict the defect formation before they become large or otherwise significant enough to affect the macroscopic weld quality level, defined by the appropriate quality requirements in the relevant standards, eg. EN-ISO 5817. Variable Autoencoder is an artificial neural network architecture type that is promising for this purpose. In AITOOLS1 use, the VAE should be able to process several input sources simultaneously, such and welding power source parameters (eg. current, voltage), different types of cameradata (eg. thermal camera, Cavitar Welding Camera, HSI), as well as other types of process monitoring sensors (photodiodes, thermocouples, pyrometers, acoustic emission, etc.). Hence, the autoencoder needs to be a multi-modal one, ie. an MMVAE.

## 4.1 Multi-modal Variable Autoencoder (MMVAE) description

Multimodal Variational Autoencoders (MMVAEs) are advanced machine learning models designed to integrate multiple data types, such as AE and Photodiode signals, into a cohesive framework for process monitoring. Building on the Variational Autoencoder (VAE) concept, MMVAEs learn a probabilistic representation of data, allowing them to capture underlying patterns and generate new samples. Unlike traditional autoencoders, which simply compress and reconstruct data, VAEs impose a structured latent space, typically resembling a standard Gaussian distribution, enabling both reconstruction and generation. MMVAEs extend this by handling multiple modalities simultaneously, creating a shared latent space that reflects the relationships between different types of signals. This shared space is key to understanding how mechanical events (e.g., cracks detected) correlate with optical phenomena (e.g., melt pool fluctuations), enhancing defect detection and process analysis.

The MMVAE operates by processing each modality through a dedicated encoder, which compresses the input into a latent distribution defined by mean value and variance. For example, for AE signals, the encoder analyzes frequency spectra to extract features like spectral peaks, while the Photodiode encoder processes light intensity data, capturing fluctuations indicative of process stability. These distributions are combined using a Product of Experts (PoE) approach, which merges the modalities into a single latent representation that emphasizes their shared information, such as a defect causing both an AE burst and a Photodiode spike. Separate decoders then reconstruct the AE and Photodiode signals from this shared space, aiming to match the originals as closely as possible. The model is trained to balance reconstruction accuracy, measured by Mean Squared Error (MSE), with latent space organization, enforced by KL-divergence, ensuring a structured representation suitable for analysis and generation. By sampling the latent space, MMVAEs can generate synthetic AE and Photodiode signal, mimicking real process conditions in applications like defect simulation, Figure 6.

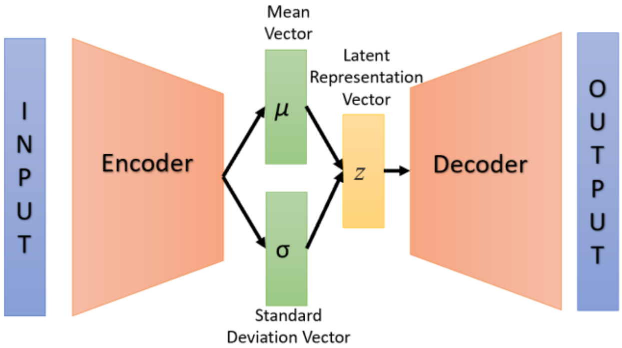


*Figure 6. An example VAE architecture.*

### 4.1.1 Need for MMVAE

Acoustic Emission (AE) and Photodiode signals serve as critical tools for monitoring the complex dynamics of Laser Powder Bed Fusion (PBF-LB) and laser welding, capturing mechanical and optical phenomena that reveal process health and defect formation. AE signals are high-frequency elastic waves generated by rapid energy release within materials, such as during crack formation, powder fusion, or weld solidification.

In PBF-LB, these waves arise from mechanical events like crack propagation or porosity formation within the melt pool, where thermal stresses from rapid heating and cooling trigger localized deformations. In laser welding, AE signals stem from keyhole collapse, spatter, or the solidification of the weld seam. These signals, captured using piezoelectric sensors mounted on the build platform or weld surface, appear as transient, noisy time-series. To extract meaningful patterns, AE signals are typically transformed into the frequency domain using Fast Fourier Transform (FFT), covering ranges like 20–500 kHz, where spectral peaks indicate defects, such as high-frequency bursts associated with cracks. Normal operations produce low-amplitude, consistent signals, while defects produce irregular, high-amplitude patterns, making AE a powerful indicator of mechanical integrity.

Photodiode signals, by contrast, measure the intensity of light emissions, in visible or infrared wavelengths, from the melt pool in PBF-LB or the plasma in laser welding. These signals reflect process stability, capturing variations in laser power, material interactions, or keyhole dynamics. In PBF-LB, stable melt pools yield consistent light patterns, while defects like porosity or overheating cause fluctuations, such as spikes from spatter or dips from insufficient energy. In welding, plasma emissions indicate keyhole stability, with instabilities like collapse producing distinct intensity spikes.

Photodiode sensors generate time-series voltage signals proportional to light intensity, which may be processed into frequency spectra via FFT for detailed analysis or used directly as time-series data.

Synchronization between AE and Photodiode signals is essential, aligning them to the same process events, such as laser scans in PBF-LB or weld passes, using timestamps or metadata. Together, these signals provide complementary insights, with AE revealing mechanical changes and Photodiodes capturing optical anomalies, enabling a holistic view of process dynamics.

An example of an MMVAE developed as a part of this project used the inputs such as images from a welding camera and current and voltage from power source. Both the modalities were combined to train an MMVAE as seen in Figure 7. As a result, the model could reconstruct the video signal from the electric signal only. Analysing the reconstructed video signal, the formation of defects can be detected, ie. once the model has been trained, the defect detection can be done based on power signal only, without the need for a camera.

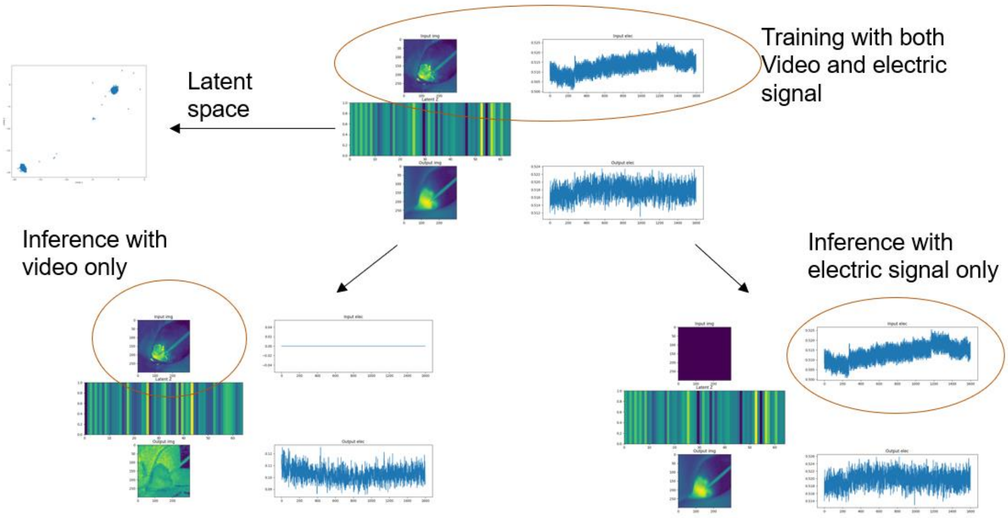


*Figure 7. An MMVAE model developed as a part of AITOOLS1 project.*

### 4.1.2 MMVAE applicability in PBF-LB and laser Welding

Laser Powder Bed Fusion (PBF-LB) and Laser welding are critical manufacturing processes in industries such as aerospace, automotive, and medical device production. PBF-LB builds complex 3D parts by fusing metal powder with a laser, while laser welding joins pre-fabricated parts with high precision. Both processes are prone to defects like porosity, cracks, or spatter, which compromise quality and reliability [1]. Effective monitoring is essential to detect these defects in real time. Acoustic Emission (AE) signals, which capture mechanical stress waves, and Photodiode signals, which measure optical emissions from the melt pool or plasma, provide complementary insights into process dynamics [2]. Multimodal Variational Autoencoders (MMVAEs) enable robust defect detection, process optimization, and data generation. This chapter explores the applicability of MMVAEs to PBF-LB and laser welding, detailing their methodology, benefits, challenges, and future potential [3].

MMVAEs are particularly well-suited for PBF-LB and laser welding due to the complex, multimodal nature of their process data. The integration of AE and Photodiode signals allows MMVAEs to capture a comprehensive view of process dynamics, combining mechanical and optical perspectives.

In PBF-LB, defects like porosity or cracks produce distinct AE patterns, such as high-frequency bursts, while Photodiode signals reveal melt pool instabilities, such as light spikes from spatter. Similarly, in laser welding, AE signals detect keyhole collapse or weld solidification, while Photodiode signals indicate plasma fluctuations. By modeling these signals together, MMVAEs can identify defects that might be missed by single-modality systems, enhancing detection accuracy.

The probabilistic latent space is robust to the noise inherent in AE and Photodiode signals, ensuring reliable performance in industrial environments. Furthermore, the ability to generate synthetic signals supports data augmentation, allowing manufacturers to simulate rare defects or test process variations. The shared latent space also enables analysis of process parameters, like laser power or scan speed, facilitating optimization to reduce defects.

### 4.1.3 Methodology of applying MMVAEs

The application of MMVAEs to PBF-LB and laser welding involves a structured methodology to ensure effective integration of AE and Photodiode signals. Data preprocessing is the first step, transforming raw signals into a suitable format for modeling. AE signals, captured as time-series from piezoelectric sensors, are processed using FFT to produce frequency spectra (e.g., 20–500 kHz), highlighting defect-related patterns like crack-induced bursts. Photodiode signals, recorded as light intensity time-series, may be used directly or transformed into frequency spectra, depending on the application. Both signals are normalized to a common scale (e.g., 0 to 1) to stabilize training, and synchronization is achieved using timestamps or process metadata to align mechanical and optical events, such as laser scans in PBF-LB.

The MMVAE architecture employs convolutional neural networks tailored to each modality. The AE encoder uses convolutional layers to extract spectral features, followed by dense layers to produce a latent distribution (e.g., 64 dimensions). The Photodiode encoder follows a similar structure, adapted to light signal characteristics. The PoE mechanism combines these distributions into a shared latent space, capturing correlations between modalities. Decoders, using convolutional transpose layers, reconstruct the AE and Photodiode signals, with sigmoid activation to match normalized inputs. The model is trained on paired AE and Photodiode data, typically split into training and validation sets (e.g., 80/20), using an optimizer like Adam with a low learning rate (e.g., 0.0001). Training spans several hundred epochs, balancing reconstruction accuracy (MSE) with latent space organization (KL-divergence, weighted by a factor like 1.0).

## 4.2 Applications in PBF-LB and Laser Welding

MMVAEs enable a range of applications critical to improving quality in PBF-LB and laser welding. Anomaly detection is a primary use, where the model identifies defects by analyzing reconstruction errors. If the reconstructed AE or Photodiode signals deviate significantly from the originals, indicated by high MSE, it suggests defects like porosity in PBF-LB or spatter in welding. Additionally, outliers in the latent space, detected using techniques like Isolation Forest, can reveal subtle anomalies not evident in reconstruction errors, leveraging the combined AE and Photodiode data for higher sensitivity.

Process optimization is another key application, as the shared latent space captures relationships between signal patterns and process parameters, such as laser power or scan speed. By analyzing these relationships, manufacturers can adjust settings to minimize defects, for instance, optimizing laser power to reduce lack of fusion in PBF-LB. Data augmentation is facilitated by generating synthetic AE and Photodiode signals, which can simulate rare defects or augment training data for other models. Real-time monitoring is also feasible, with MMVAEs processing streaming data to enable immediate defect detection and process correction during production.

#### 4.2.1 Benefits and challenges

The integration of AE and Photodiode signals through MMVAEs offers significant advantages for PBF-LB and laser welding. By combining mechanical and optical data, MMVAEs achieve enhanced defect detection, capturing anomalies that single-modality systems might miss, such as a crack producing a subtle AE signal but a clear Photodiode spike. The probabilistic latent space is robust to noise, a common issue in AE and Photodiode signals, ensuring reliable performance in industrial settings. The PoE mechanism provides flexibility, allowing the model to operate with only one modality if the other is unavailable, such as during sensor failures. Synthetic signal generation supports data augmentation, enabling simulation of rare defects or testing of process variations, which is particularly valuable for training robust models. The ability to analyze process parameters through the latent space facilitates optimization, reducing defect rates and improving efficiency.

MMVAEs are also scalable, capable of handling large, high-dimensional datasets typical of manufacturing processes. However, challenges must be addressed for successful implementation. Synchronizing AE and Photodiode signals is critical, as misalignment disrupts the model's ability to capture correlations, requiring precise data acquisition systems. The computational cost of training MMVAEs, with dual encoders and decoders, is significant, necessitating powerful hardware like GPUs, particularly for real-time applications. The quality of the latent space is crucial; insufficient regularization can lead to a disorganized representation, reducing effectiveness for anomaly detection or generation. Ensuring both AE and Photodiode data are available can be challenging, as some setups may lack Photodiode sensors. Finally, interpreting the latent space to link specific features to defects requires domain expertise, complicating practical deployment.

#### 4.2.2 Future Directions

The potential of MMVAEs in PBF-LB and laser welding can be expanded through several avenues. Incorporating a validation set and cross-validation techniques will improve model robustness across diverse process conditions. Conditional MMVAEs, which include process parameters like laser power as inputs, could directly model their impact on defects, enhancing optimization. Adding more modalities, such as thermal imaging or vibration data, could provide a more comprehensive view of process dynamics. Transformer-based models, which excel at capturing temporal relationships, may outperform convolutional MMVAEs for time-series signals. Real-time deployment is a key goal, requiring optimized inference pipelines for production environments. Finally, developing defect-specific thresholds, informed by materials science expertise, will improve the interpretability of anomaly detection, linking model outputs to specific issues like porosity or cracks

### 4.3 Conclusion on MMVAE in laser processes

Multimodal Variational Autoencoders represent a transformative approach to monitoring Laser Powder Bed Fusion and laser welding, leveraging the complementary strengths of Acoustic Emission and Photodiode signals. By integrating mechanical and optical data into a shared latent space, MMVAEs enable enhanced defect detection, process optimization, and synthetic data generation. Their robustness to noise, flexibility with missing modalities, and scalability make them well-suited for the complex, high-dimensional datasets of advanced manufacturing. While challenges like data synchronization and computational cost remain, careful preprocessing, model tuning, and hardware optimization can address these issues. Future advancements, including conditional models and additional modalities, promise to further elevate MMVAEs' impact, ensuring higher quality and reliability in PBF-LB and laser welding applications.

# 5. Integrated data collection and analysis system Proof of Concept

VTT and Kemppi agreed together with Cavitar on preparing a Proof-of-Concept (PoC) of an integrated data collection system. The system was specified as capable of including Kemppi WeldEye and custom Data Acqusition system of power source measurements (AD box), VTT HSI camera, as well as Cavitar Welding Camera. All this is carried out while being able to run MMVAE defect detection AI module in real time. This system was built on Nvidia Jetson platform. This platform was chosen as it has powerful hardware capable of running complex AI inference models in real time, and was already used by Cavitar as a platform for their camera development of analysis and related data collection system. Sharing the same platform should decrease the compatibility challenges between VTT, Cavitar and Kemppi systems. The goal is to prepare the PoC technically in welding experiments carried out in Kemppi lab and once operational, arrange a demonstration at Kemppi facilities for validation and the basis for ideation of future development plans.

The work on real-time defect prediction using multimodal data (camera and power source signals) directly supports the AITOOLS1 goal of integrating advanced AI-based monitoring and quality assessment into welding processes. The PoC demonstrates practical application of the project outcome, aiming at enabling automated, real-time detection of welding defects, which aligns with the project's objectives to improve process reliability and facilitate future industrial adoption. It leverages hardware and software integration, data synchronization, and AI modelling, reflecting the project's emphasis on combining technical innovation with actionable solutions for industry partners. The MMVAE model “recognizes” - or actually, represents - the correlation between existence of a tack weld and weld current and voltage, providing a means to indicate where something changes in welding process.

The aim of the system development is to achieve real-time visualization of defect detection, with the system indicating weld quality on-screen as welding progresses. There is potential in the data collection and analysis system for further refinement and deployment of the real-time defect prediction system as hardware and synchronisation challenges are resolved.

## 5.1 Kemppi Proof of Concept (PoC ) development

Some challenges were met in the execution of the development work on the PoC for an integrated data collection and analysis system for robot welding. In initial experimental development session at Kemppi, video synchronization (eg. more than 10 000 frames) to electrical measurements (voltage and current), produced challenges to be addressed as there were no available signals which would allow for proper data alignment between the different signals obtained and this is a crucial element of being able to establish a correlation between the signals and the process quality using the Multi-Modal Variational Autoencoder model (MMVAE). In order to train the model, it was required to manually process the different signals to align the data based on the live torch data tagged from the images. But due to the different sampling frequency between different sources, especially between welding camera picture frames and power source time series, this will lead to unreliable results. Moreover, this is not possible to implement properly in real time.

In order to solve this problem, PoC architecture also used a hardware generated signal to trigger the different sensors and align the data with great accuracy in real time. The architecture of the complete system is presented in Figure 8.

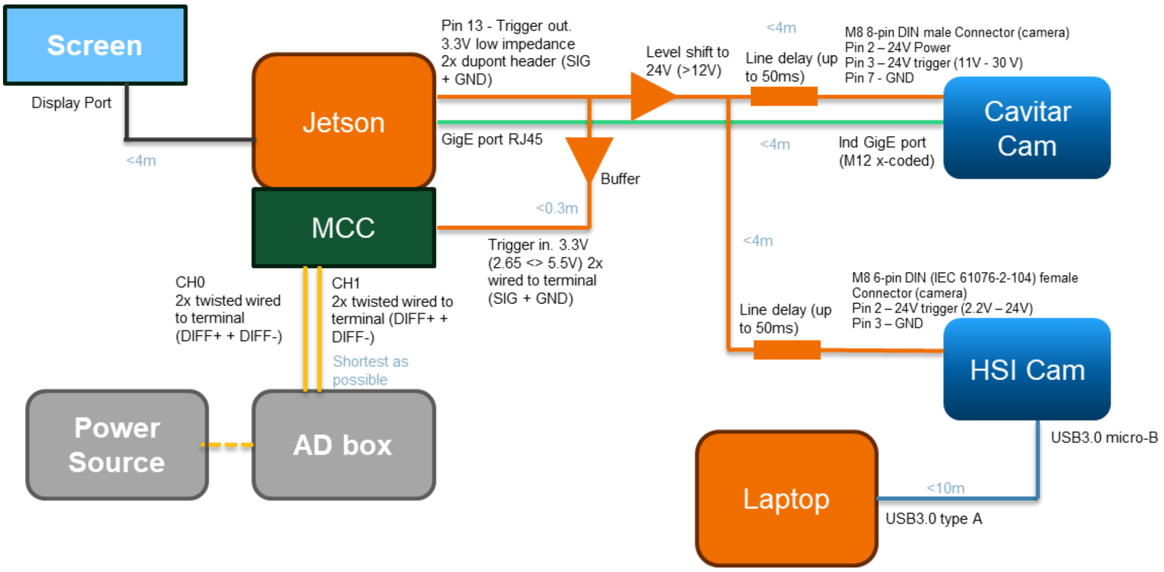


*Figure 8. The architecture of the VTT integrated data collection system.*

The MMVAE model is unsupervised in nature: it can detect whether a deviation is happening but initially, it is not capable of providing an explanation on the source of the deviation. The next step will be to identify the correlation between causality and deviation detection provided by the MMVAE model, eg. tack weld or a defect of which kind, and eventually, characterize the disturbance (dimensions, geometry, etc.). However, it takes extensive amount of work to reach the characterization stage, and even more to be able to do it repeatedly and with sufficient confidence for practical purposes.

The mechanical assembly of the prototype setup and software development for control was finalized. Initial tests showed some errors in the response of the sensor but this was an easy fix, however, calibration of the alignment needs still to be finalized. In order to ensure RT analysis of the model (at over 70 fps of welding camera data acquisition and 80 kS/S of power source data acquisition) initially only 2 sensors were used. The next step is the integration of HSI in this AITOOLS1 data acquisition framework, followed by planning and executing the physical integration of the hyperspectral imager with the existing welding system.

The experimental schedule was delayed drastically due to the unexpected passing away of the Kemppi responsible person. Therefore, the PoC final testing and demonstration sessions will need to be realised with minimum VTT contribution after the closure of the AITOOLS1 project. However, the plan is to still conduct two more sessions: one for collecting synchronized data, including welded plates with intentional defects, to retrain the prediction model, provided that the sychronisation test is successful. Finally, a live demo will be prepared for Kemppi management where the system will display real-time defect predictions during welding.

## 5.2 Future potential

The PoC work opens possibilities for real-time, automated defect detection in welding, with potential expansion towards more nuanced defect classification and integration into industrial quality management systems. The MMVAE defect detection approach suggests future applications in broader manufacturing contexts, enabling advanced process control and defect detection through multimodal data fusion and AI, with ongoing improvements in sensor integration and model optimization. Both these advancements indicate a path toward smarter, AI-driven manufacturing processes, with continued collaboration and development needed to address technical challenges and realize full industrial impact.

At VTT, one of the key future application areas will certainly be the L-DED process that VTT will introduce in 2026. The DED methods possess challenges in process thermal control and utilising the MMVAE concept in combination with melt pool monitoring with HSI, adaptive process control and real-time quality assurance (QA) is aimed at in the future work.

# 6. International collaboration and dissemination

## 6.1 International collaboration

The AITOOLS1 project plan included several researcher visits, the preparation of which was initiated immediately after the project commenced. During the MSEC 2023 Manufacturing Science and Engineering Conference, Joni Reijonen, partially funded by AITOOLS1, visited Professor Hui Yang at Penn State University to plan researcher exchange. However, scheduling conflicts at Penn State prevented the visit from taking place.

VTT doctoral researcher Aditya Gopaluni prepared for a visit to Professor Milan Brandt's group at RMIT University in Australia. Ultimately, the timing of the visit was deemed too late to benefit the project, and the plan was discontinued.

In autumn 2024, Tommi Aihkisalo spent one month at Simon Fraser University (Vancouver, Canada) in Professor Gary Wang's group. The focus of the visit was further development of the MMVAE methodology and its application to adaptive control in LW-DED and arc welding. During the visit, a joint publication on the topic was initiated. The visit was conducted in collaboration with the TANDEM project, which funded the travel expenses, and the working time was allocated to the AITOOLS1 project.

During a TANDEM project meeting trip to Canada, Mika Sirén also visited the Canadian Center for Welding and Joining at the University of Alberta to explore future collaboration opportunities in the field of robotic welding. This collaboration would also be relevant to AITOOLS1 welding topics and is largely based on contacts established through IIW meetings with Professor Patricio Mendez, as well as a previous Fulbright visit to VTT by Professor Leijun Li in the late 2000s.

Outside the AITOOLS1 project, Mika Sirén networked and collaborated internationally by participating in the 76$^{th}$ International Institute of Welding (IIW) Annual Assembly & Conference in Singapore in summer 2023, the largest annual gathering of welding experts. For example, the connection to the University of Alberta partly originates from these IIW annual meetings. The trip was organized jointly with the TANDEM project. Mika also attended the 78$^{th}$ IIW Annual Assembly in Genoa, Italy, in June 2025, in collaboration with VTT's SUGAR project. The IIW annual assemblies and related conferences are the most important global networking events in welding research across its various subfields.

Mika Sirén also visited the Schweissen & Schneiden 2023 trade fair in Essen, Germany. Attending this quadrennial event alongside a project meeting provided opportunities to learn about the latest industry developments and equipment innovations, as well as to meet potential future collaborators.

Following a TANDEM project steering group meeting in Trollhättan, Sweden, the VTT project team also visited the Elmia Svets trade fair in Jönköping, where robotic welding related to the AITOOLS1 project was prominently featured. This combined trade fair included dedicated halls for welding, machine tools, 3D printing, and production automation.

Additionally, Mika Sirén attended two trade fairs - Smart Factory + Automation World at COEX, Seoul, and SIMTOS Seoul International Manufacturing Technology Show at KINTEX, Goyang - during a SUGAR project meeting trip. Although the trip was funded by the SUGAR project, the themes and contents of the fairs were highly relevant to AITOOLS1, and part of the working time was allocated accordingly.

Project meeting trips and the associated visits have strengthened existing relationships and created new ones, providing a natural foundation for future joint projects and the implementation of related researcher exchanges and visits.

## 6.2 Dissemination

The launch of the AITOOLS1 project was announced as a two-page article was published about in the first 2023 issue (1/23) of Hitsaustekniikka, the bi-monthly magazine of the Welding Society of Finland [1]. Additionally, Tekniikka & Talous weekly magazine published a piece of news about the start of the AITOOLS1 project in January 2023 [2].

Another article on the interim results of the AITOOLS1 project was published in Hitsaustekniikka magazine as well, issue 1/25 [3]. Both articles from Hitsaustekniikka magazine were also actively shared on social media, primarily on LinkedIn.

Together with the TANDEM project, a joint publication was submitted to the IEEE International Conference on Web Services (ICWS 2025), Helsinki, 7–12 July 2025 [4]. This paper by Tommi Aihkisalo and Petri Tikka was based on Aihkisalo's research visit to Simon Fraser University (Vancouver, BC, Canada), focusing on the development of the MMVAE model and its application to arc welding. This first paper described the data underlying the development of the MMVAE model, which was published separately on an online platform. However, the conference paper manuscript was not accepted, as it was deemed outside the scope of the conference. Publication of the paper in other relevant journals is still being considered after the projects conclude. Instead, the data discussed in the paper was published separately [5].

## 6.3 Dissemination references

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## 7. Summary

The work by VTT in AITOOLS1 was carried out together with various project partners. The collaboration allowed utilizing the individual partners´ results to the fullest to support VTT research activities. The ke VTT project outcomes can be summarised as follows:

1. The welded Wärtsilä mock-up structure designed for the AITOOLS1 project was used as the basis to extract simpler subcases, ie. typical mock-up welds, whose primary use is to produce true welding data for the AI development work. In the mock-up there were two main weld types welded in several positions and containing different types of artificial defect sources, eg. air gaps and tack welds. Most of the welding experiments were carried out and recorded in Kemppi robot welding laboratory.

2. VTT developed and manufactured a new Hyperspectral Imager HSI in AITOOLS1 collaboration project Eureka! SMART TANDEM for monitoring of molten metal processes, such as Additive Manufacturing (AM). The use of HSI technology in welding applications was one of the main collaboration topics. The HSI camera captures melt pool shape, collects specific emissions from alloy elements, and provides relative comparisons between wavelengths to estimate temperatures. HSI was to complement the Cavitar welding monitoring camera for data collection during the AI model development development phase.

3. The AI technology work in AITOOLS1 project at VTT focussed on developing self-learning control models and algorithms that could detect any abnormal anomalities during welding that indicate later formation of weld defects. The detection should take place at an early enough stage to allow corrections in process parameters – including robot trajectory and poses – to avoid defect formation.

   A Multimodal Variational Autoencoders (MMVAE) represent a transformative approach to monitoring Laser fusion processes, such as welding. The MMVAE developed in AITOOLS1 used the images from a welding camera and current and voltage from power source as inputs. Both the modalities were combined to train an MMVAE and as a result, the model could reconstruct the video signal from the electric signal only. Analysing the reconstructed video signal, the formation of defects can be detected, ie. once the model has been trained, the defect detection can be done based on power signal only, without the need for a camera.

4. VTT, Kemppi and Cavitar agreed together on preparing a Proof-of-Concept (PoC) of an integrated data collection system. The system was specified as capable of including Kemppi WeldEye and custom Data Acqusition system of power source measurements (AD box), VTT HSI camera, as well as Cavitar Welding Camera. All this is carried out while being able to run MMVAE defect detection AI module in real time. The system was built on Nvidia Jetson platform due to its capability of running complex AI inference models in real time. The goal was to prepare the PoC technically in welding experiments carried out in Kemppi lab and once operational, arrange a demonstration at Kemppi facilities for validation and demonstration and the basis for ideation of future development plans.

## Concluding remarks

The PoC work opens possibilities for real-time, automated defect detection in welding, with potential expansion towards more nuanced defect classification and integration into industrial quality management systems. The MMVAE defect detection approach suggests future applications in broader manufacturing contexts, enabling advanced process control and defect detection through multimodal data fusion including HSI and AI, with ongoing improvements in sensor integration and model optimization. Both these advancements indicate a path toward smarter, AI-driven manufacturing processes, with continued collaboration and development needed to address technical challenges and realize full industrial impact. At VTT, one of the key future application areas will certainly be the L-DED process that VTT will introduce in 2026. The DED methods possess challenges in process thermal control and utilising the MMVAE concept in combination with melt pool monitoring with HSI, adaptive process control and real-time quality assurance (QA) is aimed at in the future work.

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