Cognitive plants through proactive self-learning hybrid digital twins

COGNITWIN

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Deliverable Report

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1   Executive Summary

This D5.4 report is a report on the technologies and methods that are being developed in the "COGNITWIN Hybrid and Cognitive Twin Toolbox" and which were applied in the developments for the COGNITWIN industrial pilots. The information provided in the report will further be useful for aligning the concepts and available tools among the COGNITWIN partners but should also give external readers ideas about new Industry 4.0 possibilities.

The COGNITWIN projects aims toward supporting the digitalization of the European heavy industries. A main ambition of the COGNITWIN project is to develop cognitive digital twins that can support a significant improvement in industrial operation. To do so, COGNITWIN is working with combining data, physics-based models, machine learning (ML), and Artificial Intelligence (AI) in the best possible manner to solve the industrial challenges. Cognition is introduced into the models through self-learning and AI. In COGNITWIN WP5, where this report belongs, the aim is to identify which ML/AI methods are suited for such problems and extend and/or develop new algorithms to further improve performances of the control systems. By developing a Cognitive Twin Toolbox, comprising methods to analyse data, exploit the information from physics-based models, combine information from data and numerical models, and demonstrating applications to process control, this can be applied more generally to support many different process industries. A Cognitive Twin Toolbox was built out from the needs of 6 different industrial pilots, all with their specific and different challenges.

This deliverable is the final report on technologies and methods that were developed for the Hybrid AI/Analytics and Cognitive Toolbox. It includes the refinements and final results on hybrid twin development and the results of the development of cognitive twins. Most of the toolbox elements have been applied to the pilots, while other elements have a great potential for future application.

This deliverable refines and extends the D5.1, D5.2 and D5.3 deliverables by providing more technical details especially on new features. In particular it extends the description of already provided functionalities with new one developed during the last reporting period.

The D5.4 deliverable is accompanied with demonstrators that show how a subset of components play together. The demonstrators that show reusable patterns which can be replicated and adapted also in future industrial process industry settings.

The new contributions in the D5.4 update from D5.3 in particular includes the following;

- SINTEF – The PPBM methodology, and model developments for ladle lining erosion, has been completed, resulting in two papers and one submission to github.com. SINDIT[1] was extended to meet the cognition needs for the Sidenor pilot.
- Sidenor- The PPBM based model was integrated into StreamPipes, reading "near online" data pushed by Sidenor, using secure ftp. The data and model results were made available through a FA^{3}ST service, and also explored and made available to users via a knowledge graph based solution for cognition (SINDIT).
- Cybernetica - The model component for the Hydro GTC pilot has been extended to provide nonlinear model predictive control of the plant, and closed loop operation has been tested. Cybernetica Viewer has been extended with a REST interface such that it can present a user interface in a web viewer. Both process data and calculated data from Cybernetica CENIT can be displayed. Two-way communication is also possible. This has been applied in the Hydro GTC

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[1] https://cognitwin.github.io/toolbox/tools/dt-graph.html

pilot. The Cybernetica CENIT API for error detection and handling routines has been further refined.

- Nst – Focus on the Cognitive twins. A new method for cognition-driven unusuality detection is proposed and validated. It uses the analogy from the human cognition that only variation in the (external) signals will be registered and processed. In our case, it means that only the changes in the input data will be detected and trigger the cognition process for understanding these changes. We performed a validation based on the ladle degradation data from Sidenor pilot

- Fraunhofer - The FA^{3}ST service (Fraunhofer Advanced Asset Administration Shell (AAS) Tools for Digital Twins) was extended to support time series data. To do this, logic had to be added to a TimeSeries submodel that implements the required operations e.g. accessing data in a unified way. The main challenge was to implement the extension in a generic way agnostic to the type of underlying database so that it can potentially be used with any kind of database in the future.

- Tekno - New tools were added to the Teknopar Industrial Automation (TIA) Platform: TIA MONITORING, TIA STATISTICS, TIA METRICS, TIA OEE, and TIA ASP. TIA MONITORING enables predictive maintenance using condition monitoring. TIA STATISTICS is used to perform statistical analysis on the data. TIA METRICS enables the users to calculate defined criteria for any process, production unit or product. TIA ASP is an Apache StreamPipe-based tool that allows users to select and run machine learning models.

The overall structure of the toolbox has grown out from the pilot needs. In COGNITWIN WP4 infrastructure for sensors, data collection and storage, as well as orchestration of models is being developed. The needs from WP5 are a general driver for the work in WP4. The complete COGNITWIN Toolbox (https://cognitwin.github.io/toolbox/) allows for orchestration of tools and methods, from sensors all the way to operating digital twins. The way this is done is varying between the pilots and is explained in more details in the specific pilot reports.

A separate report on the "Platform, Sensor, and Data Interoperability Toolbox" (D4.4) is issued together with this report, giving a more complete overview on the COGNITWIN challenges and Toolbox.

As technical details are best presented on a per-component-basis, and our presentation on the individual tasks focusses on more abstract insights. The bulk of technical details and development status of the individual toolbox components is additionally reported as Appendix 1 and referred to in this document.

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Acronyms

AI	Artificial Intelligence
CEP	Complex Event Processing
CFB	Circulating Fluidized Bed
CFD	Computational Fluid Dynamics
CSTR	Continuous Stirred-Tank Reactor
DCS	Distributed Control System
GTC	Gas Treatment Center
ICPV	Industrial Control Panel and Visualization
JSON	JavaScript Object Notation
LSTM	Long Short-Term Memory
MEWMA	Multivariate Exponentially Weighted Moving Average
ML	Machine Learning
MPC	Model-Predictive Control
MQTT	Message Queuing Telemetry Transport
OPC-UA	OPC Unified Architecture
PCA	Principal component analysis
PLC	Programmable logic controller
PPBM	Pragmatism in Physics-Based Modelling
SWP	Spiral Weld Pipes
TMat PdM	MATLAB Predictive Maintenance for Electro Mechanical Components
TIA	TEKNOPAR Industrial Automation
UKF	Unscented Kalman filter
WER	Word Error Rate

Other acronyms are found at https://www.allacronyms.com/data/abbreviations.

2   Introduction

2.1   Scope and purpose

A purpose of the COGNITWIN Initial Hybrid AI and Cognitive Twin Toolbox is to provide the technical foundation for the realization of hybrid AI and cognitive twins in the process industry. This technical foundation takes the form of software components, methods, and processes. An important consideration is that while hybrid AI and cognitive twin concepts are not entirely unique to the process industry, certain aspects are specific to the industry. The toolbox developed in this work-package therefore comprises:

1. custom software components that are developed, extended, or adapted for the specific needs of the Use-Cases in the process industry,
2. existing components that are technically integrated to facilitate interoperability along workflows specific to the Use-Cases, and
3. workflows that that are realized entirely by existing software, but which is combined and used in patterns and ways specific to the Use-Cases in the process industry.

The toolbox started out as a collection of individiual, mostly unrelated, software tools and processes which were thought to be potentially applicable to the Use-Cases in the process industry. These unrelated components have been adapted, integrated, and combined in pipelines to support the specific needs of the Use-Cases. At the end of the process, the toolbox provides a technical foundation capable to support the requirements of the Use-Cases in known and tested usage patterns, with specifically adapted software components that are interoperable where required. The D5.4 deliverable shows the final results towards that goal and takes the form of an updated version of the previous WP5 deliverables.

The deliverable D5.4 is a result of all WP5 tasks. It defines the final specification of the COGNITWIN Hybrid AI and Cognitive Twin toolbox. It is accompanied with demonstrators that show how a subset of components play together. The demonstrators can be seen in the COGNITWIN YouTube video channel https://www.youtube.com/@cognitwin9786/videos and are also linked to from the digital twin pipelines and the various toolbox components in the COGNITWIN Toolbox portal, https://cognitwin.github.io/toolbox/.

The deliverable serves as a common project reference across all the technical work packages (WP1-WP5).

2.2   Structure of the deliverable

This deliverable is structured as follows. We will start by giving a **high-level overview** of the toolbox in its entirety, specifically design decisions and the final conceptual architecture.

The second part will contain status **descriptions on a task-level**, focusing on progress, challenges, and deviations from original planning. These descriptions will still be kept relatively short, as the bulk of the technical documentation is provided on a component level.

The third and most detailed part of this deliverable consists of detailed descriptions of the individual toolbox components – including detailed descriptions of progress made during the project so far – examples of how to use them, and their relation to the Use-Cases. We also focus on how the individual toolbox components are integrated in pipelines to meet the needs of the Use-Cases.

For the sake of completeness, this deliverable D5.4 takes the form of an updated version of deliverable D5.3, and thus contains not only updates on the tasks performed in the period M31-M42, but also the underlying work performed prior to that.

The deliverable includes a list of the various specifications of the COGNITWIN components in Annex – COGNITWIN Toolbox Components.

3   High-level overview
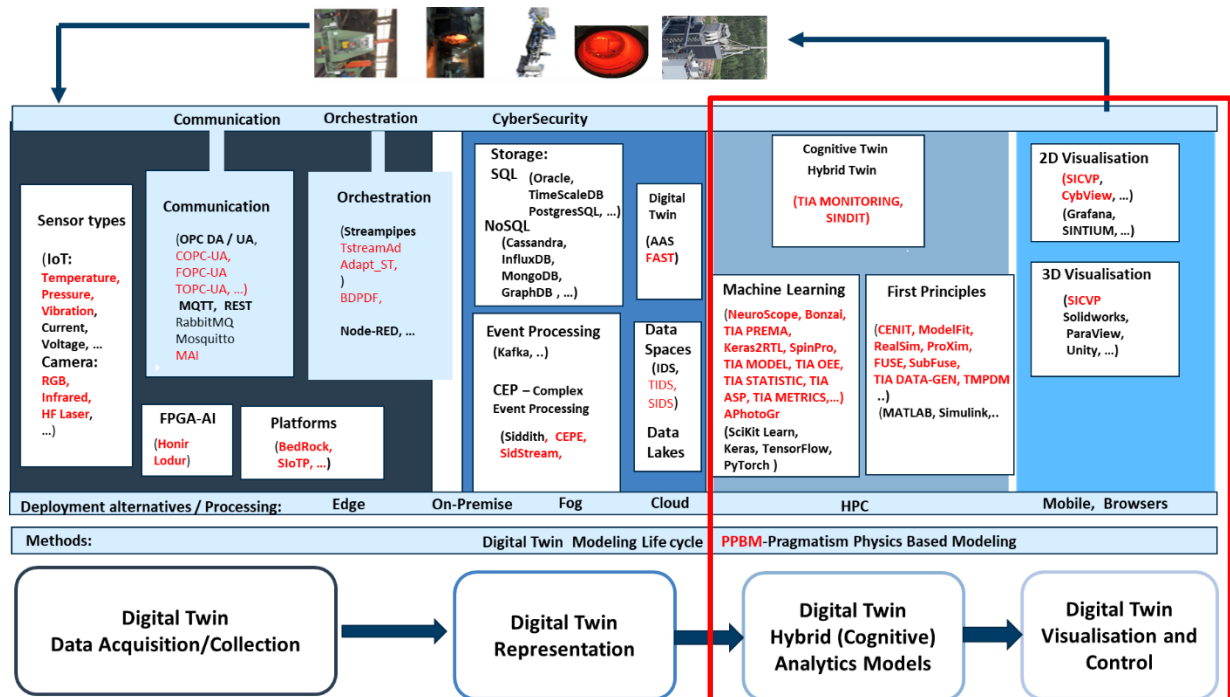
Figure 1: High-level overview of the COGNITWIN Toolbox

The goal of WP5 is to provide methods and tools for Hybrid AI and Cognitive Twins. Figure 1 shows the structure of the COGNITWIN Toolbox as reflected in the COGNITWIN Toolbox Portal, available at https://cognitwin.github.io/toolbox/. This report focuses on the areas in the red box on Digital Twin Analytics Models and Visualisation, while the report D4.4 introduces the areas in the Toolbox and the areas of to the left in the figure on Digital Twin Data Acquisition and Representation.

In the context of the COGNITWIN project, the Hybrid AI and Cognitive Twins should not be developed from scratch, but rather the already existing components/systems should be considered. Additionally, the new services to model the behaviour of a Hybrid AI or Cognitive Twins have already been developed by different partners. However, the partners use different technologies, develop components in several programming languages, use different protocols, etc. In previous WP5 deliverables (D5.1, D5.2 and D5.3) we have already identified a list of the components which will be reused or extended.

In this final report, we are reporting progress on the extension and development of components and reflecting on additional requirements that emerge from applying the toolbox components to the pilots.

4   Summary of toolbox elements and their relations to the pilots

The COGNITWIN toolbox is developed to support the pilots and enable similar projects in the future, but where the developments be done faster due to exploitation of toolbox elements. The requirements from the pilots, presented in Chapter 5, has been driving the contents of the toolbox. In addition, we have tools that may be significant contributors to future projects in this domain.

In WP4 we have supplied infrastructure to provide sensors, data and methods to orchestrate this together with models. In the companying COGNITWIN D4.4 report[2] information about these tools are given, such as MAI, Cybernetica OPC UA, FUSE OPC UA, Tstream, BD Pipelines DF, Honir, Lodur, Bedrock, Steel4 which IoTP has been renamed as TIA PLATFORM, where TIA IOT toolbox contains TIA SENSOR, TIA PLC and TIA CONTROL tools, and TIA DATA toolbox of TIA PLATFORM includes TIA STORAGE and TIA STREAM tools, FAST, DT Graph, StreamPipes + Siddhi, CEP Editor, IDS Connectors, Trusted Factory Connector , COGNITWIN Toolbox Portal, Steel4 ICP, Cybernetica Viewer, Sensor library, and Sensor data quality framework. These elements are used as infrastructure for the model developments.

Toolbox elements (i.e. tools) serving for the purposes of WP5 are: in TIA APPS toolbox: TIA MONITORING, TIA METRICS, TIA STATISTICS, TIA OEE, TIA PREMA, TIA MODEL, TIA ASP, and TIA DATA-GEN, in TIA UX toolbox: TIA DASHBOARD.

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[2] https://www.sintef.no/projectweb/cognitwin/public-reports/

Table 1: The table show the toolbox elements and their uses or potential uses across the industrial pilots

Pilot type	Pilot	Task	DFKI: Generation of photorealistic data	DFKI: Neuroscope	Nissatech: D2Lab-C	Nissatech: StreamPipes Siddhi-Processor	SINTEFs BEDROCK	TEKNOPAR: TIA DATA (TIA STREAM, TIA STORAGE, TIA CONTROL)	TEKNOPAR: TIA APPS (TIA MODEL, TIA PREMA)	TEKNOPAR: TIA UX (TIA DASHBOARD, TIA UX)	TEKNOPAR: TIA APPS (TIA ASP)	TEKNOPAR: TIA APPS (TIA DATA-GEN)	SINTEF Open Framework and Tools (SOFT)	Machine learning for hybrid models (SINTEF)	Pragmatic framework for development of hybrid models (SINTEF)	Cybernetica CENIT	Cybernetica Cognitive CENIT	Cybernetica ModelFit	Cybernetica RealSim	Cybernetica Viewer	Cybernetica ProXim	Cybernetica OPC UA Server	Bonzai (Scortex)	Como (Scortex)	Keras / tensorflow (Scoretex)	Finite Markov Chains Matlab toolbox (MCPC) (UOULU)	SpinPro (Fraunhofer)	Weather API interface MAPI (SINTEF)	Correlation Analysis Toolbox (SINTEF)	FUSE Fuel state estimation (UOULU)	SubFUSE Subspace identification and state estimation (UOULU)	FouMon Fouling monitoring (UOULU)	FouCon Fouling management and control (UOULU)	SINDIT (SINTEF)
Non-ferrous	**Hydro**	Plant Digital Twins with ML/AI					(x)									x		(x)	(x)	(x)								x						
		Multi-variate Sensor analytics, Deep Learning																										x	x					
		Deep Learning Performance																										x	x					
		Hybrid Digital Twins					(x)						(x)	(x)	(x)	x					x							x		(x)		(x)		
		Cognitive Digital Twins			(x)	(x)										x	x										(x)							(x)
	Elkem	Plant Digital Twins with ML/AI					(x)									x		(x)	x	(x)			(x)	(x)	(x)									
		Multi-variate Sensor analytics, Deep Learning																					(x)	(x)	(x)									
		Deep Learning Performance																					(x)	(x)	(x)									
		Hybrid Digital Twins					(x)						(x)	(x)	(x)	x					x									(x)		(x)		
		Cognitive Digital Twins			(x)	(x)										x	x										(x)							(x)
Steel	**Saarstahl**	Plant Digital Twins with ML/AI	x	x																			x	x	x									
		Multi-variate Sensor analytics, Deep Learning	x	x																			x	x	x									
		Deep Learning Performance	x	x																			x	x	x									
		Hybrid Digital Twins	x	x																														
		Cognitive Digital Twins	x	x																							(x)							
	Sidenor	Plant Digital Twins with ML/AI					(x)			(x)						(x)	(x)	(x)	(x)															
		Multi-variate Sensor analytics, Deep Learning																																
		Deep Learning Performance																																
		Hybrid Digital Twins					(x)						(x)	(x)	x	(x)					x									(x)		(x)		
		Cognitive Digital Twins			x	x	(x)									(x)	(x)										(x)							x
	Noksel	Plant Digital Twins with ML/AI					(x)	x		(x)	x		(x)	(x)																				
		Multi-variate Sensor analytics, Deep Learning						x		x	x		(x)	x																				
		Deep Learning Performance																																
		Hybrid Digital Twins					(x)	x		x	x		(x)	(x)																(x)		(x)		
		Cognitive Digital Twins			(x)	(x)	(x)	x		x	x		(x)	(x)													(x)							(x)
Engineering	**Sumitomo**	Plant Digital Twins with ML/AI														(x)	(x)	(x)	(x)				(x)	(x)	(x)					x		x	(x)	
		Multi-variate Sensor analytics, Deep Learning																					(x)	(x)	(x)									
		Deep Learning Performance																					(x)	(x)	(x)									
		Hybrid Digital Twins					(x)	(x)		(x)			(x)	(x)	(x)	(x)					(x)				(x)				(x)	x	x			
		Cognitive Digital Twins			(x)	(x)	(x)	(x)		(x)						(x)	(x)										(x)				(x)	x	(x)	

In Table 1 we see an overview of the toolbox elements and their relations to the pilots. Toolbox elements which are directly used in a pilot is marked with an "x", while identified toolbox elements that were not planned used, but had the potential to be used, are marked with "(x)".

From the table we can get a good overview over the tools used in each of the pilots. As the resources for each pilot were limited, it has not possible to involve all research partners in each and all of the pilots. Therefore, each pilot team, being a subset of the technology partners, have worked with the tools that they know best, and which were the most efficient to support a given pilot. The tools with only "(x)" was not a preferred tool now, due to partner preferences, but may be important contributions in similar future projects.

The tools provided by Scortex has unfortunately not be continued due to bankruptcy. As a result, the tools could not be used in the final deliverable to the Saarstahl pilot.

Looking across the pilots we can see that we have tools related to image processing and modelling (largely the Saarstahl pilot), tools related to machinery optimization and maintenance (largely the NOKSEL pilot) and tools related to process control and optimization (largely the Hydro, Elkem, Sidenor and Sumitomo SHI FW pilots). Some of the tools have the potential to be used across this rough classification of the pilots.

4.1   Relations to WP6 "Business impact"

The tools provided by DKFI, Fraunhofer, Nissatech, Oulu and SINTEF are considered as open. This indicates that as much as possible of the tools and methods will be made publicly available and published. However, it is expected that the work in the COGNITWIN project has supplied these partners with a competitive edge that may be exploited in future similar projects for the process industries.

The developments of Cybernetica have resulted in proprietary tools which will be protected but made available to the industry at any time. The developments of these tools in COGNITWIN will be a significant contribution to resolve similar pilot challenges in the future.

The tools that have been developed and enhanced by TEKNOPAR are proprietary tools that will be made available to the industry upon request and for the specific requirements of the customers/users. Al the tools will be promoted through the COGNITWIN Digital Twin Toolbox.

4.2   Relations to WP7: Communication, Dissemination, Standardisation

The work to support the pilots has generated multiple publications, where we have explained the models and methods that have been developed. Such publications are not only important to market COGNITWIN as such but are critical to advance the use of the developed tools in future projects. The publications do not only market the tools, but also market the research partners and bring these into new projects and developments.

5   Requirement analysis and utilization for the pilots

5.1   HYDRO Pilot

5.1.1 User requirements specification and user stories

Table 2: Use case Hydro-UC-1

Use Case Template	Description
Use Case Name	Optimal alumina feed to GTC
Use Case ID	Hydro-UC-1
User story expression of use case	• As a GTC process operator, I want recommendations for corrective action to keep the HF content of alumina as even as possible so that disturbances to downstream processes are minimized. • As a staff member in electrolysis process control room, I want alumina HF content to be as stable and predictable as possible so that primary alumina production proceeds optimally.
Goal	Achievement of even distribution of adsorbed HF in secondary alumina
Measurable KPIs for the goal (if any)	Reduced process disturbance
Actors and stakeholders involved	• GTC/electrolysis operation • GTC IT and sensor support/supplier • Digital service provider
Input data	• GTC operational data (Opc Ua) • Electrolysis operational data (Opc Ua) • Weather measurements and forecast (MET Norway => Opc Ua) • Alumina certificate (manual)
Output data / actions	• HF evolvement predictions (Opc Ua) • HF-content predictions (Opc Ua) • Optimised primary alumina feed rate (Opc Ua) • Optimised GTC recycle rate (Opc Ua)
Summary description – Main success scenario	A hybrid digital twin-based user interface for model insight/communication of optimisation recommendations is evaluated/tested by GTC operators and technical staff
Extensions, exceptions, variations	None
Possible generalisation of use case	Technical aspects (e.g. estimation/optimisation of flow rates) can be applied to other cases

Use case analysis – related to which Digital Twin pipeline steps	This use case will be supported through the following Digital Twin pipeline steps (Delete if not related): Digital Twin Data Acquisition, Hybrid/Cognitive Digital Twin Generation, Digital Twin Visualisation and Control.

Table 3: Use case Hydro-UC-2

Use Case Template	Description
Use Case Name	Temperature control of gas flow into GTC
Use Case ID	Hydro-UC-2
User story expression of use case	• As GTC and Electrolysis, I want the tuning of the integrated heat exchanger (IHEX) controllers to be set so that temperature targets are consistently achieved.
Goal	Maintain constant "ideal" temperature of gas entering GTC filter chambers, to ensure adsorption of HF to alumina
Measurable KPIs for the goal (if any)	Reduced process disturbance
Actors and stakeholders involved	• GTC operation • GTC IT and sensor support/supplier
Input data	• Temperature sensor measurement • General GTC operational data
Output data / actions	• Controller setting
Summary description – Main success scenario	Robust online control of the IHEX
Extensions, exceptions, variations	None
Possible generalisation of use case	Strategy can be applied to other temperature control needs

Table 4: Use case Hydro-UC-3

Use Case Template	Description
Use Case Name	Control of main GTC fans
Use Case ID	Hydro-UC-3
User story expression of use case	• As GTC and electrolysis, I want the main fan operation to be adjusted based on mass flow from the potroom so that the overall suction rate is reduced.
Goal	Reduce power consumption to the GTC main fans
Measurable KPIs for the goal (if any)	Energy/emissions savings

Actors and stakeholders involved	• GTC operation • GTC IT and sensor support/supplier
Input data	• Pressure sensor measurement gas flow measurement • Mass flow estimation • GTC operational data
Output data / actions	• Controller setting
Summary description – Main success scenario	Robust online control of the main fan
Extensions, exceptions, variations	None
Possible generalisation of use case	Strategy can be applied to other fan control needs

5.1.2 Final status and resolved challenges

Most of the CogniTwin toolbox elements utilised by the Hydro pilot have been implemented online. The collective system formed of toolbox elements is aimed at regulating operation of the Gas Treatment Centre (GTC).

A dynamic physics-based model has been developed and implemented as a Cybernetica Application and Model Component and was previously tuned offline using Cybernetica Modelfit. This model forms the backbone of the hybrid digital twin running online as a Cybernetica CENIT application. The main predictions of the physics-based model are 1) HF emissions levels from the pot room to the GTC, which can be compared to process data, and 2) the HF content of secondary alumina leaving the GTC and proceeding to the potroom, which cannot currently be compared to measurements. The digital twin uses the residuals of the HF emissions predictions to develop a data-driven model for adaption of the first-principles model, thus generating a hybrid digital twin.

Input data for the hybrid digital twin is made available online using the Cybernetica OPC UA Server toolbox component. Amongst the online input data required for the hybrid digital twin is weather data – both the current weather and the weather forecast, such that the hybrid digital twin can anticipate future changes in HF emissions and content. The weather data is collected by the SINTEF MET-API Interface (MAPI) which has now been embedded into an online service where the most recent weather measurements and forecast are retrieved and prepared from the databases of the Norwegian Meteorological Institute (MET Norway).

Hydro recently installed a new laser sensor to measure HF concentrations in the process fumes. The sensor is capable of measuring the passage of HF in a conduit through a glass window that provides a view inside the conduit to the laser. The sensor gives precise readings but is affected by several environmental challenges, e.g. small changes in position due to vibrations, or the layer of the glass window facing the inside of the conduit losing clearness due to chemical erosion by the inner fumes. These challenges can, if not detected, degrade the sensor's readings to a point of rendering them unusable. Work has then been initiated on a framework to detect and possibly predict the status of the sensor's readings. Currently, an anomaly detection framework is being put into place, based on ML methods such as autoencoders, that can analyze and flag a stream of data for suspected anomalies.

Other options are also being considered, for instance a numerical score for the trustworthiness of the measurements.

A challenge to the online digital twin implementation is the strict firewall separating the process network from external data sources. A solution to this problem has been reached by using a virtual PC with a selectively opened firewall. This data retrieved by MAPI is processed by the Cybernetica OPC UA server (with a custom weather extension) and the data is made available on OPC UA tags to be read by the digital twin.

A web-based interface using Cybernetica Web Viewer is now available for operators to access. The interface displays the main digital twin trends and predictions on three different time horizons: 6 hours, 24 hours and 72 hours. In addition, the web interface allows for two-way access with the digital twin by giving operators the option to adjust the optimisation target value.

The pilot challenges in the Hydro pilot which relate to WP5 are summarized in Table 5 and Table 6. For more in-depth description of the data acquisition / collection challenges and solutions, we refer to deliverable D4.4

Table 5: Pilot challenges for Digital Hybrid and Cognitive Digital Twins for the Hydro pilot

Analytics Models	• N/A
Physical Models	• **Challenge**: No dynamic GTC model existed prior to pilot work • **Requirement**: Model must be realistic and accurate while also being able to be evaluated many times faster than real time in order to enable hybrid techniques (state and parameter estimation) and nonlinear model predictive control • **Solution**: Physical model is tested and tuned offline by Cybernetica Modelfit, Cybernetica RealSim and implemented online by Cybernetica Cenit
Machine Learning	• **Challenge**: Quality of vital sensor measurements (HF) is difficult to assess • **Requirement**: Data-driven/machine learning approaches should give a safe, secure result such as to ensure best online operation of the hybrid Digital Twin • **Solution**: Anomaly detection algorithms are carefully tested and validated offline
Hybrid Digital Twins	• **Challenge**: Combination of various data driven and Physical models require an approach for understanding the relationships between the various models • **Requirement**: Ensure consistent mapping and relationship between data driven and physical models. • **Solution**: Provide mappings between the data driven and physical models, consider the usage of the AAS Digital Twin representation for supporting links and relationships.
Cognitive Digital Twins	• **Challenge**: Self-learning, reactive/smart hybrid digital twins - for cognitive plants.

	• **Requirement**: Methods for automatically identifying faults in the Hybrid Digital Twins should be developed. • **Solution**: By employing fault detection methods, the system can let the operators know if the results should be discarded or trusted, and automatically suggest suitable actions for fault mitigation.

Table 6: Pilot challenges for Digital Twin Visualisation and Control for the Hydro pilot

2D visualisation	• **Challenge**: Design of a new GUI for GTC operator support • **Requirement**: Operators need to be able follow digital twin solutions and adjust model behaviour (change value of optimisation target) • **Solution**: Interactive operator interface in Cybernetica Web Viewer
3D/4D visualisation	• N/A
Control	• **Challenge**: Optimal control requires characterization of a feasible cost function and efficient tools for finding solutions. The involvement of decision maker / user in the loop needs to be addressed. Operations can be partly automated, but only partly. • **Requirement**: Closed-loop control should minimize process disturbances while staying within operating constraints of GTC operation (silo levels, achievable feed rates, feasible recycle rates) • **Solution**: Nonlinear model predictive control is available and implemented as part of Cybernetica Cenit

5.1.3 Utilization of toolbox components

Four CogniTwin toolbox elements form an online data pipeline – beginning with external data retrieval, data being made available via an OPC UA server, processing of the data by the hybrid digital twin and the (planned) display of digital twin predictions for operator support.

SINTEF MET-API Interface ⇨ Cybernetica OPC UA Server ⇨ Cybernetica CENIT ⇨ Cybernetica Viewer
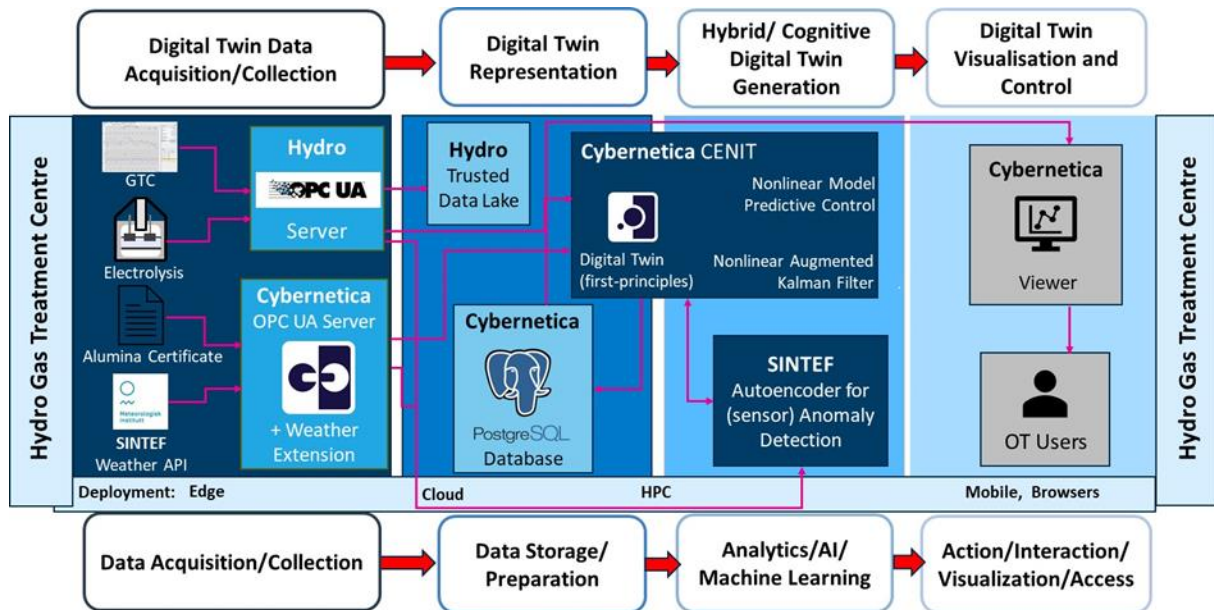
Figure 2: IoT architecture for the Hydro pilot showing interconnectivity of data and toolbox components.

Data Sources:

- Weather data is collected from Norwegian Meteorological Institute
- Process data from cells and GTC

Data Processors:

- MAPI queries and collects weather data through Python service, prepares data for OPC UA
- Hydro OPC UA and GTC OPC UA expose process data to data processors
- OPC UA collects data from various sources and makes it available to Cybernetica CENIT, Cybernetica ModelFit & Cybernetica Viewer
- Cybernetica CENIT and Cybernetica ModelFit perform online/offline optimization, respectively

Data Sinks:

- Optimal control sequence as calculated by Cybernetica CENIT is implemented in control system
- Data is visualized graphically to the user using Cybernetica Viewer.

5.2 ELKEM Pilot

5.2.1 User requirements specification and user stories

Processing of liquid alloys require precise information about compositions, temperature and amounts, preferably continuous but this is difficult to achieve with conventional measurement techniques. By applying Infrared Cameras (IR) there is potential to measure more frequently but also enabling access to process parameters such as slag in the liquid metal, which traditionally has not been properly accounted for in the decision support model. It is expected that improvements both in yield and quality will be possible by adapting new measuring methods, image analysis and mass/energy balance models.

Table 7: Use Case Elkem-UC-1

Use Case Template	Description
Use Case Name	Temperature in tapping stream
Use Case ID	Elkem-UC-1
User story expression of use case	As process responsible for furnace operation, I want to be able to measure the temperature of the tapped ferrosilicon to establish a link between output and furnace operation and adjust operation as necessary when the temperature gets too low.
Goal	Automated temperature measurement of tapping stream
Measurable KPIs for the goal (if any)	Post-taphole yield
Actors and stakeholders involved	Furnace operators, process owners
Input data	Infrared images
Output data / actions	Temperature of tapping stream
Summary description – Main success scenario	Installation of IR camera – programming – recording of data – development of algorithm to determine temperature – visual output to operator/process owner
Extensions, exceptions, variations	
Possible generalisation of use case	Setup and methods can be applied to all plants
Use case analysis – related to which Digital Twin pipeline steps	This use case will be supported through the following Digital Twin pipeline steps: Digital Twin Data Acquisition, Digital Twin Representation, Hybrid/Cognitive Digital Twin Generation,

Table 8: Use Case Elkem-UC-2

Use Case Template	Description
Use Case Name	Slag in refining ladle
Use Case ID	Elkem-UC-2
User story expression of use case	As process responsible for refining and alloying, I want to know the amount of slag that accompanies the liquid metal at the start of the refining process so that proper adjustments to the operator decision support can be made
Goal	Quantify the amount of slag per ladle
Measurable KPIs for the goal (if any)	Product quality, post taphole yield
Actors and stakeholders involved	Refining operators, post taphole process owner

Input data	Infrared images of liquid metal surface in refining ladle
Output data / actions	Kilogram slag per tap – modification of total metal weight
Summary description – Main success scenario	Installation of IR camera – programming – recording of data – development of algorithm to determine slag coverage and thickness – visual output to operator/process owner
Extensions, exceptions, variations	
Possible generalisation of use case	Setup and methods can be applied to all plants where slag amount in ladle is important for correct liquid metal processing
Use case analysis – related to which Digital Twin pipeline steps	This use case will be supported through the following Digital Twin pipeline steps: Digital Twin Data Acquisition, Digital Twin Representation, Hybrid/Cognitive Digital Twin Generation,

5.2.2 Final status and resolved challenges

The Elkem pilot case has focused on online implementation of CogniTwin toolbox elements. The collective system formed of toolbox elements is aimed at supporting the operators of the post taphole process.

A first-principles model has been developed and implemented as a Cybernetica Model and Application Component and has been tuned to the plant offline using Cybernetica ModelFit. The model is employed online using Cybernetica CENIT. Cybernetica CENIT uses the model to predict temperature and concentration, which in turn is used in a nonlinear model predictive control scheme to calculate the optimal amount of each addition.

Not all measurements were available on OPC, therefore a bespoke Cybernetica OPC UA server was created to query relevant databases and publish the measurements to OPC. This server will also be used to connect the data from the different toolbox elements.

Infrared cameras have been installed for the tapping station, refining station and at the casting station. Images were gathered for offline analysis. The offline analysis resulted in a set of machine vision algorithms (described in detail in D.1.4). Due to operational challenges related to the harsh operating conditions at the pilot it has not been possible to test these algorithms online. The initial analysis looks promising, with the machine vision temperature and modelled temperature in good correspondence. Once the operational challenges are overcome the machine vision will provide real-time measurements; most importantly temperature of the metal during tapping, refining, and casting. Additional information may be extracted from the thermal cameras, for example ladle slag coverage, metal/slag ratio in tapping, and chemistry/dynamics during refining.

In parallel a data-driven model for estimating the amount of slag tapped from the furnace was tested. The model used machine-learning algorithms with data from the furnace and the post taphole process. However, the data-driven model was not successful in giving meaningful predictions of the slag..

The hybrid digital twin that has been developed for this pilot combines the elements described above. Once the IR-cameras are reliably providing measurements online, Cybernetica CENIT will use a recursive estimation algorithm to correct the first-principles model in real-time. Elkem has taken the following mitigation steps for the further operational deployment of the ir cameras and COGNITWIN

technologies: Allocated additional internal funding from Elkem to COGNITWIN project partner Cybernetica evolve and continue with the deployment for one more year – until summer 2024.

Hired a new trainee that will help out at physically at the plant from summer 2023 – in particular regarding IT-tasks related to the (internally extended) COGNITWIN project

The pilot challenges in the Elkem pilot which relate to WP5 are summarized in Table 9 and Table 10. For more in-depth description of the data acquisition / collection challenges and solutions, we refer to deliverable D4.4.

Table 9: Pilot challenges for Digital Hybrid and Cognitive Digital Twins for the Elkem pilot

Analytics Models (Plant DT with ML/AI) (task 5.1) (by task 5.1)	• **Challenge**: Low correlation between measured variables and desired output. • **Requirement**: Accurate estimation of key variables used by physical model. • **Solution**: Utilize data from infrared cameras and physical model when training ML model
Physical Models	• **Challenge**: Adapt physical model to pilot • **Requirement**: Model must be realistic and accurate while also being able to be evaluated many times faster than real time in order to enable hybrid techniques (state and parameter estimation) and nonlinear model predictive control • **Solution**: Physical model is tested and tuned offline by Cybernetica Modelfit, Cybernetica RealSim and implemented online by Cybernetica Cenit
Machine Learning – + any needs for Deep Learning /imagery, Performance (tasks 5.2/5.3)	• **Challenge**: Machine vision algorithms are difficult to develop for every scenario due to moving equipment and a harsh environment • **Requirement**: Data-driven/machine learning approaches should give a safe, secure result such as to ensure best online operation of the hybrid Digital Twin • **Solution**: Automatic detection of regions of interest in images of moving equipment.
Hybrid Digital Twins (by task 5.4)	• **Challenge**: Combination of various data-driven and physical models require an approach for understanding the relationships between the various models. • **Requirement**: Integration between data-driven and physical models and results from machine vision algorithms • **Solution**: Cybernetica OPC UA Server to make data available between the different applications
Cognitive Digital Twins (by task 5.5)	• **Challenge**: Introduce cognition through knowledge and learning from past data and situation in order to provide operator guidance

	Requirement: Interact in a suitable way with operators to provide guidance and recommendations **Solution**: Ensure inclusion of operators knowledge combined with system situation understanding.

Table 10: Pilot challenges for Digital Twin Visualisation and Control for the Elkem pilot

2D, 3D/4D visualisation and Human interaction (including speech) (by task 5.1)	• **Challenge**: It is difficult for the operator to act on recommendations from digital twin hybrid unless it is visualized • **Requirement**: Data from the decision support system needs to be made available into the control room operator in an easy-to-act-upon, visual manner • **Solution**: Use Cybernetica Viewer to visualize data
Control – system interaction (related also to autonomous Cognitive Twins) (by task 5.5)	• **Challenge**: Optimal control requires characterization of a feasible cost function and efficient tools for finding solutions. The involvement of decision maker / user in the loop needs to be addressed. Operations can be partly automated, but only partly. • **Requirement**: Closed-loop control should minimize process disturbances while staying within operating constraints • **Solution**: Nonlinear model predictive control is available and implemented as part of Cybernetica Cenit

5.2.3 Utilisation of toolbox components

Four CogniTwin toolbox elements, together with Cybernetica InSight, form an online data pipeline – beginning with external data retrieval, data being made available via an OPC UA server, processing of the data by the hybrid digital twin and the display of digital twin predictions for operator support. An illustration of the pipeline is shown in Figure 3.
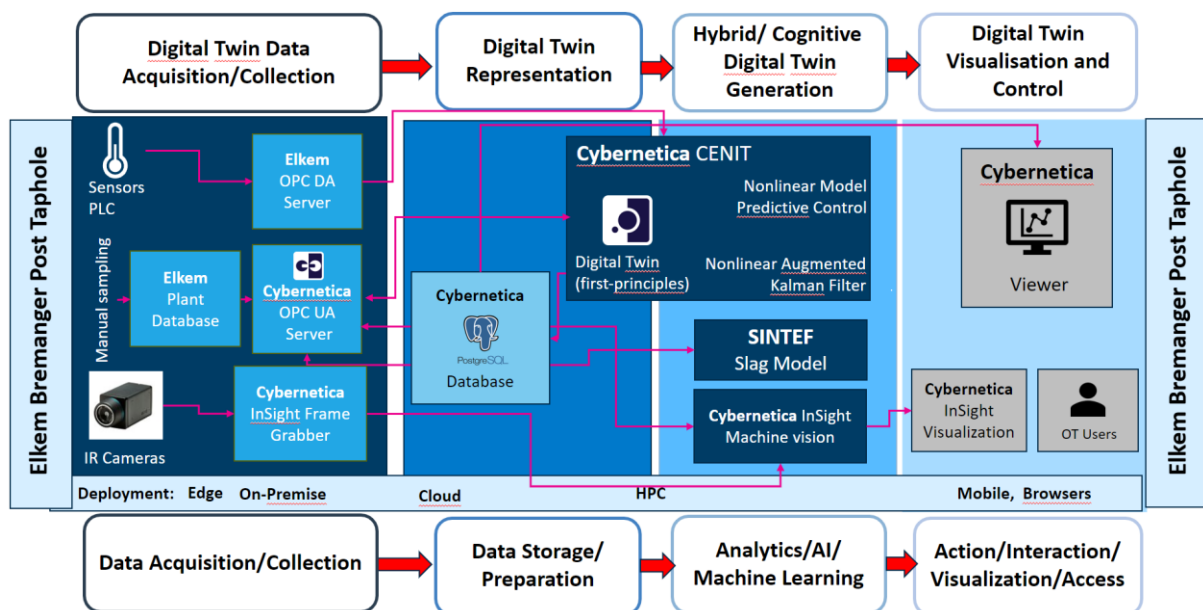
Figure 3: Pipeline for the Elkem pilot

5.3 SUMITOMO Pilot

5.3.1 User requirements specification and user stories

The Engineering pilot (Sumitomo SHI FW) in WP3 considers monitoring and control of fouling on the heat exchange surfaces in biofuel combustion. The fouling monitoring can be approached from various angles, using direct process data or model-based approaches. On-line characterization of the incoming fuel feed is expected to provide significant improvement to fouling monitoring. The final goal is to optimize the boiler maintenance, e.g., maximize profits vs. costs in soot blowing, or long-term maintenance.

Table 11: Use Case SFW-UC-1

Use Case Template	Description
Use Case Name	Boiler fouling management
Use Case ID	SFW-UC-1
User story expression of use case	As an asset manager I want to ensure that the heat exchange surfaces of the energy boiler are cleaned so that the benefits-losses are optimized, both in the short term (steam losses vs. improved heat transfer) and in the long term (maintenance costs vs. erosion of boiler parts). As a plant operator I want a clear indication of when to clean heat exchange surfaces and in what way.
Goal	Primarily to have an indication of when to start the soot blowing sequence (i.e., pause time between soot blowing), secondarily to have the properties of soot blowing sequence optimized if possible (length of soot blowing sequence, indication of which soot blowers to run, order of running the individual soot blowers) and to adapt soot blowing process to the process operation (e.g., regarding the load levels and production schedule)
Measurable KPIs for the goal (if any)	An economic cost function to be optimized needs to be developed. It will be linked with plant KPI's on efficiency and availability.
Actors and stakeholders involved	Boiler owner, boiler operator, boiler supplier, digital service provider
Input data	Decisions are based on on-line/historical process operation data.
Output data / actions	Output will indicate the need for cleaning the heat exchangers or their state of fouling, and suggest/automate management actions (e.g., starting a soot blowing sequence or the optimal pause time between soot blowing sequences)
Summary description – Main success scenario	The cleanness of surfaces is monitored on-line. The costs of soot blowing are continuously evaluated against the heat losses due

	to soot covered surfaces, and control/maintenance actions are timed optimally and performed in an optimal way.
Extensions, exceptions, variations	There can be various alternative/supporting ways for gaining information on surface cleanness: using direct and indirect measurements from heat exchange surfaces, physical and/or data-driven models for phenomena, knowledge of recent plant operation (e.g. on past fuel properties), specialized measurements, etc. Knowledge gained during past soot blowing sequences is used to improve future operation (a learning system).
Possible generalisation of use case	Fouling is a common and significant phenomenon in all combustion boilers. Potentially, the methodology and tools developed here can be expanded to any other industrial case in which heat exchange surfaces are regularly cleaned and in which basic quantities like temperatures and pressures are being measured or monitored. Fusion of models and on-line data provides a fundamental tool for solving a large variety of monitoring problems in the heavy industry.
Use case analysis – related to which Digital Twin pipeline steps	This use case will be supported through the following Digital Twin pipeline steps: Digital Twin Data Acquisition, Hybrid/Cognitive Digital Twin Generation, Digital Twin Visualisation and Control

5.3.2 Final status and resolved challenges

In phase I, the fuel state estimation (FUSE) component was constructed for characterization of different fragments in the incoming fuel. FUSE consists of a physical model for the CFB furnace (combustion, fluidization and heat transfer), a PMFIR tool for tuning the physical model with process historical data, and an unscented Kalman filter (UKF) tool for on-line state estimation of the uncertain fragments in boiler fuel feed. The FUSE component algorithmic/methodological development is complete. The component has been successfully applied to two plant cases. The tool is valid for power plants operating with varying fuel fractions, i.e., depending on the available set of fuels and the current process operating policy.

In phase II, the work focused on the development of the fouling monitoring (FouMon) component, on monitoring of fouling at the heat exchange surfaces. A physical model for a heat exchanger was developed and tuned to pilot superheater conditions. Improved model-based state estimation was then sought via implementation of ensemble Kalman filtering (EnKF) tool. The FouMon approach has been successfully tested with pilot plant data. The development work is ongoing.

Phase III focused on fouling management and control (FouCon). An alternative approach for fouling monitoring was developed based on subspace identification, enabling the application of linear state estimation and a highly reduced computational load in online applications. In addition, tools for ensuring better data quality for data-driven modeling were implemented (see D4.4). . An optimization

scheme making use of the model has been developed, and applied for solving the sootblowing timing problem. The FouCon approach has been successfully tested with pilot plant data.

It is expected that the cognitive features of a digital twin supporting integration and decision making will play an important role when deriving approaches for the management of the fouling phenomena. The research work eventually expects to look at improvements to automatic control and/or prescriptive maintenance procedures.

The challenges in the Sumitomo SHI FW pilot which relate to WP5 are summarized in Table 12 and Table 13. For more in-depth description of the data acquisition / collection challenges and solutions, we refer to deliverable D4.4.

Table 12: Pilot challenges for Digital Hybrid and Cognitive Digital Twins for SUMITOMO SHI FW pilot

Analytics Models	**Challenge**: Optimization tools require proper formulation and are highly dependent on the type of the problem. **Requirement**: High robustness of solutions is required, especially with automated actions without human decision-making. Obtaining of solutions (even suboptimal) should be ensured. **Solution**: Careful selection of cost function vs. solvers. - Toolbox components: FouCon is to include optimization
Physical Models	**Challenge**: Physical models for boilers are highly complicated to build and maintain. Tuning of physical models is laborious and may lack data. Physical models for heat exchangers are complicated and require maintenance. **Requirement**: Model must provide realistic and accurate enough estimates/predictions. **Solution**: Modelling is based on laws of physics and validated model structures. - Toolbox components: FUSE including PMFIR, FouMon
Machine Learning	**Challenge**: Fusion of physical models and process measurement data is complicated as data may be very sparse and models not accurate/detailed enough. **Requirement**: Algorithms must survive with sparse data, and iterative computations cannot be excessive. **Solution**: Solutions will be sought by using up-to-date model-based state estimation techniques. - Toolbox components: FUSE including UKF, FouMon including EnKF
Cognitive Twin	Cognitive DT requires abilities in human-in-the-loop considerations and feedback of HDT outcomes to the plant/KPI. The challenges are in extending from monitoring to prediction, and establishing feasible approaches in optimization. These are developed in FouCon.

Table 13: Pilot challenges for Digital Twin Visualisation and Control for SUMITOMO SHI FW pilot

2D visualisation	N/A
3D/4D visualisation	N/A
Control	• **Challenge**: Optimal control requires characterization of a feasible cost function and efficient tools for finding solutions. The involvement of decision maker / user in the loop needs to be addressed. Operations can be partly automated, but only partly. • **Requirement**: Solutions must be robust in the industrial environment. • **Solution**: Suitable solutions will be selected by focusing on formulation of the cost function and feasible optimization techniques. • Toolbox components: FouCon

5.3.3 Utilisation of toolbox components

The estimator in FUSE was based on applying a detailed circulating fluidized bed (CFB) furnace model in conjunction with nonlinear Bayesian state estimation tool, both implemented in Matlab. A generalized version of the fuel characterization UKF tool – enabling application of other prediction models and setups of plant measurements – was provided for the COGNITWIN toolbox as a set of Matlab code. An example of a setup of data communication was demonstrated via an OPC-UA tool, consisting of free software (Prosys) and existing properties of Matlab (MathWorks) and StreamPipes (Apache). The included PMFIR provides a tool for tuning the physical model with historical process operation data; the UKF tool implements Bayesian model-based state estimation able to exploit a physical process model.

The FouMon component contains the EnKF-tool as an alternative Bayesian state estimation algorithm, applied for the fouling monitoring problem. A physical model for heat transfer in the heat exchanger surfaces was constructed and tuned for pilot site conditions. The model was used in the model-based fouling monitoring. The PMFIR and UKF/EnKF are general purpose tools which can be applied to solve various tuning and state estimation problems in process engineering.

The FouCon contains a futher development of the SubFUSE subspace identification tool, implementing the Prony approach. The FouCon optimization is problem dependent, developed for solving the sootblowing timing problem for the pilot case. The tools are described in more detail in the Appendices of component descriptions and past deliverables.

The components use the same data pipeline structure, in that the model and estimators are built in Matlab, and a connection to StreamPipes and plant data is made possible via OPC-UA.
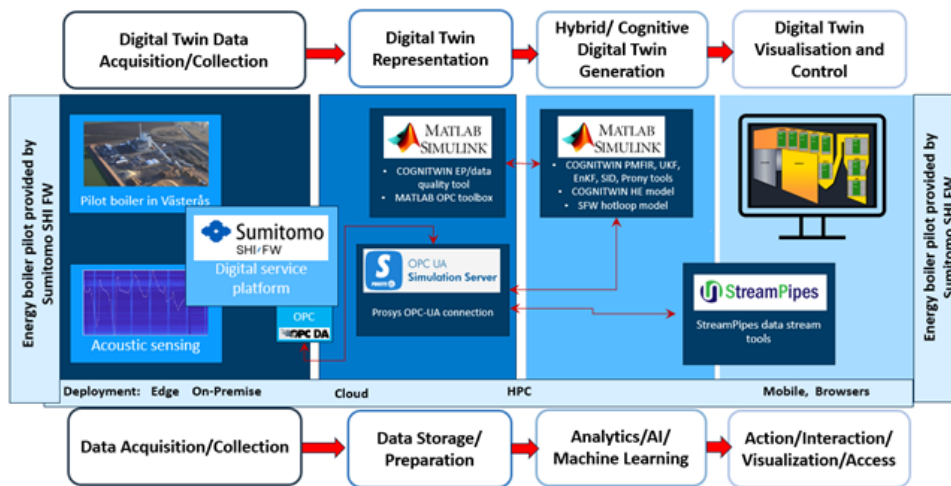
Figure 4: Pipeline for the Sumitomo SHI FW pilot

5.4 NOKSEL Pilot

5.4.1 User requirements specification and user stories

Table 14: Use Case NOKSEL-UC-1

Use Case Template	Description
Use Case Name	Industrial Big Data Processing
Use Case ID	NOKSEL-UC-1
User story expression of use case	As a user, I want conduct data pre-processing so that the data set becomes ready to be used for ML/DL model training.
Goal	To prepare data for ML/DL training
Measurable KPIs for the goal (if any)	There will be no empty cell in the data set All data fields in the data set will be labelled
Actors and stakeholders involved	Maintenance operator or maintenance manager
Input data	Sensor data, and data from the PLC (alarm and status data) used for remaining useful life estimation and type of ML/DL algorithm to be trained
Output data / actions	Quality data that is cleaned, scaled, filled in, analysed, normalized, and pre-processed and get ready to be used for ML/DL model training
Summary description – Main success scenario	1. Data set is selected and uploaded. 2. Rules to fill in empty data is selected by the user. 3. Data is normalized. 4. Mean, median and variation of the data set is calculated.

	5. Processed data is stored.
Extensions, exceptions, variations	None
Possible generalisation of use case	The objective function of the ML/DL models to be trained may be functions other than predictive maintenance.
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Digital Twin Data Acquisition, Digital Twin Representation

Table 15: Use Case NOKSEL-UC-2

Use Case Template	Description
Use Case Name	Real time anomaly detection using pretrained ML/DL models
Use Case ID	NOKSEL-UC-2
User story expression of use case	As a user, I want to execute selected ML/DL models so that I detect anomalies in real time.
Goal	To estimate anomalies on stream data.
Measurable KPIs for the goal (if any)	None
Actors and stakeholders involved	Maintenance operator and/or maintenance manager
Input data	Sensor data, PLC data, alarm and status data
Output data / actions	Anomalies will be detected by the selected ML/DL models and the results will be graphically displayed
Summary description – Main success scenario	1. The users select the pre-trained ML/DL model set to be executed on the stream data. 2. The selected models are executed on the stream data. 3. The results of the selected ML/DL models are calculated and displayed to the user
Extensions, exceptions, variations	If the user does not select any ML/DL model a warning message is displayed to the user in order to state that at least one model must be selected.
Possible generalisation of use case	The pretrained ML/DL models can be generated for purposes other than predictive maintenance and anomaly detection
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Hybrid/Cognitive Digital Twin Generation, Digital Twin Visualisation and Control

Table 16: Use Case NOKSEL-UC-3

Use Case Template	Description
Use Case Name	Big Data Visualization
Use Case ID	NOKSEL-UC-3
User story expression of use case	As a user, I want to visualize past sensor data so that I see the data trend of sensors.
Goal	To display collected past sensor data in graphs.
Measurable KPIs for the goal (if any)	The zoom in and zoom out of displayed data should be <200ms.
Actors and stakeholders involved	Maintenance operator, maintenance manager
Input data	Past sensor data collected
Output data / actions	Sensor data displayed in graphics with respect to time
Summary description – Main success scenario	1. The user wants to visualize past sensor data in graphs 2. The data is displayed to the user
Extensions, exceptions, variations	When the user zooms in and/or zooms out the time scale of the x-axis changes, and the data is displayed in the graphs accordingly
Possible generalisation of use case	The visualized big data does not need to belong to the sensors in the NOKSEL pilot, any time series big data can be graphically visualized.
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Digital Twin Representation, Digital Twin Visualisation and Control

Table 17: Use Case NOKSEL-UC-4

Use Case Template	Description
Use Case Name	Operational Data Visualization
Use Case ID	NOKSEL-UC-4
User story expression of use case	As a user, I want to visualize operational data so that monitor the real-time condition of the SWP machinery.
Goal	To monitor operational data regarding the SWP components
Measurable KPIs for the goal (if any)	Latency in visualization > 200ms
Actors and stakeholders involved	Maintenance operator, maintenance manager
Input data	Sensors and PLC
Output data / actions	Graphical representation of operational data

Summary description – Main success scenario	1. The user selects the component of the SWP machine for which the condition is to be monitored. 2. The system displays the 3D model of the component and graphics associated to the hotspots on the component. 3. The user selects the hotspot. 4. The system displays the values of the sensors associated with the selected hotspot in suitable graphics.
Extensions, exceptions, variations	None
Possible generalisation of use case	The component visualized may belong to a different machine other than SWP, and the sensor set installed on the component may be different.
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Digital Twin Visualisation and Control

Table 18: Use Case NOKSEL-UC-5

Use Case Template	Description
Use Case Name	New trained ML/DL model inclusion
Use Case ID	NOKSEL-UC-5
User story expression of use case	As a user, I want to add a new pre-trained ML/DL model so that it can be used for anomaly detection in real-time on stream data
Goal	To include a new ML/DL model in the list of the models to be executed without updating the source code
Measurable KPIs for the goal (if any)	None
Actors and stakeholders involved	System Administrator, maintenance manager
Input data	Pre-trained ML/DL models
Output data / actions	Updated list of ML/DL model
Summary description – Main success scenario	1. The user selects the new model to be added to the list of pretrained ML/DL models 2. The system displays the list of files to be selected. 3. The user selects the model to be included in the model set. 4. The selected model is added to the list of pre-trained ML/DL models.
Extensions, exceptions, variations	If the file selected by the user is not a model, the system displays a warning message to the user.

Possible generalisation of use case	The pre-trained model can be for a different purpose other than anomaly detection. Any process can be called and added to a multi selection list.
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Hybrid/Cognitive Digital Twin Generation, Digital Twin Visualisation and Control

Table 19: Use Case NOKSEL-UC-6

Use Case Template	Description
Use Case Name	Synthetic data generation for generic electromechanical components
Use Case ID	NOKSEL-UC-6
User story expression of use case	As a user, I want to generate synthetic data for electro-mechanical components so that I create machine break down and/or faulty cases.
Goal	To generate synthetic data needed for the ML/DL training
Measurable KPIs for the goal (if any)	None
Actors and stakeholders involved	Maintenance Manager
Input data	Matlab model for the electro-mechanical components, parameters, real-data, limits
Output data / actions	.mat file including the faulty data generated
Summary description – Main success scenario	1. The user selects the Matlab model for the electro-mechanical component. 2. The system loads the model. 3. The user installs the virtual sensors. 4. The system generates data including faulty cases. 5. The system saves the data in .mat file.
Extensions, exceptions, variations	None
Possible generalisation of use case	Different model files and sensor types can be used to generate synthetic data
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Hybrid/Cognitive Digital Twin Generation

Table 20: Use Case NOKSEL-UC-7

Use Case Template	Description
Use Case Name	Predictive Maintenance
Use Case ID	NOKSEL-UC-7
User story expression of use case	As a Maintenance Operator, I want to be notified about the anomalies detected so that I take actions in advance before machine breakdowns occur. As a Maintenance Manager, I want to be able to perform predictive management so that the cost of maintenance is decreased.
Goal	To conduct predictive maintenance
Measurable KPIs for the goal (if any)	All anomalies detected will be accurate, and that there will be no anomaly that is left undetected. Thus, False Positive, and False Negative values of the defect detection algorithms used for remaining useful time estimation will both be zero.
Actors and stakeholders involved	Actors: Maintenance operators and/or maintenance managers
Input data	Data that is stored by TIA STORAGE and streamed by TIA STREAM
Output data / actions	Based on anomalies detected, remaining useful time estimation is displayed
Summary description – Main success scenario	1. The detected anomalies are sent to related actors (Maintenance operator) in the form of selected notification 2. The operator evaluates the case 3. The operator takes necessary actions to overcome the anomaly
Extensions, exceptions, variations	In some cases, despite the determined anomaly, the reason for the anomaly is not associated with the common cause of the failure, ie. wire-cut, but with a reason other than wire-cut.
Possible generalisation of use case	The use case is applicable to similar SWP machines that are used in the steel pipe production process industry
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Digital Twin Representation, Digital Twin Hybrid Analytics Models, Digital Twin Visualisation and Control

Table 21: Use Case NOKSEL-UC-8

Use Case Template	Description
Use Case Name	Preventive Maintenance
Use Case ID	NOKSEL-UC-8
User story expression of use case	As a Maintenance Manager, I want the system to be able to control welding cell temperature so that the system acts

	proactively and eliminates human-in-the-loop for climate control operation.
Goal	To conduct preventive maintenance
Measurable KPIs for the goal (if any)	Energy consumption reduced by at least 10%
Actors and stakeholders involved	Actor: TIA CONTROL Stakeholders: Maintenance operators, Maintenance managers, Air Conditioner in the Welding Cell
Input data	Indoor environment, Welding Machine Generators temperatures, and Welding Machine Generators current value
Output data / actions	The command to manipulate air conditioner in the welding cell
Summary description – Main success scenario	1. For each welding machine generators current (voltage) are measured. If any of these values is greater than 0.1 amper, air conditioners are turned on. 2. Temperature in the welding cell and welding machine generator are measured. If for more than one hour welding cell temperature is in between 20-25 Celsius or if environment temperature is less than 20 Celsius then, the air conditioner status is set to close.
Extensions, exceptions, variations	The cause of machine breakdown may stem from a reason that is not associated with welding wire cut
Possible generalisation of use case	The use case is applicable to similar SWP machines that are used in the steel pipe production process industry
Use case analysis – related to which Digital Twin pipeline steps	This use case has been supported through the following Digital Twin pipeline steps (Delete if not related): Digital Twin Acquisition, Digital Twin Representation, Digital Twin Hybrid Analytics Models, Digital Twin Visualisation and Control

5.4.2 Final status and resolved challenges

The most important challenges determined so far are related to the data set: 1) not sufficient data has gathered on system break downs, 2) some conflict has been determined in between the data set provided by the experts, and the system collected data.

The collected data does not have many machine breakdowns, in order to cope with the first challenge, synthetic data has been created to align the data set. While the machine is working, data is collected. Missing failure related real data has been solved partially by means of a tool used to generate synthetic data as close as possible to the real cases.

Labelling a dataset for failed data is a challenge, not only does it require real data for machine failures, but also should expert knowledge be inserted into the models. To cope with the second challenge, several online and face to face meetings with the domain experts have been conducted, and thorough analysis of collected data has been performed. Data labelling took many of the effort spend for TMML related studies.

Multiple methods have been used for feature selection. Feature importance method is applied until the cumulative sum reached to 0.99, Pearson correlation, was utilized. Analysis of variance was performed to determine the distribution of the sensors and data diversity.

Based on the real data collected, followings were determined: Electric current and vibration values of the SWP machine components should be checked in order to detect the mechanical failures. The most common unplanned machine downtime is related to Wire Cut, and the most important feature for the detection of Wire Cut is the electric current values coming from the Welding Machine. The components that affect the machine downtimes and the sensors that can impact the machine downtimes have been determined. Pandas profiling library was used, which allows us to to analyze the attributes on the entire data set one by one. to analyze the attributes on the entire data set one by one. As a different method, a size reduction study was carried out by determining the qualities that cover each other. With the determination of the qualifications, machine learning and deep learning studies started. Depending on the type of algorithm, standard or 0-1 (min-max) scaling was performed on the features.

Seven different algorithms were used. Classification and regression studies were performed with SVM, RF, GBT, LSTM, KNN, LGBM and MLP algorithms. During the classification algorithms, it was made with a different label before the failure in order to ensure the pre-detection of the data (MultiClassClassification). This label has the quality of a failure. In another scenario, the data before the failure is labelled and the information about the time of failure and the moment of stopping is not added to the data. In this way, it is aimed that the algorithms capture a pattern here by labelling only the data before the failure. In the regression studies, the dependent variable RUL was added to the studies.

High accuracy results were obtained during the analysis of energy data. It is possible to predict the energy that the factory will consume in the coming months. Energy efficiency is achieved with the prevention of downtimes. Future energy consumption data is provided by the regression module of the LGBM algorithm. The correlations of energy consumption with all other qualities were calculated and reported. Meanwhile, it has been observed that the 'HGÜ-2 Pressure Line Filter' attribute has a high correlation with the SWP Energy analyzer. These correlation values were examined during the meetings with the experts in the field. The conclusion that the contamination of the filter would increase the current of the motor and increase the power consumption was confirmed by the expert engineers in the field, and the filter was changed.

The pilot challenges in the Noksel pilot which relate to WP5 are summarized in Table 20 and Table 21. For more in-depth description of the data acquisition / collection challenges and solutions, we refer to deliverable D4.4

Table 20: Pilot challenges for Digital Hybrid and Cognitive Digital Twins for NOKSEL pilot

Analytics Models	**Challenge**: Data cleaning and labelling **Requirement**: Pre-processing for ML/DL for predictive maintenance **Solution**: Industrial Big Data Processing implementation **Challenge**: The number of features is high **Requirement**: Efficient ML models generation **Solution**: PCA on data **Challenge**: Difficulty in analysis due to high volume of data **Requirement**: Efficiency and performance **Solution**: Pandas Profiling is used **Challenge**: SWP is a heavy energy consumer, and reduction on energy consumption is required. **Requirement**: Energy efficient system **Solution**: Applied data analytics using correlation to suggest changing hydraulic power unit pressure filters
Physical Models	**Challenge**: Missing models **Requirement**: 1st order model generation **Solution**: Models are generated in Matlab Simulink
Machine Learning	**Challenge**: Algorithms did not learn very well on the collected data set **Requirement**: Quality ML models trained **Solution**: A thorough analysis was conducted, and feature selection is applied **Challenge**: Missing data **Requirement**: ML/DL model training for predictive maintenance **Solution**: Synthetic data generation and data balanced sampling
Cognitive Digital Twins	**Challenge**: To ensure that the predictive maintenance takes operators' knowledge and experiences into account, and enable preventive maintenance for one of the most common factors of machine unplanned breakdowns **Requirement**: Combine the Digital Twin based recommendations with the inclusion of operators' knowledge **Solution**: Extract the tacit knowledge from experts as a basis for developing the cognition. Partially by applying unusuality detection on past data, ontology development and storing ontology in relational databases, and design an autonomous system that is self-learning and proactive. (ON2RDB)

Table 21: Pilot challenges for Digital Twin Visualisation and Control for NOKSEL pilot

2D visualisation	**Challenge**: Slowness in big data visualization **Requirement**: Latency < 200ms **Solution**: View creations for zoom in and zoom outs
3D/4D visualisation	**Challenge**: Custom 3D visualizations **Requirement**: none **Solution**: User preferred visual elements adjustments (i.e., colour, light, etc.)
Control	**Challenge**: To prevent machine failure due to increases in welding temperature **Requirement**: Set the temperature of the welding cell to the state that enables the machine to work properly without break **Solution**: TI: Performed data analytics and TIA CONTROL (a control system to control temperature)

In the beginning of the project, no control has been planned for the NOKSEL pilot. However, after TEKNOPAR's analysis of the collected big data, a common reason for SWP machine's failures has been detected. The reason has been associated with increased temperature in the closed environment where the welding machines are located. A control system has been designed and implemented by TEKNOPAR to control the air conditioner in the welding room, and one of the major reasons. As a result, TEKNOPAR's solution at NOKSEL facility not only predicted the failures due to high temperature, but also by controlling the temperature value prevented that failure to happen (Temel, et. Al. IEEE Big Data 2022).

5.4.3 Utilisation of toolbox components

The toolbox component set utilized for the NOKSEL pilot contains the followings: TEKNOPAR Industrial Big Data Analytics (IDBA) renamed as TIA DATA, TIA APPS composed of multiple tools/applications namely TIA MODEL, TIA PREMA, TIA OEE, TIA METRICS, TIA STATISTICS, TIA ASP and TIA DATA-GEN, and TIA UX previously named as TEKNOPAR Industrial Control Panel and Visualisation (ICPV). The TEKNOPAR StreamPipes (TStreamPipes ML) tool renamed as TIA ASP, and a synthetic data generator named as TEKNOPAR TMat-SynDat renamed as TIA DATA-GEN.

Table 21 maps the Use Cases, and their associated requirements to the components developed by TEKNOPAR:

Table 21: NOKSEL Use Cases and TEKNOPAR Components Mappings

Use Case No	Realizing Component Name
NOKSEL-UC-1	TIA STREAM, TIA STORAGE of TIA DATA
NOKSEL-UC-2	TIA MONITORING, TIA PREMA, TIA MODEL, TIA DATA-GEN, TIA ASP of TIA APPS
NOKSEL-UC-3	TIA DASHBOARD, TIA 3D of TIA UX
NOKSEL-UC-4	TIA MONITORING of TIA APPS and TIA DASHBOARD and TIA 3D of TIA UX

NOKSEL-UC-5	TIA MODEL of TIA APPS
NOKSEL-UC-6	TIA DATA-GEN of TIA APPS
NOKSEL-UC-7	TIA PREMA of TIA APPS
NOKSEL-UC-8	TIA CONTROL of TIA IOT and TIA STATISTICS of TIA APPS

 The components are all used together in a pipeline. Big Data acquired and analyzed by TIA DATA is processed by the TIA APPS toolbox tools. Outputs of TIA DATA, TIA ASP and TIA PREMA are visualized by TIA UX. Data generated by TIA DATA-GEN can be used by different tools within the TIA APPS toolbox.**Error! Reference source not found.**
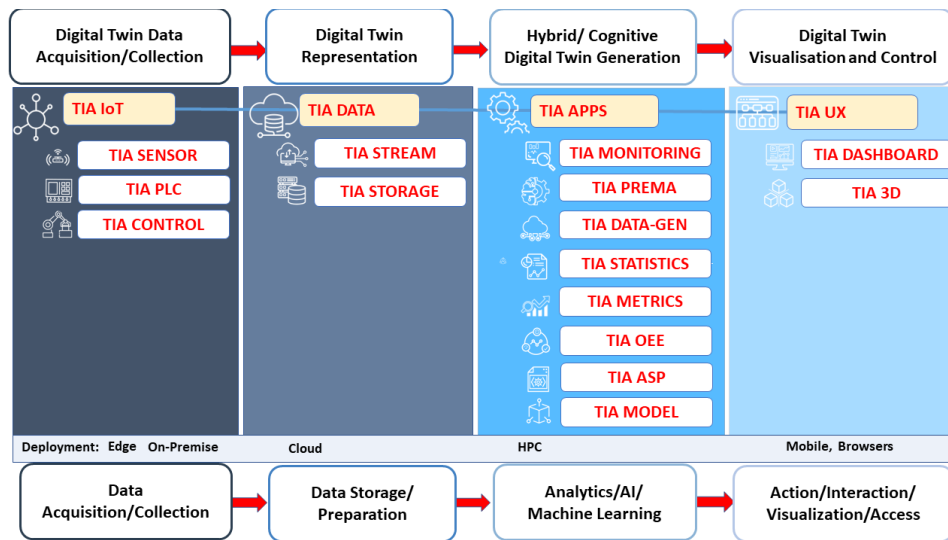
Figure 5: Pipeline for the NOKSEL pilot

6

5.5   SAARSTAHL Pilot

5.5.1 User requirements specification and user stories

Table 22: Use Case SAG-UC-1

Use Case Template	Description
Use Case Name	(Rolling Mill) Tracking System
Use Case ID	SAG-UC-1
User story expression of use case	As a SAG Data Scientist, I want a seamless tracking such that process data throughout the entire production process can be linked to the respective billet. This closes the missing link in the digital twin representation of individual billets and lays the

	groundwork for the usage of innovative AI tools spanning the production process, aiding in optimizing production routines and reducing environmental impact. As a rolling mill technician, I want a linkage of blooming train rolling parameters with finished goods & surveillance of blooming train, e.g. for predictive maintenance/root cause.
Goal	A seamless (near) real-time tracking of billets in the rolling mill
Measurable KPIs for the goal (if any)	Tracking system performance, i.e. ratio of correctly tracked billets, inference speed of tracking system.
Actors and stakeholders involved	Rolling mill personnel, works council, IT integration, technical development of system, maintenance of system.
Input data	Video data from (rtsp) camera stream, tabular data (datetime, character string, numerical) provided in JSON format
Output data / actions	Tabular data (datetime, character string, numerical) provided in JSON format; optional: video stream output. With sufficient inference speed, resulting action could be blooming train operator interfering to prevent deviation before it occurs if system triggers a warning with sufficient lead time.
Summary description – Main success scenario	- Identify/Assess (investment) requirements based on local site characteristics - Set up necessary infrastructure - Collect/Generate training data for Deep Learning network - Develop DL model for localization of to-be-tracked goods - Develop tracking system - Integrate tracking system into ambient infrastructure
Extensions, exceptions, variations	None
Possible generalisation of use case	Tracking of miscellaneous goods in a large variety of possibly demanding environments, especially also over large scales. Current implementation is for moderate velocity of to-be-tracked goods, but could be adapted for high speed settings.
Use case analysis – related to which Digital Twin pipeline steps	This use case will be supported through the following Digital Twin pipeline steps: Digital Twin Data Acquisition, Digital Twin Representation, Hybrid/Cognitive Digital Twin Generation, Digital Twin Visualisation and Control

5.5.2 Final status and resolved challenges

The pilot challenges in the Saarstahl pilot which relate to WP5 are summarized in Table 23 and Table 24. For more in-depth description of the data acquisition / collection challenges and solutions, we refer to deliverable D4.4

Table 23: Pilot challenges for Digital Hybrid and Cognitive Digital Twins for SAARSTAHL pilot

Analytics Models	Analytical modelling for matching DL detections over consecutive frames and different camera viewpoints
Physical Models	• **Challenge**: Billet location needs to be known accurately for ML algorithms to be able to optimize the process • **Requirement**: Seamless billet tracking movement, constrained by physical environment • **Solution**: Instance segmentation technology is used to track the billets
Machine Learning	• **Challenge**: Need to analyse video imagery in order to understand the movement of billets • **Requirement**: Need to have effective training and use of Image analytics including aerial photogrammetry including use Deep Learning Neural Network. Analytical modelling for matching DL detections over consecutive frames and different camera viewpoints. • **Solution**: A visual debugger for neural networks Neuroscope with use of aerial photogrammetry.
Cognitive Digital Twins	• **Challenge**: Support self-learning of the system also after initial machine learning. • **Requirement**: The system should provide alerts and recommendations for operators and be able to learn continuously • **Solution**: Provide interactive operator guidance

Table 24: Pilot challenges for Digital Twin Visualisation and Control for SAARSTAHL pilot

2D visualisation	• **Challenge**: Suitable visualization for operators. • **Requirement**: tracking of billets must be accurate and in real-time • **Solution**: User preferred visual presentations in Neuroscope tool
3D/4D visualisation	N/A
Control	• **Challenge:** interfere in real time if critical situation is detected to prevent damage to billet or the roll stand • **Requirement**: sufficiently short inference time of model and suitable visualization for operator • **Possible Solution**: alert operator with sufficient lead time and provide suggestion for action

5.5.3 Utilisation of toolbox components

There has been **substantial progress in the Saarstahl use case** related to the installation of optical tracking sensory hardware onsite at the Saarstahl production facility, the implementation of integrational components that allow the interoperability of the optical tracking system described in the Use-Case with Saarstahl production planning systems, and the photogrammetric capturing of the Saarstahl production plant to form a generative 3D model allowing the creation of training data for a tracking system.

A **technical issue** for the Use-Case is that from the realizable camera angles, the rolled bars cannot be separated optically. This means that rolled bars overlap in the image. A consequence is that the envisioned software architecture consisting of a neural network for the semantic segmentation (i.e. pixel-wise labelling) of rolled bars, followed by a manually programmed component for the linking of bars to sequences, will not work. The reason is that for overlapping bars, a semantic segmentation will lose the information that the two objects are separate bars – information that cannot be retrieved later. Rather than using this two-component approach, we will need to shift more responsibility to the machine learning system by using either a network from the class of multi-object detection and localization networks, or instance segmentation networks. Multi-object detection and localization networks means that the output of the network is a list of objects, each specified by a label and a bounding box. The technology is well understood and mature, but is likely to encounter problems with the very elongated shape of the rolled bars, which will lead to a very high degree of overlap between the bounding boxes. Instance segmentation means that the output of the network is a label per pixel (as for semantic segmentation), but different instances of the same object class are recognized and receive separate labels. The technology is more promising for very elongated objects, but in general is less mature and less understood, leading to a higher development risk and effort. A consequence for the toolbox components is that Neuroscope will be extended for support of the respective network types. By the end of the project Saarstahl has taken over the results for the further customisation and deployment of this through an internally funded project for the fall of 2023 and spring of 2024.
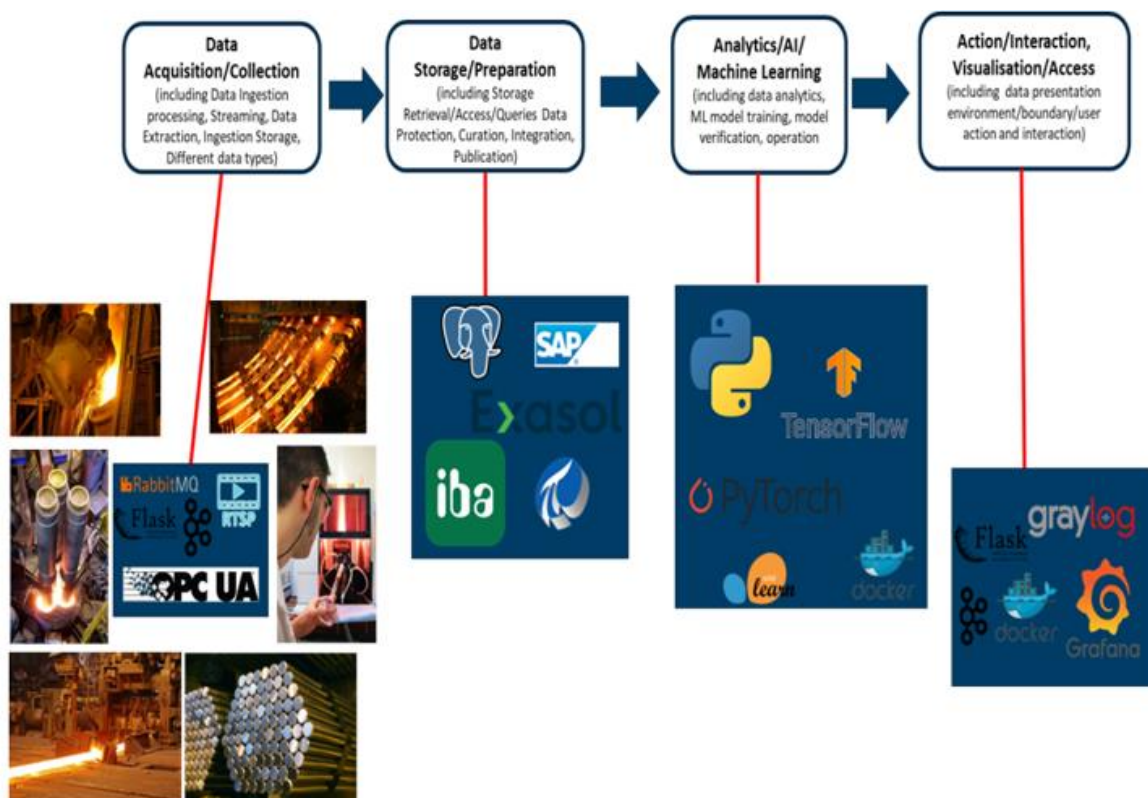
Figure 7: Illustration of the Saarstahl pilot pipeline

5.6   SIDENOR Pilot

5.6.1 User requirements specification and user stories

5.6.1.1   Background

The steel production in the melting shop process is based on three main steps. The first one lies in obtaining the liquid steel by melting iron ore (blast furnace, BF) or scrap (electrical arc furnace, EAF or induction furnace). The second step (Secondary Metallurgy, SM) is necessary for refining the liquid steel, and the last one solidifies the steel during ingot or continuous casting processes.

The steel industry uses the ladles, which are cylindrical or tapered vessels, for processing and transport the liquid steel. Once the liquid steel is produced in the furnace, it has to be stored and the steel makers use the ladles for this purpose. Depending on the steelmaker, the ladle can contain from tens to hundreds of tons of liquid steel.

Most ladles have installed a porous plug at the bottom. It is responsible of the liquid steel stirring, which is obtained by the injection of Ar or N_2 through it. The rising flow of the liquid steel promotes the inclusion decantation from the steel to the slag and homogenizes the temperature and chemical composition.

The main objective of the SM is to obtain the correct chemical composition and have enough temperature for the casting process. In addition, there are several important tasks which must be complete during the SM, as for example inclusion and gases removal. In order to reach these objectives, Sidenor has a SM mill consisting of two Ladle Furnaces (LF) and a Vacuum Degasser (VD). Each of the LFs have three electrodes, which are responsible of heating the slag, steel and ferro-additions. The ladle contains the steel and the slag for all the production process from the EAF to the end of the casting process. The liquid steel has a temperature of around 1700 K in the ladle, and it is covered with slag. The slag avoids the contact between the steel and the atmosphere, has lower density than steel and consists basically of lime and oxide elements. The slag conditioning can be improved during the SM by adding slag-formers.

In order to store the liquid steel and slag with such high temperature, the ladle is built with a strong outer steel shell and with an inside covered with layers of insulating materials (refractory). The refractory is made of ceramics and its most important properties are:

-          handle the high temperature
-          favourable thermal properties
-          high resistance against erosion when in contact with steel and slag

The inner layer of refractory bricks, which are in contact with the liquid steel, are eroded by the interaction with the hot metal and the slag. The bricks are worn away by each heat, and after several heats they are so eroded that it is not safe to use the ladle one more time/heat. The refractory is visually checked after each heat and depending on its state, the ladle may be used one more heat, put aside for repair or demolished. In case of repair, the upper bricks of the ladle, which are more eroded will be replaced by new ones. Once the ladle is repaired, it is taken back into production. Later, based on continuing visual inspection, the ladle may be deemed ready for demolition. In this case the entire inner lining is removed and relined with new bricks.

One important goal for Sidenor is to reduce the refractory costs by finding new methods for extending the refractory life. One of the key points is to use the same ladle during more heats without compromising the safety, but another important issue is to understand better the mechanism that drives the refractory erosion, in order to avoid as much as possible the worst working practices and so to prolong the working life.

5.6.1.2   Initial status

The ladle refractory lifetimes vary a lot depending on many production parameters. Moreover, it is well known that if the ladle is not cyclically working, and it is out of use for several hours or days, the lifetime is substantially reduced.

In a previous stage of the project, the use of 3D camera was considered for measuring the erosion distribution inside the ladle, but this approach was rejected due to economical and operational costs. On the other hand, analyzing thermal images from outside of the ladle was considered to be a good solution. This latter technique is being explored by the consortium, because it can match the results obtained from developed models with the experience of the operators, who analyzes the refractory situation, and takes into account the security, productivity and process parameters when using the tool.

5.6.1.3   Target for development

The main goal is to develop a model whose results can help to decide whether the ladle could be used one more time safely. The model should exploit both historic and current production data. The model added to the knowledge of the operators could be exploited and contribute to cognitive elements of the model.

In addition, the model should give information about which parameters dominates the ladle refractory erosion and give tips about which precautions may be taken to extend the refractory lifetime.

5.6.1.4   User stories

Table 25: Use case Sidenor-UC-1

Use Case	Description
Use Case Name	Development of a physics-based model for ladle refractory wear
Use Case ID	Sidenor-UC-1
User story expression of use case	As a user, I want the model to deliver erosion states and wall temperatures so that this information can be used as input to other models or give a direct advice about if more use of the refractory is safe
Goal	Predict the temperatures and erosion state of the ladle refractory walls after N uses
Measurable KPIs for the goal (if any)	Enable one more safe use of the refractory, compared to pure human assessment
Actors and stakeholders involved	Sidenor personnel: End user Nissatech personnel: Integrate the model into StreamPipes application, hybrid modelling

	SINTEF personnel: Developers, hybrid modelling
Input data	Data provided as *.xlsx and *.csv files
Output data / actions	Output data, provided as *.xlsx and *.csv files and plots from Python (screen or *.png to file)
Summary description – Main success scenario	To be explained in paper on the PPBM method.
Extensions, exceptions, variations	Model has multiple simplifications, but also the potential to be improved where necessary.
Possible generalisation of use case	The model can be extended to any ladle process which involves refractory challenges and metal refining.
Use case analysis – related to which Digital Twin pipeline steps	This use case will be supported through the following Digital Twin pipeline steps: Digital Twin Data Acquisition, Digital Twin Representation, Hybrid/Cognitive Digital Twin Generation, Digital Twin Visualization and Advice

5.6.2 Final status and resolved challenges

As the model development progressed it became clear that a more direct way was needed to push data from Sidenor to the development team. Data was then pushed to an SFTP server, and then organized in a database at Nissatech. The input part of the PPBM-model was adapted to read from the database, such that it can operate continuously in data that is coming from the production. Measured temperatures from the upstream Electric Arc Furnace (EAF) was provided due to needs for having initial data for the PPBM model and was clarified earlier. The model is now using an optimization scheme to find the initial steel temperature if reliable data is not available. The result is satisfactory predictions of the steel temperature evolution during the heats.

During the COGNITWIN consortium M36 meeting in Bilbao in October 2021 it was noticed that the agitation in the steel is extremely powerful during simultaneous gas purging and vacuum treatment. Consequently, CFD calculations were performed that incorporates the physical effects of vacuum treatment. This effect was previously deemed less important. The result is that the model now predicts considerably larger erosion rates during times with vacuum treatment.

The data that was provided on detailed erosion distribution, at time of repair and at time of demolition, has now been red and used to tune the model and for model validation.

The model has been applied to simulate the entire lifespan all ladles and heats operated in 2019. The PPBM-model is now simulating the temperature evolution in metal, slag and refractory, during time with metal, and then simulating the temperature in the refractory during waiting time for the next use. During time with metal the erosion is simulated. The erosion from the previous heat is input to the next heat. The model was slightly tuned to reproduce the erosion at the time of repair. At repair, the model is repaired in the same manner as the physical ladle. The mayor tuning constants now are the intergrain diffusion lengths for dissolution of carbon into the steel and the thermal conductivity of the MgOC lining bricks.

A general tuning strategy was developed, but it was not applied in its general form. The challenge here may be quite typical for this type of industrial application:

i)   A very important input to the model is the steel mass in the ladle. The steel mass is not feasible to measure directly but is done downstream, by measuring the mass of steel that was casted through the casting machine. In cases with operational trouble the cast mass may deviate considerably from real mass of steel in the ladle. As a result, all steel mass below 110 tons was assumed to 110 tons.

ii)   The measurements of ladle corrosion-erosion are picking the most worn bricks at each height in the ladle. The variations along the ladle perimeter is therefore unknown. This knowledge would be crucial for detailed tuning of the model and for assessing the probabilistic accuracy of predictions.

The work has demonstrated the importance of the project development team having a very good understanding of the process. This is a prerequisite for building the best possible model. The Sidenor data is typical for this type of heavy industry and cannot be used directly without qualified pre-processing. It is therefore critical to have a close interaction with the pilot owner.

The Sidenor pilot case has been progressing as planned and model predictions underline the importance of operational parameters, such as duration of metal treatment, duration of vacuum application, gas injection and injection gas flow rate. The development team has built one physics-based model of the erosion process. The thermal part of this model indicated earlier that it might be possible to obtain a mapping of the internal erosion state of the ladle by combining a physics based model and thermal images of the outside wall of the ladle. Interesting, the physics-based model indicates that the steel is penetrating in-between refractory bricks and thereby increased the effective thermal conductivity of the refractory. This seems to be the only way to explain the thermal data. In addition, this is consistent with early ThermCam images that show that the ladle outside is hotter in the lower part where erosion, at least at the beginning heats, is less pronounced.

We have combined the methods mentioned above, to arrive at a hybrid twin that exploits the best of the different approaches. **Hybridization methods, based on StreamPipes, are developed to orchestrate the hybridization and the cognitive twin.**

The pilot challenges in the Sidenor pilot which relate to WP5 are summarized in Table 26 and Table 27. For more in-depth description of the data acquisition / collection challenges and solutions, we refer to deliverable D4.4

Table 26: Pilot challenges for Digital Hybrid and Cognitive Digital Twins for the Sidenor pilot

Analytics Models (Plant DT with ML/AI) (task 5.1) (by task 5.1)	• **Challenge**: Predict the maximum number of heats before demolition • **Requirement**: Exploit all the data that can be provided by Sidenor. Data quality must be assessed. The model must provide an answer, at the end of each heat: Is one more heat safe? • **Solution**: Arrive at the best ML/AI model that may explain the data, after normal cleaning.
Physical Models	• **Challenge**: Predict the thermal evolution and the degradation of the refractory and based on that, predict the maximum number of heats before demolition

	• **Requirement**: Model must be fast and tuneable to the available data. The model should qualitatively explain the relations that has been observed by operators. • **Solution**: Develop a python-based numerical model, based on all possible simplifications (PPBM method)
Machine Learning – + any needs for Deep Learning /imagery, Performance (tasks 5.2/5.3)	• **Challenge**: Interpret thermal images taken of the outside of the ladle • **Requirement**: Based on the images, tell if the ladle refractory on the inside have problems. • **Solution**: Combine predictions by the physics model with image analysis. This may indicate another special application, based on the PPBM-based model. •
Hybrid Digital Twins (by task 5.4)	• **Challenge**: Exploit the physics-based model and the data, to arrive at an improved model with improved prediction power. • **Requirement**: Model should be able to incorporate the physical elements that has not been considered by the physics-based model. • **Solution**: The ML/AI model may use the predictions from the physics-based model, together with other data that was not directly explored and arrive at an improved prediction.
Cognitive Digital Twins (by task 5.5)	• **Challenge**: Involve cognition into the pilot - *self learning and reactivity with operator interaction* • **Requirement**: The knowledge of operators must be acknowledged • **Solution**: Train the operators to work with the model and build confidence that the operators, based on model predictions, may make a correct decision.

Table 27: Pilot challenges for Digital Twin Visualisation and Control for the Sidenor pilot

2D, 3D/4D visualisation and Human interaction (including speech) (by task 5.1)	• **Challenge**: Visualization of the thermal and erosion state of the refractory • **Requirement**: Fast and simple • **Solution**: Combination of Paraview-based visualization and simple line plots to show the current refractory state, according to the model. This will be assessed by the operators
Control – system interaction (related also to autonomous Cognitive Twins) (by task 5.5)	No interaction with control system is planned

5.6.3 Utilisation of toolbox components

The toolbox elements, being developed and used in the pilot, are "Pragmatism in physics-based modelling" (PPBM), the " Hybrid model Designer for StreamPipes-based Toolbox ", " Set of adapters for StreamPipes-based Toolbox " and " Services for resolving tool wear / equipment degradation

problems in process industry". In addition, several classical machine-learning methods (Python libraries) have been applied.

An illustration of the Sidenor pilot hybrid digital twin pipeline is shown in Figure 8.
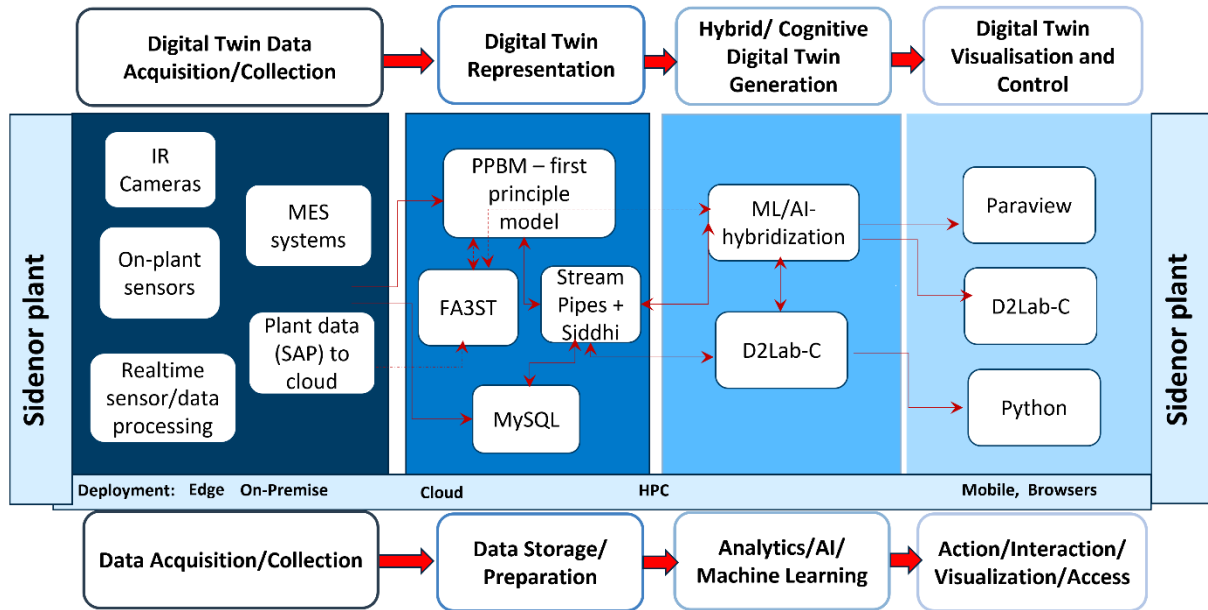
Figure 8: Utilisation of the toolbox components in the Sidenor pilot

6   Plant Digital Twins with ML/AI

A plant digital twin is a digital replica of the real plant. A modern digital twin gets is essential behavioural contents from a plant model, linking simulations with on-line data and various services such as data visualization and analytics, what-if analyses, or 3D plant animations. Currently, the huge potential of the digital twin technology is reflected in a better design of an asset, based on extensive simulations in various conditions. A model can be used for improving system dynamic behaviour, designing a model-based controller, or a state-estimator. Model-based fault detection and isolation, operator training simulators, or plant analysis as well as integrated plant and control design are other examples of applications requiring a proper dynamic process model.

The models can be very detailed and enable powerful simulations. In the heavy process industry, the models are often built based on physical considerations, tuned and complemented in various ways by data from experimental tests or normal operation. Task 5.1 aims to promote use of ML/AI methods suited for such problems and extend and/or develop new algorithms to further improve the performance of the control, monitoring, and maintenance systems.

6.1   Objectives, challenges, and components

Task 5.1 (T5.1) examines the role of simulation models and data to effectively model real-world assets. T5.1 identifies, selects, and extends/develops further ML/AI methods particularly suited to challenges of the process industry. Eventually, it will provide help and assistance for selection and parameterization of ML methods, as justified and illustrated by pilot case experimentation.

The state-of-the-art of the T5.1 methodology was described in the COGNITWIN WP5 M6 deliverable (D5.1) Sec. 4.2. The methods of analytics are developing in a fast pace, and much of the required infrastructure for sensor, data, and automation exists. However, due to the nature of the heavy process industry, the changes in the industrial practice can be slow. Discussion of these topics is emerging in the scientific community.

The heart of most ML/AI approaches is in learning from data. This poses serious challenges in the heavy process industry, which is typically characterized by slow processes, large size and complexity of plant installations, and heavy safety requirements, which prohibit approaches based heavily on exploratory data generation and testing. Plants are typically operated in production mode, which leads to the operation data not being rich in information. Therefore, the role of physical models is particularly pronounced. A significant challenge is to assess the feasibility of various proposed ML/AI approaches in the process engineering context.

T5.1 participates in providing components to the COGNITWIN toolbox, focusing on the full exploitation of physical plant models and ML/AI approaches in data-analytics and data-driven model tuning. The work in COGNITWIN associated with T5.1 largely originates from the development of solutions to pilot case problems. The case pilot problems were briefly described in Sec. 5, more extensive descriptions are given in the pilot work package deliverables (D1.4, D2.4 and D3.4). The role of T5.1 is to focus on the exploitation of physical modelling aspects on one side, and on data-driven techniques – such as ML/AI – on the other. The fusion of data and physical knowledge (hybridization) aspects are partially considered in T5.4 on hybrid digital twins and extended to human and cognitive aspects in T5.5. The work in T5.1 has been pilot-driven, in that the methods have been examined in solving the COGNITWIN

pilot case problems, and promising solutions have been generalized for extended use via the T5.1, to be cross-utilized in other COGNITWIN pilot cases or future process industry applications.

Table 28 and Table 29 summarize the challenges, requirements and solutions related to analytics models and machine learning models, respectively, for the six pilots. As this is a fundamental issue for all the pilots, several different challenges have been identified. A common thread for all the pilots is that large amounts of data are available, that can be utilized to develop models to aid operation. Visualisation of the data is another important aspect, and the challenges, requirements and solutions pertaining to visualisation are summarized in Table 30. In Table 31, we show the mapping between the toolbox components and the pilots for task 5.1.

Table 28: Analytics Models – challenges, requirements and solutions

Pilots	Analytics Models (Plant DT with ML/AI) (task 5.1) – Challenges, Requirements and Solutions
Hydro	• **Challenge**: Sensor measurements of HF is available for analytics • **Requirement**: Data-driven/machine learning approaches should give a good basis for analytics • **Solution**: Predictive analytics based on collected sensor data.
Elkem	• **Challenge**: Low correlation between measured variables and desired output. • **Requirement**: Accurate estimation of key variables used by physical model. • **Solution**: Utilize data from infrared cameras and physical model when training ML model
Saarstahl	• **Challenge**: • **Requirement**: Analytical modelling for matching DL detections over consecutive frames and different camera viewpoints. • **Solution**:
Noksel	• **Challenge**: Data cleaning and labelling • **Requirement**: Pre-processing for ML/DL for predictive maintenance • **Solution**: Industrial Big Data Processing implementation • **Challenge**: The number of features is high • **Requirement**: Efficient ML models generation • **Solution**: PCA on data • **Challenge**: Difficulty in analysis due to high volume of data • **Requirement**: Efficiency and performance • **Solution**: Pandas Profiling is used
Sidenor	• **Challenge**: Predict the maximum number of heats before demolition

	• **Requirement**: Exploit all the data that can be provided by Sidenor. Data quality must be assessed. The model must provide an answer, at the end of each heat: Is one more heat safe? • **Solution**: Arrive at the best ML/AI model that may explain the data, after normal cleaning.
Sumitomo SHI FW	• **Challenge**: Physical models can be slow to evaluate for on-line use. • **Requirement**: Means for model simplification and tuning are needed. • **Solution**: Development of suitable tools. Toolbox components: FUSE/PMFIR, FouMon/HX model.

Table 29: Machine learning – challenges, requirements and solutions

Pilots	Machine Learning – + any needs for Deep Learning /imagery, Performance (tasks 5.2/5.3) – Challenges, Requirements and Solutions
Hydro	• **Challenge**: Quality of vital sensor measurements (HF) is difficult to assess • **Requirement**: Data-driven/machine learning approaches should give a safe, secure result such as to ensure best online operation of the hybrid Digital Twin • **Solution**: Anomaly detection algorithms are carefully tested and validated offline
Elkem	• **Challenge**: Machine vision algorithms are difficult to develop for every scenario due to moving equipment and a harsh environment • **Requirement**: Data-driven/machine learning approaches should give a safe, secure result such as to ensure best online operation of the hybrid Digital Twin • **Solution**: Automatic detection of regions of interest in images of moving equipment.
Saarstahl	• **Challenge**: Need to analyse video imagery in order to understand the movement of billets • **Requirement**: Need to generate training data for Deep Learning Neural Networks in specified quality and composition using aerial photogrammetry . • **Solution**: A visual debugger for neural networks Neuroscope with use of aerial photogrammetry
Noksel	• **Challenge**: Algorithms did not learn very well on the collected data set • **Requirement**: Quality ML models trained • **Solution**: A thorough analysis was conducted and feature selection is applied • **Challenge**: Missing data • **Requirement**: ML/DL model training for predictive maintenance • **Solution**: Synthetic data generation and data balanced sampling

Sidenor	• **Challenge**: Interpret thermal images taken of the outside of the ladle • **Requirement**: Based on the images, tell if the ladle refractory on the inside have problems. • **Solution**: Combine predictions by the physics model with image analysis. This may indicate another special application, based on the PPBM-based model.
Sumitomo SHI FW	• **Challenge**: Fusion of physical models and process measurement data is complicated as data may be very sparse and models not accurate/detailed enough. • **Requirement**: Algorithms must survive with sparse data, and iterative computations can not be excessive. • **Solution**: Solutions will be sought by using up-to-date model-based state estimation techniques. Toolbox components: FUSE/UKF, FouMon/EnKF., SubFUSE, FouCon/Prony

Table 30: Visualisation and Human Interaction – challenges, requirements and solutions

Pilots	2D, 3D/4D visualisation and Human interaction (by task 5.1)
Hydro	• **Challenge**: Design of a new GUI for GTC operator support • **Requirement**: Operators need to be able to evaluate the reliability of digital twin solutions and read recommendations for optimal alumina flow control • **Solution**: Custom user interface to meet operator needs in Cybernetica Viewer
Elkem	• **Challenge**: It is difficult for the operator to act on recommendations from digital twin hybrid unless it is visualized • **Requirement**: Data from the decision support system needs to be made available in to the control room operator in an easy-to-act-upon, visual manner • **Solution**: Use Cybernetica Viewer to visualize data
Saarstahl	• **Challenge**: Suitable visualization for operators. • **Requirement**: tracking of billets must be accurate and in real-time • **Solution**: User preferred visual presentations in Neuroscope tool
Noksel	• **Challenge**: Slowness in big data visualization • **Requirement**: Latency < 200ms • **Solution**: View creations for zoom in and zoom outs, User preferred visual elements adjustments (i.e. color, light, etc.)
Sidenor	• **Challenge**: Visualization of the thermal and erosion state of the refractory • **Requirement**: Fast and simple • **Solution**: Combination of Paraview-based visualization and simple line plots to show the current refractory state, according to the model. This will be assessed by the operators
Sumitomo SHI FW	• **Challenge**: Suitable visualization for operators. • **Requirement**: Simple and illustrative

• **Solution**: Use technology developed by Sumitomo SHI FW • **Challenge**: Optimization tools require proper formulation and are highly dependent on the type of the problem. • **Requirement**: Automatic updating by pre-determined interval. High robustness of solutions is required, especially with automated actions without human decision-making. Obtaining of solutions (even suboptimal) should be ensured. • **Solution**: Careful selection of cost function vs. Solvers. • Toolbox components: FouCon is to include optimization

Table 31: Toolbox components per pilot used by task 5.1 Plant digital twins with ML/AI

			DFKI: Generation of photorealistic data	DFKI: Neuroscope	Nissatech D2Lab-C	Nissatech StreamPipes Sidifn-Processor	SINTEF: BEDROCK	TEKNOPAR: TIA DATA (TIA STREAM, TIA STORAGE, TIA CONTROL)	TEKNOPAR: TIA APPS (TIA MODEL, TIA PREMA)	TEKNOPAR: TIA UX (TIA DASHBOARD, TIA UX)	TEKNOPAR: TIA APPS (TIA ASP)	TEKNOPAR: TIA APPS (TIA DATA-GEN)	SINTEF Open Framework and Tools (SOFT)	Machine learning for hybrid models (SINTEF)	Pragmatic framework for development of hybrid models (SINTEF)	Cybernetica CENIT	Cybernetica Cognitive CENIT	Cybernetica ModelFit	Cybernetica RealSim	Cybernetica Viewer	Cybernetica Prosim	Cybernetica OPC UA Server	Bonzai (Scortex)	Como (Scortex)	Keras / tensorflow (Scortex)	Finite Markov Chains Matlab toolbox (MCPC) (UOULU)	SpinPro (Fraunhofer)	Weather API interface MAPI (SINTEF)	Correlation Analysis Toolbox (UOULU)	FUSE Fuel state estimation (UOULU)	SubFUSE Subspace identification and state estimation (UOULU)	FouMon Fouling monitoring (UOULU)	FouCon Fouling management and control (UOULU)	SINDIT (SINTEF)
Non-ferrous	Hydro	Plant Digital Twins with ML/AI						(x)								x	(x)	(x)	(x)			(x)								x				
	Elkem	Plant Digital Twins with ML/AI						(x)								x	(x)	x				(x)	(x)	x	x									
Steel	Saarstahl	Plant Digital Twins with ML/AI	x	x																			x	x	x									
	Sidenor	Plant Digital Twins with ML/AI						(x)		(x)						(x)	(x)	(x)	(x)															
	Noksel	Plant Digital Twins with ML/AI					(x)	x		(x)	x	(x)	(x)																					
Engineering	Sumitomo	Plant Digital Twins with ML/AI														(x)	(x)	(x)	(x)			(x)	(x)	(x)					x			x	(x)	

6.2 Detailed description of activities performed

The progress in task T5.1 on plant digital twins with machine learning and artificial intelligence until M18 was reported in the deliverable D5.2 and M19-M30 in D5.3. Here, a summary of all contributions up to M42 is provided.

6.2.1 Monitoring of fuel characteristics and fouling

The UOULU (University of Oulu, Intelligent Machines and Systems research unit) has largely focused on the Sumitomo SHI FW power plant pilot case problem (WP3). This case considers the monitoring and control/maintenance of heat exchange surface fouling.

As a component for solving the problem, a fuel characteristic estimator has been developed (the FUSE component), as well as a tool for tuning physical models (the PMFIR tool). The work then considered tools for on-line monitoring of fouling (FouMon component, including the physical modelling of a heat exchanger and it's use in model-based state estimation), to be followed by development of optimization tools (FouCon component). The tools emerge from solving the WP3 pilot case problem, but are intended and applicable for a much wider set of problems in the heavy process industry.

The development of the approach and methodology of FUSE (fuel state estimation) and PMFIR (physical model finite impulse response) tools were covered in deliverable D5.2. The main suggestion in PMFIR is to use dynamic tuning elements at the outputs of a physical model, which enables both the

application of robust parameter estimation ML techniques and availability of the original physical model results (see Fig. 9<mark>Error! Reference source not found.</mark>). The FUSE component then implements estimation of uncertain inputs via unscented Kalman filter, an implementation of Bayesian state estimation using simulations from the tuned physical model.

The PMFIR methodological outputs have been published in journal paper (Ikonen & Selek, 2021). The paper provides a more thorough examination of the capabilities of the PMFIR approach, and also extends comparison of the approach from finite state Markov chains to multilayer sigmoid neural networks time series. An application to state estimation using UKF (unscented Kalman filtering) is also provided.
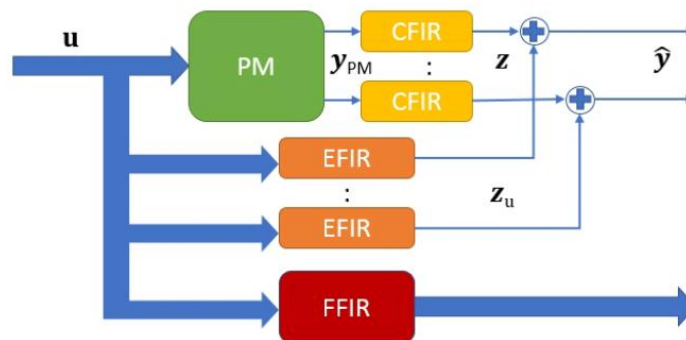
Figure 9: The PMFIR approach

The PMFIR principle of tuning physical model outputs was applied for the WP3 pilot problem. In the considered case (at pilot sister plant), the fuel feed consisted of fractions of demolition wood, peat and woodchips. Using the tuned model, the fractions were estimated on-line using the FUSE-tool (described in more detail in D3.2). The FUSE method was then applied to the actual WP3 pilot plant. However, the operation mode of the WP3 pilot was different from that of the sister plant and the validation of the estimation of fuel characteristics was left incomplete. In conclusion, the FUSE approach was judged as successful, though potentially not feasible with the pilot due to the current operating practices of the pilot plant.

The FUSE-component and the examined method/procedure is expected to be applicable for other input/parameter/state estimation problems as well. A generalized FUSE UKF-tool has been provided for the COGNITWIN toolbox, providing a flexible implementation for the UKF state estimation using a physical plant model. An alternative EnKF state estimation tool is also provided. The PMFIR tool algorithms have been published in detail, and a Matlab tool is available for download.

A parallel SubFUSE component has been developed in view of the WP3 pilot problem. The SubFUSE focuses on data-driven process identification using subspace techniques, as an alternative to physical modeling. The solution for the state estimation problem is then simple and computationally much more affordable. The SubFUSE approach was published in a meeting paper in 2021 (Neuvonen, Selek, & Ikonen, 2021)[OBJ].

The model-based state estimation requires a physical model of the plant. In order to solve the fouling monitoring and control problem, a physical model of a heat exchanger was constructed, considering the main phenomena between flue gas and the water-steam system. The heat exchanger model can be used for simulation of other heat exchangers as well, given proper dimension, medium, and material data.
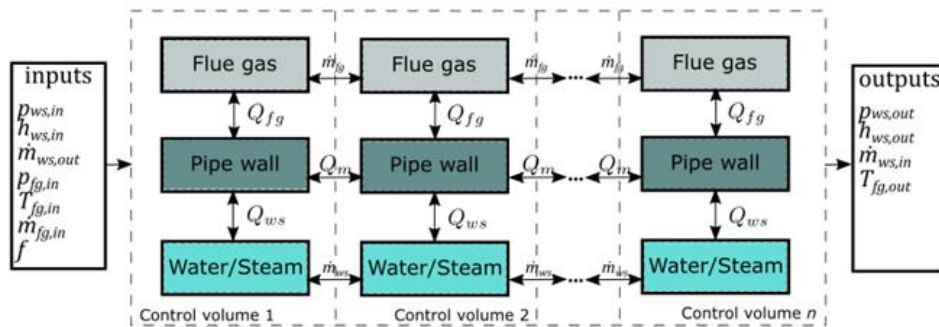
Figure 10. A heat exchanger model.

The methodology using nonlinear Bayesian state estimation tools as well as subspace identification and associated observer design tools, has been further developed and used to solve the WP3 pilot problem in fouling monitoring. The model-based tool palette is extended with ensemble Kalman filtering. This part of the work by UOULU is reported in task T5.4 (hybrid digital twins), as it involves more heavily also data-driven tools in addition to physical model-based. The further developments towards cognitive aspects are reported in task T5.5 (cognitive digital twins).

6.2.2 TEKNOPAR TIA PREMA

TEKNOPAR has focused on the NOKSEL pilot case of a metal sheet roller system of spiral welded pipes (SWP). The goal is to monitor the production process machine malfunctioning and enable predictive maintenance.

STEEL 4.0 Teknopar Machine Learning Library (TMLL) was renamed as TIA PREMA. TIA PREMA is being continuously developed for Task 5.1 and T5.2. A library of **ML/DL** (machine learning/ deep learning) algorithms has been created and tested. In TIA PREMA different machine learning algorithms are applied through the incremental PCA stage to detect anomalies. Prediction results are produced using different machine learning libraries. Both Spark MLlib and Keras were used. Spark MLlib is produced entirely by Spark, and uses Spark's engine optimized for largescale data processing. Keras library, that uses TensorFlow, is used for deep learning purposes. The Long Short-Term Memory (LSTM) algorithm of this library is utilized. This open-source neural network library makes it simpler to work with artificial neural networks through its user interface facilities and modular structure. The Scikit-Learn library is another open-source machine learning library that contains several algorithms for regression, classification, and clustering. We used algorithms like RF, GBT, LSTM, SVM, KNN, and multi-layer perceptron (MLP) from the Scikit-Learn library for data modelling and prediction. The trained algorithms have been compared in predictive maintenance.

The TIA PREMA and TIA UX tools are described in the component/tool template in the Appendix.

6.2.3 Predicting the Slag Generated in the Furnace and Measured After Tapping

SINTEF Digital used machine learning models for predicting the slag generated in the furnace and measured after tapping, in the Elkem pilot in WP1. The input time series data are measurements from the furnace, materials added, and post tap hole measurements from previous tappings. Several machine learning models were evaluated and compared, including support vector machines, a k-nearest neighbour algorithm, and ensembles of decision trees. The results from testing these methods have proved useful in getting a better understanding of the underlying process, e.g. with respect to parameter importance. Still, neural network-based models outperformed the other models. The best results have been obtained from models which take sequences of data as input. A model consisting of one convolution layer followed by three LSTM layers have been trained on filtered data to predict the trend in slag measurements. Many sequence models have been tested, but all give similar or worse results compared to LSTM models. Even if the current models show some predictive abilities, their results are still quite unreliable. This makes it difficult to tune models and compare similar results. Further development on the model is on hold, awaiting data from the tap camera recently installed in Bremanger. This will be analyzed and implemented into the model. The new model will then be evaluated, and further improvements rely on a cooperative and iterative process; by analyzing and discussing the results of the current best models, more insight into the process might help in the tuning of the models.

The status of BedRock tool is given in Chapter 9.2.2.2, and is explained in the Appendix of COGNITWIN report "D5.1 Baseline Hybrid AI and Cognitive Twin Toolbox[3]".

6.2.4 Estimation Technique for Parameters of the First-Principles Models

Cybernetica is applying a recursive estimation techniques to estimate parameters and states of the first-principles models of the Elkem ferrosilicon refining pilot and the Hydro Gas Treatment Centre (GTC) pilot. The physical models are formulated as a nonlinear state-space model, which typically includes an integration from one sample time to the next. Some of the parameters are quite uncertain and vary with time in a manner that is difficult to model. The interfacial area between slag and metal is one such parameter in the Elkem model, as it varies due to complex fluid dynamics which is unsuitable for modelling in a real-time application. This parameter is important for calculating the rate of the reactions taking place at the slag metal interface and thus affects the composition of the metal. In order to estimate this parameter using the available measurements online, the state vector is augmented with the parameter vector and the model is extended with a data-driven noise model. Applying a recursive estimation algorithm to this extended model, such as a Kalman Filter or a Moving Horizon Estimator, allows us to estimate uncertain parameters online. Great care has to be taken when choosing which parameters to estimate online, and combining the knowledge of which parameters are uncertain from a physical point of view, together with the knowledge of which parameters the model is most sensitive to has proven powerful in previous applications.

6.3   Progress beyond State of the Art or State of the Practice

A number of physical models and ML/AI methods have been developed/applied in solving the COGNITWIN pilot case problems. The LSTM recurrent neural network approach has been found applicable in several pilots. The novel methods of model-based state estimation have been considered

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[3] Public reports (sintef.no)

as very promising and feasible approaches in the fusion of physical models with plant data in solving the pilot case problems.

Development and execution of detailed physical models require a specialized software. Typical data storage/communication platforms do not support established ways of representing and solving standard physical model forms, such as ordinary/partial differential equations. Highly sophisticated physical modelling tools do exist, however, such as Matlab (including Simulink and Simscape), CENIT, and others, used in the COGNITWIN. A digital twin requires a means for connecting to external tools. Following the basic principle of WP4 interoperating toolbox, this connection has been developed using e.g. OPC-UA and MQTT services for data transfer.

The significant lesson learned from the applied work is the importance of fusing physical modelling with plant data. This has been experienced in several (if not all) pilots, where it has been observed that the operation data history is of limited range. In the development of plant operation optimization and control, the models need to cover areas not typically visited by the plant (as the optimization is likely to change the operation point). A similar problem appears in maintenance/fault detection and isolation in data-driven modelling of rare events. Therefore, data-driven approaches alone are not sufficient. Digital twin provides a tool for a fusion of data and models. A general approach for physical process model tuning based on plant data has been proposed. In an alternative approach, the physical model has been used to generate complementing data for ML/AI learning.

6.4   Summary of the key achievements

Since M30, much of the work has already moved from plant digital twins with ML/AI (T5.1) to hybrid digital twins (T5.4) and towards cognitive digital twins (T5.5).

Papers on the COGNITWIN T5.1 outcomes were published in a scientific journal and in a scientific conferences.

- Ikonen, E. and I. Selek (2021) Fusing Physical Process Models with Measurement Data Using FIR Calibration. *Control Engineering and Applied Informatics*, 23 (2), 67-76.

- Ikonen, E., M. Neuvonen, I. Selek, M. Salo and M. Liukkonen (2022). On-line estimation of circulating fluidized bed boiler fuel composition. *13th UK Automatic Control Council* (UKACC) International Conference (CONTROL2022), 22–24 April 2022, Plymouth, UK. DOI: 10.1109/Control55989.2022.9781460

- Neuvonen, M., I. Selek and E. Ikonen (2021) Estimating Fuel Characteristics from Simulated Circulating Fluidized Bed Furnace Data. *Int. Conf. on Systems and Control* (ICSC'21), 24–26 Nov 2021, Caen, France, 2021, pp. 107–112.

- Ikonen. E and I. Selek (2020) Calibration of physical models with process data using FIR filtering. *The 2020 Australian and New Zealand Control Conference* (ANZCC 2020), 26-27 Nov 2020, Gold Coast, Australia.

- (Neuvonen, Selek, & Ikonen, 2021) (Ikonen & Selek, 2021)

TEKNOPAR's publication which is a result of its WP5 related work, have been accepted for publication and presentation

- Seyithan Temel, Emre Ummak, Abdülkadir Tokgöz, Furkan Işık, Özlem Albayrak, Perin Ünal, and Murat Özbayoğlu (2022) Control System Design and Implementation Based on Big Data and Ontology, IEEE BigData 2022.

TEKNOPAR's publications which are associated with WP5 related work, are as follows:

- Selçuk, Ş. Y., Ünal, P., Albayrak, Ö., & Jomaa, M. (2021). A Workflow for Synthetic Data Generation and Predictive Maintenance for Vibration Data. *Multidisciplinary Digital Publishing Institute.*
- Temel, S., Ummak, E., Tokgöz, A., Işık, F., Albayrak, Ö., Ünal, P., & Özbayoğlu, M. (2022). Control System Design and Implementation Based on Big Data and Ontology. Osaka, Japan.
- Ünal, A. F., Kaleli, A. Y., Ummak, E., & Albayrak, Ö. (2021). A Comparison of State-of-the-Art MAchine Learning Algorithms on Fault Indication and Remaining Useful Life Determination by Yelemetry Data. *The 8th Interhational Conference on Future Internet of Things and Cloud (FiCloud 2021).*
- Ünal, P., Albayrak, Ö., Jomaa, M., & Berre, A. J. (2022). Data-Driven Artificial Intelligece and Predicitve Analytics for the Maintenance of Industrial Machinery with Hybrid and Cognitive Digital Twins. In *Technologies and Applicatipns for Big Data Values* (pp. 299-320). Springer.
- Deveci, B. U., Çeltikoğlu, M., Albayrak, Ö., Ünal, P., & Kırcı, P. (2023). Transfer Learning Enabled Bearing Fault Detection Methods Based on Image Representaions. *Information Systems Frontiers.*
- Deveci, B. U., Çeltikoğlu, M., Alp, T., Albayrak, Ö., Ünal, P., & Kırcı, P. (2021). A Comparison of Deep Transfer Learning Methods on Bearing Fault Detection., (p. The 8th International Conference on Future Internet of Things and Cloud (FiCloud 2021)).
- Kaleli, A. Y., Ünal, A. F., & Özer, S. (2022). Simultaneous Prediction of Remaining-Usedul-Life and Failute-Likelihood with GRU based Deep Netwroks fpr Predictive Maintenance. *The 44th International Conference onf Telecommunications and Signal Processing* (pp. 301-304). IEEE.

The following components tools in the COGNITWIN toolbox, were developed:

- FUSE-component (Fuel state estimation), with PMFIR and UKF tools.
- TIA MODEL machine learning library,
- TIA APPS (TIA STATISTICS, TIA METRICS,
- TIA UX industrial control panel and visualization (3D modelling and digital twin),
- Bedrock tool.
- FouMon (Fouling monitoring) /Heat exchanger model tool.

These tools/methods have been validated in at least one COGNITWIN pilot and are available for the development of applications in other pilots in the COGNITWIN toolbox. Video demonstrations are available, the tools are described in more detail in the appendix. Their applications are described in the associated pilot cases (D1.4-D3.4).

6.5 Conclusion

Task 5.1 focused on the use of physical modelling, visualization, and ML/AI related tools for solving problems in the heavy process industry. Some main conclusions can be drawn. (i) The computation times associated with solving physical models still remain an obstacle for fluent use for on-line monitoring and control. Modern methods of nonlinear model-based state estimation provide implementations requiring more economical amounts of simulations for the fusion of physical models with plant data. (ii) In many cases, the performance of physical models can be further improved by methods relying on external tuning based on data, not requiring excessive simulations. (iii) In many cases, the operational history data is limited. Good experiences were obtained from synthetic data generation for application of ML/AI learning techniques.

7 Multi-variate Sensor analytics with Deep Learning on Imagery

7.1 Objectives, challenges and components

The possibility to process multi-variate sensor data using Deep Learning will be crucial for the realization of hybrid AI and cognitive twins. While the extraordinary performance of Deep Learning systems to many classification and regression problems has been demonstrated in many contexts, key challenges remain. Their challenges are generally recognized to be: (1) high demand in compute power, (2) high demand in training data, and (3) difficulties in obtaining trustworthy results or even finding good technical explanations in cases when unintended system behaviour occurs. The generally high demand in compute power is less problematic for many applications in the process industry as high-performance hardware is readily available. For situations where latency is critical, we dedicate a specific task (Deep Learning Performance) to finding solutions. This task will therefore focus in the two remaining core problems of Deep Learning: the availability of training data and trustworthiness concerning explainability.

For the availability of training data, we will focus on the generation of training data using parametric models and sensor simulations, specifically on capturing of 3D information using **photogrammetry**. For improved explainability, we will adapt a visual debugger for neural networks called **Neuroscope** for the specific needs of the Use-Cases.

Table 32 summarizes the challenges, requirements and solutions related to machine learning for the six pilots. Common challenges for the pilots are the difficulty in analysing images, and the lack of good datasets. In Table 33, we show the mapping between the toolbox components and the pilots for task 5.2.

Table 32: Machine learning – challenges, requirements and solutions

Pilots	Machine Learning – + any needs for Deep Learning /imagery, Performance (tasks 5.2/5.3) – Challenges, Requirements and Solutions
Saarstahl	• **Challenge**: Need to analyse video imagery in order to understand the movement of billets • **Requirement**: Need to have effective training and use of Image analytics including aerial photogrammetry including use Deep Learning Neural Network. Analytical modelling for matching DL detections over consecutive frames and different camera viewpoints. • **Solution**: A visual debugger for neural networks Neuroscope with use of aerial photogrammetry
Noksel	• **Challenge**: Algorithms did not learn very well on the collected data set • **Requirement**: Quality ML models trained • **Solution**: A thorough analysis was conducted and feature selection is applied • **Challenge**: Missing data • **Requirement**: ML/DL model training for predictive maintenance • **Solution**: Synthetic data generation and data balanced sampling

Sidenor	• **Challenge**: Interpret thermal images taken of the outside of the ladle • **Requirement**: Based on the images, tell if the ladle refractory on the inside have problems. • **Solution**: Combine predictions by the physics model with image analysis. This may indicate another special application, based on the PPBM-based model.

Table 33: Toolbox components per pilot used by task 5.2 Multi-variate Sensor analytics with Deep Learning on Imagery

7.2 Detailed description of the activities performed

7.2.1 Neuroscope & Aerial Photogrammetric

DFKI have worked in improving two key components: a visual debugger for neural networks called Neuroscope and a process for the photogrammetric capturing of plant sites using aerial photogrammetry. A planned improvement for Neuroscope (integration of Explain-to-fix) was cancelled for technical reasons. The photogrammetric workflow was consolidated technically.

A detailed description of the activities can be found in the component descriptions for the toolbox components **photogrammetry** and **Neuroscope**, which are detailed in the Appendix.

Working closely with DFKI, Scortex has prepared an evaluation of the synthetic data processing approach using photogrammetry under high performance conditions using our technology.

7.2.2 LSTM deep learning algorithm

Focused on NOKSEL pilot, TEKNOPAR has conducted a LSTM deep learning algorithm. Multiple sources of sensor data (vibration, temperature, pressure, etc.) have been used and DL (deep learning) models have been applied. The Keras library, that uses TensorFlow, is used for deep learning purposes. The LSTM algorithm of this library is utilized. This open-source neural network library makes it simpler to work with artificial neural networks through its user interface facilities and modular structure.

TIA MODEL of TEKNOPAR is detailed in the Appendix.

7.3   Progress beyond State of the Art or State of the Practice

For Neuroscope, we have initially assumed our Use-Case would require semantic segmentation networks (i.e., output of the network is a class label per pixel). We have therefore adapted the methods for applicability to semantic segmentation problems (see last progress report).

From working with the Use-Case it became clear that semantic segmentation (label per pixel) output is insufficient, but instance segmentation output (multiple bounding boxes plus labels per pixel inside the bounding box) will be required. We have started to extend Neuroscope for the support of instance segmentation networks. The most relevant instance segmentation architectures consist of two stages. The first stage is a conventional multi object detection architecture that generates bounding boxes. The second stage extracts sub-images per bounding box and assigns labels. We have therefore started to implement object detection support first with the plan to extend this to instance segmentation later.

One promising method for visual decision explanations in object detection networks is called Explain-to-fix. We started to integrate explain-to-fix in Neuroscope. The attempt to integrate the method failed for technical reasons, though. As we found out during the development, Explain-to-fix heavily relies on modifications of the network under investigation, i.e. in order to perform the visualization, the investigated network needs to adapted. This collides with the basic idea of Neuroscope to load arbitrary networks (from a certain class of network architectures) and debug them. We investigated the possibility to automate the required modifications of the network but found that currently, the scientific understanding of the method is insufficient to facilitate such automation. We are in contact with the authors of Explain-to-fix and currently consider writing a joint proposal for basic research on the topic. However, for the purpose of COGNITWIN, this endeavor is out of scope. See the following references for further information on the subject (Gudovskiy, Hodgkinson, Yamaguchi, Ishii, & Tsukizawa, 2018) (Petsiuk, et al., 2020)

7.4   Summary of the key achievements

We have published a useable version of the software Neuroscope in version 1.0, available at: https://github.com/c3di/neuroscope.

We have published a manuscript describing the Neuroscope software (Schorr, Godarzi, Chen, & Dahmen, 2021)

We have also prepared and submitted a manuscript detailing the application of Photogrammetry in the context of the Saarstahl Use-Case (Schorr, Luschkova, & Dahmen, 2021)

We published the following journal article: Bilgin U. Deveci, Mert Çeltikoğlu, Özlem Albayrak, Perin Ünal and Pınar Kırcı, Transfer Learning Enabled Bearing Fault Detection Methods Based on Image Representations of Single-Dimensional Signals, Information Systems Frontiers, https://doi.org/10.1007/s10796-023-10371-z.

7.5 Conclusion

As a route forward, we have cancelled the work of integrating Explain-to-fix in Neurosope and started reviewing alternative techniques. The technique CRP derives from Explain-to-fix and inherits the problems with integration. The recently published method D-RISE [PET+20], however, seems promising. We investigated the integration of D-RISE into Neuroscope in order to achieve support for object detection networks, then instance segmentation networks.

8   Deep Learning Performance

8.1   Objectives, challenges, and components

The previous tasks "Multi-variate sensors analytics with deep learning"' is about the ability to train deep learning algorithms and achieve a good enough accuracy for a task. In order to be able to deploy such models in production, a specific focus has to be set on the pipeline performance in terms of inference time, memory used, compute resources needed, etc. This is especially true when it comes to Industry 4.0, where systems are deployed in the 3D world and have real time. For example, in the field of quality inspection, dozens of images of high resolution may be used to take a decision in real time. This means that standard architectures from the literature designed on the ImageNet dataset may be too slow to be used in practice. This task is about finding solutions which allow engineers to deploy state of the art deep learning algorithms in practice, in factories.

Table 34 shows the mapping between the toolbox components and the pilots for task 5.3.

Table 34: Toolbox components per pilot used by task 5.3 Deep Learning Performance

Pilot type	Pilot	Task	WPS Toolbox COMPONENTS			
	Hydro	Deep Learning Performance				
	Saarstahl	Deep Learning Performance	x x		x x x	
	Sidenor	Deep Learning Performance				
	Noksel	Deep Learning Performance				
	Sumitomo	Deep Learning Performance			(x) (x) (x)	

8.2   Detailed description of the activities performed

The work in the area of Deep Learning Performance was performed by COGNITWIN partner Scortex until month 30 in the project. Sadly the financial crisis related to COVID led to challenges and bankruptcy for Scortex and they ceased to continue their work in the project after that. See more in section 8.5 Conclusion.

The Keras2HLS tool that is responsible of converting a machine learning model into an FPGA compatible bitstream was improved to better allocate resources. Each machine learning layer can be understood as a step in a pipelined architecture. In a pipelined architecture, improving one step can't guarantee an improvement of the overall performances since each step occur once the previous one is done.

Considering a 3 steps pipeline with 50 ms of execution of each step, improving only the second step to allow it to run at 1 ms doesn't improve the overall throughput since the step 2 will wait the step 1 to be done, before being able to compute net data. In a general manner, a simple pipeline throughput is computed by the number of step * the slower step time to execute.

The improvement in progress on Keras2HLS allows to better analyse each machine learning model layer to dedicate the amount of FPGA resources needed to allow computing in a coherent speed considering the other steps of the pipeline.

In a machine learning model based on convolution, the first layers are dense and require a lot of computing capabilities compared to the latest layers. Then, the idea is to consumes more FPGA resources to compute the first layers and making them more parallelised and using less resources on latest layers while keeping an homogeneous computation time.

Scortex has experimented on several ways to solve the deployment issues. Because Scortex is a quality inspection company, it encounters the issue more often than other companies. Indeed, high resolution images are often required to detect very small defects.

The work in the second period follow up on the following work that was done in the first period:

Network architecture design: Architectures were specially designed to enable inference on high resolution images (from 1000x1000 pixels up to 2000x2500 pixels) using only one GPU or FPGA. These networks were trained and evaluated on Scortex datasets. The tasks of interest were supervised semantic segmentation / detection as well as anomaly detection.

Pruning of the network: Pruning strategies were implemented. Though this method helps lowering disk space and RAM/GPU memory constraints, it does not provide faster inference. We believe this will be the case as long as TensorFlow/Keras does not provide a better sparse tensor support.

Distillation: We successfully managed to transfer knowledge from a large network to a smaller one. The performance is not as good as the large model, but better than the performance of the smaller model trained on its own.

Inference graph optimization: We investigated "folding" Batch Normalization which provided 30% speed in inference time. Details can be found in Scortex blog:

https://scortex.io/batch-norm-folding-an-easy-way-to-improve-your-network-speed/

Quantization of networks: This is a necessary step in order to deploy networks on FPGA hardware (see task 4.4). We also work on a Keras2RTL component which enables converting a Keras model into something usable by the FPGA platform (see Honir, task 4.4)

Efficient inference pipeline: Scortex is currently working on an end-to-end library called "sensei" to acquire images, apply preprocessing and deep learning networks as well as post processing on top of them. This library supports asynchronous and parallel inference on GPU so that real time capabilities can be achieved in a robust fashion.

Scortex now uses its "bonzai" library to train models and its "sensei" library to deploy such models at its customers. Scortex is ready to scale the methodology to the use case partners who have need for fast deep learning technology.

TIA MODEL is used by TEKNOPAR for comparing the different machine learning models. While setting up a machine learning model, it is difficult to predict which model architecture will provide the best result. The parameters which affect the model architecture are called hyper-parameters. For each machine learning algorithm utilized, hyper-parameter tuning has been performed by first comparing the previously determined success criteria, and then selecting the best result combination by examining the results obtained through testing possible combinations of the hyper-parameters' values

in a certain range. For each ML algorithm used, additionally, various parameters - such as precision, recall, F1 score, error detection rate, total training time, total test time, average training time, Type 1 error, Type II error - were calculated and displayed to the user.

The user is offered a voting option to decide on the algorithm to use. The application enables users to select the machine learning model for a given set of data, and then compares the output using graphical elements. For developing and testing purposes, the AML Workshop dataset from Microsoft (AML data set) is used in TIA MODEL module. The Scikit-learn library has been used for Random Forest, Gradient Boosted Tree, MultiLayer Perceptron, Support Vector Machine, and K-Nearest Neighbors. For the LSTM, Keras has been used.

 TIA MODEL of TEKNOPAR is briefed in Appendix.

8.3   Progress beyond State of the Art or State of the Practice

The work done in period 1 by by Scortex on "Batch Norm Folding" has been published on its blog:

https://scortex.io/batch-norm-folding-an-easy-way-to-improve-your-network-speed/
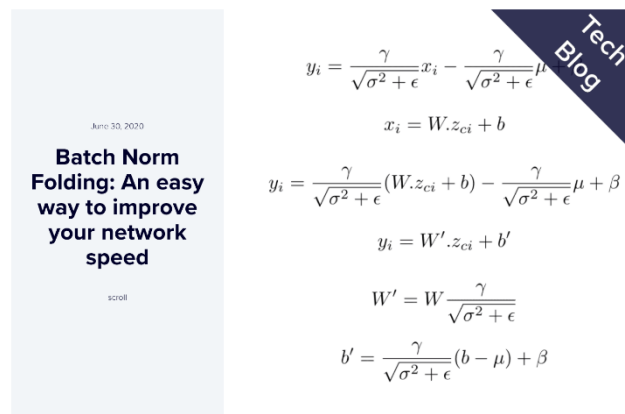
Figure 10: Tech blog entry of Scortex

It is now one of the most read articles on the subject. As of 2021/01/19, it has been read by 1683 different people according to Scortex website statistics. Readers came from recognized industry companies such as: Sony, Nokia, Daimler, AMD, Intel, Thales, Huawai, Zoom, ETH Zurich, Panasonic, etc.

By combining several ideas described above, Scortex managed to deploy a station able to perform a complex inspection of rotating parts. The Scortex box handles the inspection of 3 parts per second which requires inference of 300 (3 x 100) 1280x640 grayscale images per second. To the best of our knowledge, Scortex is the only company able to achieve such performances in a real-life deployment.

8.4   Summary of the key achievements

In the first period - Using Batch Norm Folding, we were able to reduce the inference time of light architectures by 30%. The work is summed up on Scortex blog:

https://scortex.io/batch-norm-folding-an-easy-way-to-improve-your-network-speed/.

We managed to design and quantize efficient architectures. Once deployed on FPGA, we can achieve 120 FPS (frames per second) on 1920x1200 RGB images. Deployed on 2 GPUS, we achieved 300 FPS on 1280x640 grayscale images.

In the second period there was a focus on continued development of the FPGA library to make it more versatile and more robust so that it could be easily used internally and externally. This work is mostly related to task 4.4 but does need some inputs from the task 5.3. The automatization of the conversion process of a topology and the weights from a neural network into a hardware designed platform will be done in the next steps (improvement of the Keras2RTL component). This will ease the use to the process and reduce the time needed to transition from a functional neural network design on computer to one running on an FPGA. Furhter work started to follow up on the use of very light architectures. Which can be an issue because of the lack of expressiveness and capacity they lead to. This is something that we have observed in practice. It is suggested to rework the architectures, typically using recent architecture blocks from the literature such as Efficient Net / efficient det MBconv, SE and SK blocks, or more generally the mechanism of attention (since we now have seen some transformers breakthrough for computer vision in 2021). Packaging and standardization work will be necessary to make the methods more "production-ready". Finally, these methods have been proven on internal datasets and could be tested and benchmarked on the pilot data, deep learning tasks, and network architectures.

8.5 Conclusion

The work in the area of Deep Learning Performance was performed by COGNITWIN partner Scortex until month 30 in the project. Sadly the financial crisis related to COVID led to challenges and bankruptcy for Scortex and they ceased to continue their work in the project after that. The results are still described here, as they are interesting as a conceptual basis for how deep learning performance might be enchanced through hardware support in the future. This is relevant for organisations that will consider high performance image processing.

9   Hybrid Digital Twins

9.1   Objectives, challenges and components

A Hybrid Digital Twin is an extension to the plant Digital Twin where the physics-based model is combined with data from the real process and one or more data driven models that adapts and corrects the Digital Twin such that it better represents its real-world counterpart.

A definition for a Hybrid Digital Twin as the second layer in a three-layered twin definition was given in (Abburu, et al., 2020):

"An extension of Digital Twin in which the isolated Digital Twin models are intertwined to recognize, forecast and communicate less optimal (but predictable) behaviour of the physical counterpart well before such behaviour occurs. A Hybrid Digital Twin integrates data from various sources (e.g., sensors, databases, simulations etc.) with the Digital Twin models, and applies AI analytics techniques to achieve higher predictive capabilities, while at the same time optimizing, monitoring, and controlling the behaviour of the physical asset. A Hybrid Digital Twin is typically materialized as a set of interconnected models, achieving symbiosis among the Digital Twin models."

The main goal of Task 5.4 has been to contribute to the CogniTwin toolbox with tools which support the creation, use, and exploitation of Hybrid Digital Twins. The tools originate from the development of twins in the pilots. Suitable elements have been identified and extracted from the pilot twins, generalized, and made available as components in the toolbox. Thereby they are available for later use in other processes.

The focus of the task has been on the following aspects:

- Enhancement of the digital twin technology by combining physics-based models with data driven models, including AI and machine learning functionality
- Development of soft sensing applications based on digital twins
- Development of advanced, predictive, and self-learning control applications based on digital twins

We have summarized the challenges, requirements and proposed solutions relating to hybrid digital twins in Table 35. In Table 36, we show the mapping between the toolbox components and the pilots for task 5.4.

Table 35: Hybrid Digital Twins – challenges, requirements and solutions

PIlots	Hybrid Digital Twins (by task 5.4) – Challenges, Requirements and Solutions
Hydro	**Challenge**: Combination of various data driven and Physical models require an approach for understanding the relationships between the various models **Requirement**: Ensure consistent mapping and relationship between data driven and physical models. **Solution**: Provide mappings between the data driven and physical models.

Elkem	• **Challenge**: Combination of various data-driven and physical models require an approach for understanding the relationships between the various models. • **Requirement**: Integration between data-driven and physical models and results from machine vision algorithms • **Solution**: Cybernetica OPC UA Server to make data available between the different applications
Saarstahl	• **Challenge**: Billet location needs to be known accurately for ML algorithms to be able to optimize the process • **Requirement**: Seamless billet tracking movement, constrained by physical environment • **Solution**: Instance segmentation technology is used to track the billets
Noksel	• **Challenge**: Missing models to be related to collected data • **Requirement**: 1st order model generation with data correlation • **Solution**: Models are generated in Matlab Simulink + data • **Challenge**: Big data set and complex data to train the model • **Requirement**: ML models quality need to be above a certain value • **Solution**:Undersampling has been applied to eliminate low quality data and increase model quality
Sidenor	• **Challenge**: Exploit the physics-based model and the data, to arrive at an improved model with improved prediction power. • **Requirement**: Model should be able to incorporate the physical elements that has not been considered by the physics-based model. • **Solution**: The ML/AI model may use the predictions from the physics-based model, together with other data that was not directly explored and arrive at an improved prediction.
Sumitomo SHI FW	• **Challenge**: Exploit physics-based models and plant data to arrive at an on-line model for fuel characterization and fouling monitoring. • **Requirement**: Need to combine physics-based model with online plant data in order to optimize boiler efficiency • **Solution**: FUSE: Apply a physical model for the CFB furnace (combustion, fluidization and heat transfer), a PMFIR tool for tuning the physical model with process historical data, and an unscented Kalman filter (UKF) tool for on-line state estimation of the uncertain input fuel fragments in the fuel. FouMon: Apply a heat exchanger model and an ensemble Kalman filter (EnKF) for online estimation of heat transfer coefficients.

Table 36: Toolbox components per pilot used by task 5.4 Hybrid Digital Twins

Pilot type	Pilot	Task	DFKI: Generation of photorealistic data	DFKI: Neuroscope	Nissatech: D2Lab-C	Nissatech: StreamPipes Siddhi-Processor	SINTEF: BEDROCK	TEKNOPAR: TIA DATA (TIA STREAM, TIA STORAGE, TIA CONTROL)	TEKNOPAR: TIA APPS (TIA MODEL, TIA PREMA)	TEKNOPAR: TIA UX (TIA DASHBOARD, TIA UX)	TEKNOPAR: TIA APPS (TIA ASP)	TEKNOPAR: TIA APPS (TIA DATA-GEN)	SINTEF: Open Framework and Tools (SOFT)	Machine learning for hybrid models (SINTEF)	Pragmatic framework for development of hybrid models (SINTEF)	Cybernetica CENIT	Cybernetica Cognitive CENIT	Cybernetica ModelFit	Cybernetica RealSim	Cybernetica Viewer	Cybernetica ProXim	Cybernetica OPC UA Server	Borzai (Scortex)	Como (Scortex)	Keras / zentoFlow (Scortex)	Finite Markov Chains Matlab toolbox (MCPC) (UOULU)	SpiriPro (Fraunhofer)	Weather API interface MAPI (SINTEF)	Correlation Analysis Toolbox (SINTEF)	FUSE Fuel state estimation (UOULU)	SubFUSE Subspace identification and state estimation (UOULU)	FouMon Fouling monitoring (UOULU)	FouCon Fouling management and control (UOULU)	SINDIT (SINTEF)
Hydro		Hybrid Digital Twins						(x)					(x)	(x)	(x)	x					x							x			(x)		(x)	
Elkem		Hybrid Digital Twins						(x)					(x)	(x)	(x)	x					x										(x)		(x)	
Saarstahl		Hybrid Digital Twins	x	x																														
Sidenor		Hybrid Digital Twins						(x)					(x)	(x)	x				(x)					(x)							(x)		(x)	
Noksel		Hybrid Digital Twins						(x)	x		x	x	(x)	(x)										(x)							(x)		(x)	
Sumitomo		Hybrid Digital Twins						(x)	(x)		x		(x)	(x)	(x)				(x)					(x)							(x)	x	x	

9.2   Detailed description of the activities performed

9.2.1 Methodological development

In the different pilots, hybrid digital twins have been built by combining physics-based models with data driven models in different ways. Different tools and different types of data driven models have been applied in the various pilots.

In several of the pilots, dynamical physics-based models have been developed. Such a model is, in principle, capable of tracking the behavior of the process in real-time given that it is correctly initialized and completely models the process. Neither of these conditions are normally fulfilled, so the models are combined with data driven models that reduce the uncertainty and improve the overall behavior of the model. An example of such a data driven model is an Extended Kalman Filter, which is an algorithm that use the difference between process measurements and estimated measurements from the physics-based model to update one or more parametric values that is used in the physics-based model, as shown in Figure 11:. This method is used by the Hydro, Elkem, Sumitomo SHI FW and Sidenor pilots.

Figure 11: Creating a hybrid digital twin by combining a physics-based model with a data driven parametric model updated by an Extended Kalman Filter.

Other pilots combine a physics-based model with a data driven model that is updated using machine learning or artificial intelligence. Calculation results from either model can then be used by the other model. This is used in the Sidenor, NOKSEL and Saarstahl pilots.
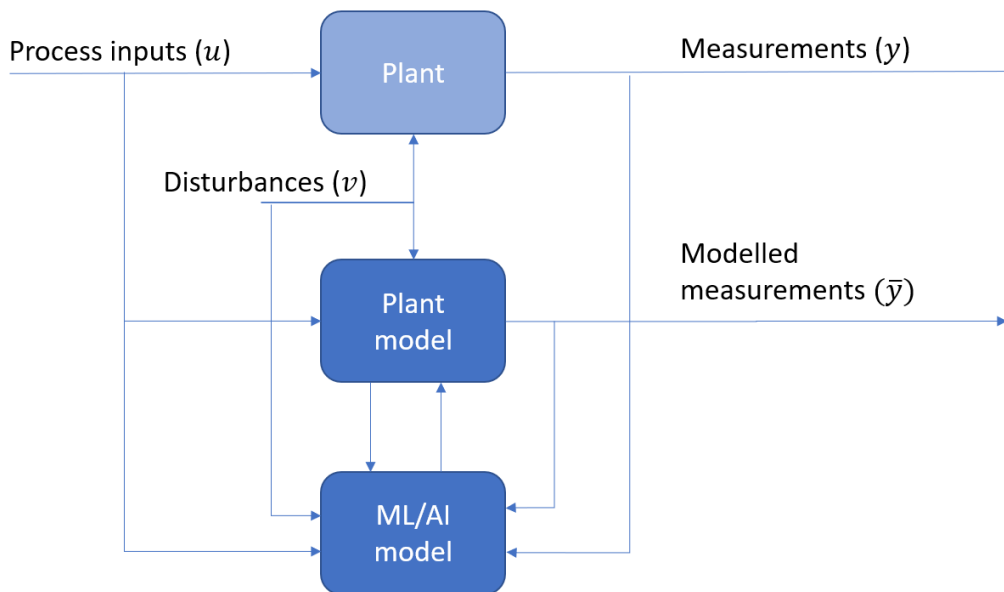

Figure 12: Creating a hybrid digital twin by combining a physics-based model with a data driven model updated by ML/AI methods.

In some of the pilots, both methods are planned to be used in combination (Figure 12:). This is the case in the Elkem, Hydro, Sidenor and Sumitomo SHI FW pilots.

The tools that support the different hybrid digital twins and are described in the next section.

9.2.2 Tools supporting hybrid digital twins

9.2.2.1   *Cybernetica CENIT*

Cybernetica's work has been focusing on the Elkem and Hydro pilot cases. A large part of the work effort has gone into building physics-based models for these two processes and to tune the model parameters such that the models replicate the physical processes as correctly as possible. The physics-based models for both pilots have been implemented as extensions to the tools Cybernetica CENIT, Modelfit, and RealSim. The extensions are in the form of application-specific modules and have been implemented in C/ C++ using a pre-made application component template. Cybernetica Modelfit has been used together with logged data from the processes for offline tuning of the model parameters, and the models now represent the processes quite well.

Cybernetica CENIT currently runs the models online for both the Elkem and Hydro pilots.

In the Hydro pilot the online model has been extended with a data-driven model that continuously adapts the physical model to the real process. Data is fed from the process via an OPC UA server, and in addition weather data is fetched from a public API by a specific component developed by SINTEF (described in deliverable D4.2). The implementation of the data-driven model enables both soft-sensing of unmeasurable variables in the process, as well as model predictive control. The models are currently running online, and model predictive control is ready to be tested. Currently the solution is

being tested with a "man-in-the-loop", where an operator manually transfers the advised controller action to the process once or twice per day.

For the Elkem model, there are so few online measurements that the data driven model could not be sufficiently updated from them. However, the process model is currently running online. It is used to produce advisory control using model predictive control, such that the product is within the specifications while at the same time maximizing the recycling of metal.

During the development phase, Cybernetica RealSim has been used as a plant replacement simulator for testing different scenarios with the twins.

The generic part of Cybernetica CENIT was extended with functionality for evaluation of the quality of both the input signals and its own calculation results. This functionality has been further refined and improved. In the case that invalid input or calculation results are detected, the application will send a notification of this via an OPC connection. Thus, the plant operators can be notified, and a proper fallback solution can automatically be activated. This extension forms an important foundation for adding more sophisticated error detection and self-examination algorithms, like the Cognitive CENIT extension.

9.2.2.2   Bedrock Toolbox

The Bedrock Toolbox by SINTEF has been developed to allow for fast configuration, scaling and orchestration of running applications. Installation, updates and monitoring of deployed docker container bundles are orchestrated from a central git repository using Ansible. This enables simultaneous remote orchestration of several instances on different servers, which is useful in several aspects, e.g. during implementation of updates on system prototypes operating on several plants at the same time.

Development activities regarding SINTEF in-house software modules in the framework, has since 2021 focused on further development of data workflow functionalities applying the OPC UA protocol. Figure 13: shows an example architecture for implementation of a digital twin with a process plant OPC server.
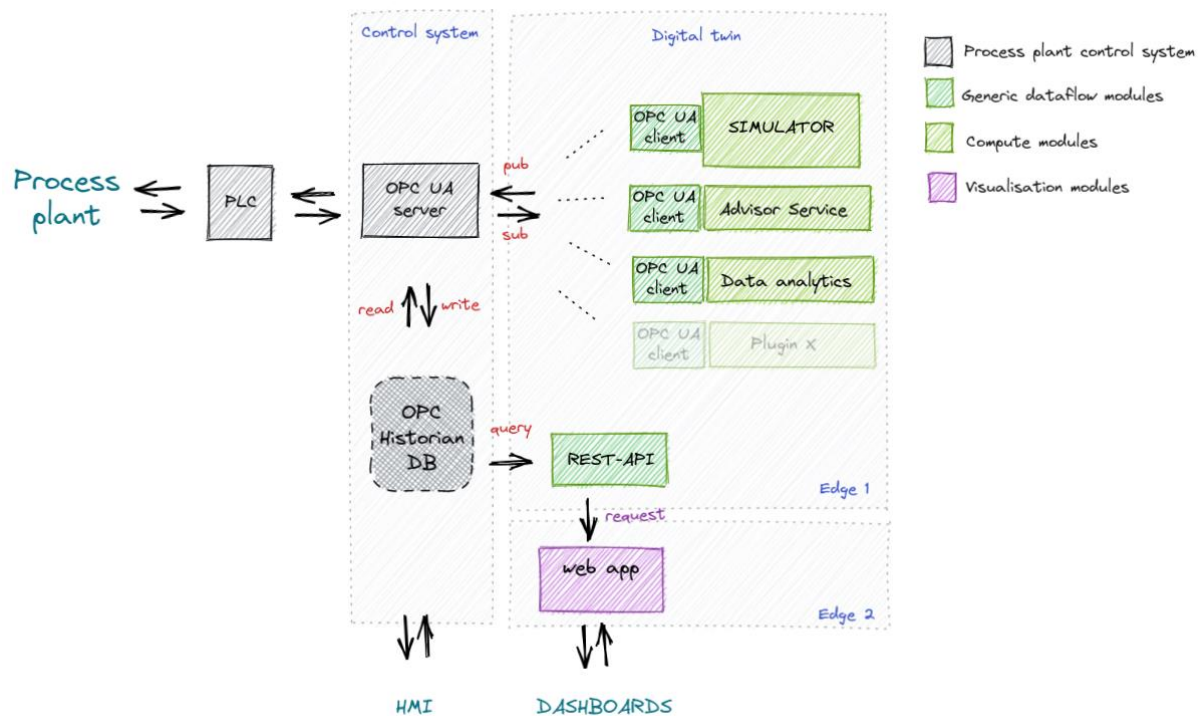
Figure 13: Data workflow architecture of BEDROCK application using the OPC UA protocol for implementation of a digital twin in a process plant control system.

In Figure 13:, the process plant OPC UA server is applied as message broker allowing for bidirectional communication of data between the process plant and the digital twin. All compute modules apply an OPC UA client submodule in order to read and write tag data in the central OPC UA server. This allows for flexibility and a modularized digital twin framework with all the modules able to read and write data and having access to both process plant data and data produced by different compute modules. New compute modules can easily be added to the framework in order to modularize different tasks and compute features.

The architecture above requires the establishment of new writable tags in the process plant OPC server for writing of simulated/calculated values or messages from the compute modules of the digital twin. During the development and testing phase, this can represent system administration and a potential challenge to the plant owners, and can worst-case introduce risk to the plant operation. Therefore, a further extension to the architecture has been developed in order to allow for deployments of digital twins that does not write setpoints or data to the plant OPC server. This solution applies 'read-only' functionality between the digital twin and process plant and does not write setpoints back to the plant control system. In this case, the digital twin framework has its own internal OPC UA server and OPC Historian database, allowing writing of calculated data, setpoints and messages from the compute modules into the framework dataflow while reading tags from the plant OPC UA server. This solution has allowed for quicker access to testing of frameworks on industrial plants in SINTEFs projects.
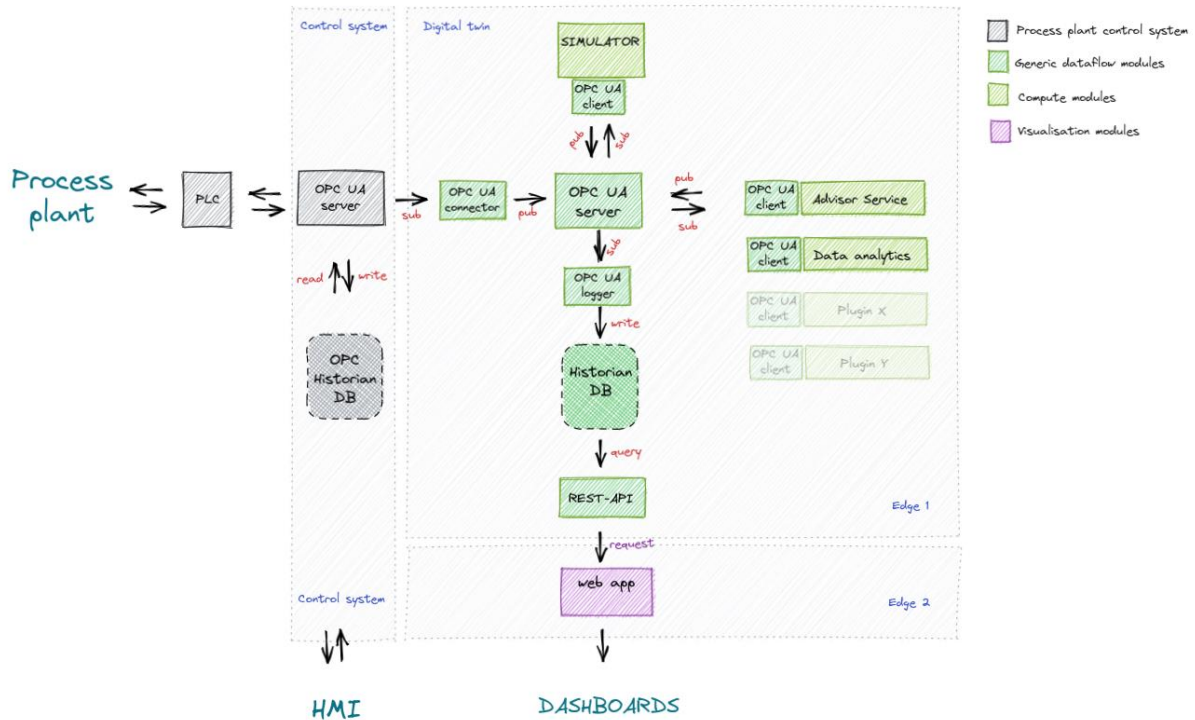
Figure 14: Data workflow architecture of BEDROCK application using the OPC UA protocol for implementation of a digital twin in a process control system with read-only permission from the plant OPC UA server.

This setup can be applied for process decision support, data analytics or predictions without writing setpoints back to the control system. Since it only requires permission to read data from the process plant OPC UA server, it does not risk interfering with the operating plant. This allows for easy testing and development of digital twins based on access to real data. The first step of implementing advanced process control with process setpoints written from a digital twin, can often be to start out with the implementation of a digital twin for decision support. Over time, decision support functionalities are validated based on experiences done with the system, the next step of implementation can then be to also allow for writing of setpoints to the plant control system, or implementing the architecture shown in Figure .

The OPC UA data workflow modules in BEDROCK are developed at SINTEF, and allow for flexibility due to no 'black-boxes' in the software. This is beneficial in the development and testing phase, but lacks industrial robustness. Since the OPC UA modules are based on a standard protocol (OPC UA), they can easily be replaced by commercial industrial OPC UA software upon final implementation.

These OPC UA data workflow modules of the framework can also be replaced or combined by other form of communication protocols, f.ex. MQTT or Kafka, depending on the data workflow needs and the data source applied. In this case, the modular approach of the BEDROCK toolbox allows for flexibility in the replacement or addition of new modules in the framework.

Data from the Sidenor pilot, currently present as Excel export files from the plant, will be imported and structured in a relational time series database. This will enable easy structuring of the data set for application in hybridization between physics-based models and machine learning. Implementing the

developed models in the above framework is possible but will not be done now as we will do this with StreamPipes.

9.2.2.3   *Pragmatism in physics-based modelling*

Pragmatism in physics-based modelling (PPBM) has been applied and further developed in the Sidenor pilot case. The industrial task is related to the lifetime of a ladle in the steel industry. A ladle is a container for liquid steel, typically filled with 100 – 180 tons of liquid steel. For each use of a ladle the refractory will be eroded and after N uses the ladle must be taken out of use in order to avoid serious accidents (more than 100 tons of extremely hot liquid steel, flowing out and onto the floor in the plant). The task is to find a method to extend the number N, without compromising with safety.

The PPBM process was applied to the above-mentioned industrial case. Based on access to offline data from the plant and multiple discussions with the pilot owner, a quite clear picture of the challenge could be formed. A physics-based model was proposed and implemented. The numerical implementation, written from scratch, has been done using Python 3. The model is aiming to predict the temperature evolution in the system (steel, slag, refractory) and the erosion evolution of the wear bricks of the refractory. A number of challenges have been faced due to the complexity of this task:

i) The model must be fast. Therefore, it is designed locally (at each height) to be one-dimensional through the refractory. Conservation equations for energy of metal, slag, and refractory (quasi 2D) are included, ii) A ladle is going through multiple operations for each use. This requires specific model boundary conditions for each part of the sequence, iii) The boundary conditions (energy and composition of dissolved species) are complex due to applications of gas-induced stirring, natural convection, radiation (only heat), and use of submerged electrodes in the slag, iv) The addition of alloying material and slag formers consume considerable heat. This necessitates an enthalpy-based description of the slag and metal that can handle heats of phase transition. Thermodynamic data is not readily available for such systems, v) The erosion of the refractory is driven by thermal shocks and dissolution of refractory when contacted by slag and metal. The solubility of refractory components into the slag and metal can only be obtained from thermodynamics software, built on lab experiments, vi) The mass transfer is depending on natural convection and forced convection due to application of gas (bubble) stirring. Both this and the additional impact of surface waves must be represented, and vii) In addition, there are processes that must be considered (waiting times between uses, use of burners and lids) and mistakes in the data input given by operators.

The model was demonstrated to be sufficiently fast, predicting the thermal evolution and erosion losses during the lifetime of the ladle, for all Sidenor ladles, during one complete year, to be finished in less than approximately one day. From the learnings, indicated by i) to vii) above, several general recommendations for improvements of the *PPBM* is extracted and documented for future application.

It was found that some transient data that is logged may not be relevant. By running the physics-based model the first temperature recorded for each ladle heat was deemed incorrect. It was later verified that this was true as this was a temperature that was sitting in the system from the previous heat. This would not be possible to detect with a pure ML/AI-approach. In addition, it was found that some heats with low reported tonnage was resulting in unreasonably large, predicted steel temperatures. It was then clarified that the steel mass data, as reported, could not be used as the reported mass was the tonnage of steel passed through the casting machines. Sometimes that cast was interrupted due to casting problems and non-cast steel was saved for later casting.

The model is currently predicting temperature evolution and refractory erosion due to mass transfer. During first tuning of the model against data, it was found that data could only be explained if the thermal conductivities in the wear bricks are significantly tuned. This indicates that steel is penetrating in between the bricks due to the large hydrostatic head of steel. This is further supported by thermal images which show that the higher outer steel shell temperatures are found at the lower part of the ladle where erosion during the first heats are low. This is in itself a significant contribution to the understanding of the phenomena the controls refractory behaviour and safe operations.

A strategy was developed to exploit all the available data and tune the model such that both temperature evolutions and refractory erosion can be exploited. The strategy involves several steps. This is one level of hybridization. In the second step, contributions to ladle life, which have not been explained by the physics-based model, is subject to direct ML modelling.

Due to the complexity of the modelling tasks, still significant simplifications were introduced. As we have been going through this process the learning were generalized and included into the *PPBM tool.*

Publication of results. The details of the learnings and recommendations for an improved PPBM tool will be published in a paper, dealing mainly with the methodology and the process for developing pragmatism-based physics models. In a second paper we will describe the physics-based model in full detail and show validation of the model against data. Details about these papers are found in Chapter 14.11 Pragmatism in physics-based modelling (PPBM).

The results from the model are shared at github.com (https://github.com/SINTEF/refractorywear). This includes source code and documentation. This code is available under the MIT open-source licence and can be reused for similar projects in the metals industry and other related industries.

9.2.2.4   FUSE and FouMon monitoring tools

The UOULU (University of Oulu, Intelligent Machines and Systems research unit) work has focused on the development of tools for modelling, monitoring, and control, driven by solving the Sumitomo SHI FW pilot problem in Work Package 3. The work involves physical modeling and model tuning (see WP5 task 1 on plant digital twins with ML/AI, reported in Section 6); model-based bayesian state estimation (task 4 on hybrid digital twins); and model reduction, on-line learning, optimization and descision making support based on these tools (task 5 on cognitive digital twins, Sec. 10). Model-based state estimation is an efficient means to hybridize the physical knowledge of process phenomena and measured data from the plant, to gain interpretable information from uncertain process quantities.

The FUSE component looks at solving the fuel state estimation problem, fusing a physics-based model for the boiler furnace with process data in stochastic nonlinear state estimation. The component is developed for the Sumitomo SHI FW pilot (see D3.2), using a dynamic physical model for a boiler furnace and data from the Sumitomo SHI FW pilot. Unscented Kalman filtering (UKF) is used for state estimation. The FUSE component contains an open access generalized UKF tool for the Matlab environment, providing an implementation of UKF with a possibility to flexibly use a physical model, select input/measurement signals, and pick states to estimate.

The FouMon component looks at solving the fouling monitoring state estimation problem, fusing a physics-based model for a heat exchanger (HX) with process data. The component is developed for the Sumitomo SHI FW pilot (see D3.3), using a dynamic physical model for a heat exchanger and data from the pilot. Ensemble Kalman filtering is used for state estimation. The FouMon component includes an

open access general-purpose implementation of the ensemble Kalman filter (EnKF) algorithm for the Matlab environment.

State estimation is model-based, it provides a means to fuse both model predictions and on-line process data. Figure 15 illustrates the concept used in both FUSE/UKF and FouMon/ENKF bayesian state estimation. A process model is run in parallel with the real plant. The information from the two sources is compared and used to adjust the estimates of the uncertain quantities. In fuel characterization, the mass flows of the input feed fuel fractions are unknown. In fouling management, the state of accumulation of deposits to heat exchange surfaces is uncertain, an estimate of heat transfer coefficient can be used as an indicator of the degree of fouling. In both cases, the process models are inaccurate and on-line data contains noise and errors, making fusion of information a tempting goal. In solving the fouling monitoring problem, the physical process knowledge was also used in the calculation of indexes, by refinement of process data information with known energy balances.
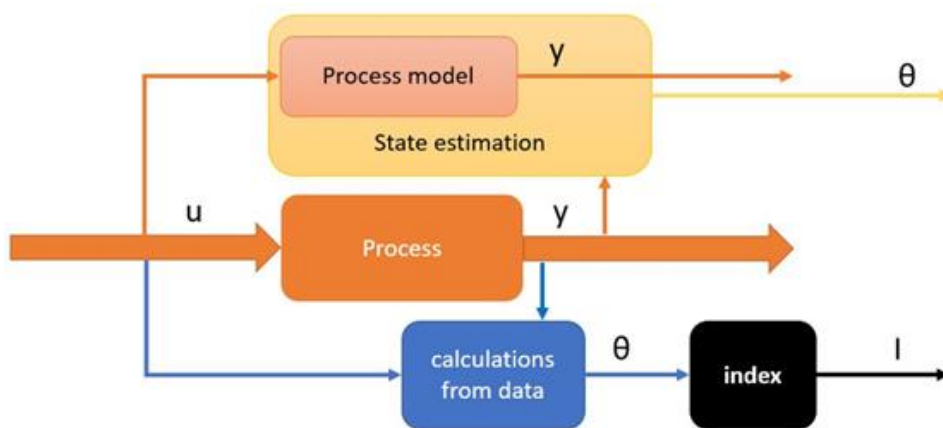

Figure 15: State estimation fuses information from process model and data.

A major problem in using physics-based models in state estimation is the computational effort required by solving the physical model equations and balances. Therefore, approaches that provide feasible estimation results with less simulations are valuable. Based on the pilot problem experiences, UKF and EnKF are implementations of bayesian state estimation that can provide reasonably accurate estimates, with a feasible number of simulations, in view of on-line applications. The computations remain resource consuming, though.

The considered state estimation algorithms are general-purpose in that they can be applied for solving many types of estimation problems. The construction of a process model can be time- and resource-consuming, however. Process identification approaches the problem from the perspective of data-driven construction of a plant model. Subspace identification looks for linear time-invariant (state-space) descriptions, for which computationally very efficient estimators can be developed, in the bayesian or non-bayesian context. These developments (SubFuse, FouCon/Prony) are discussed more in the context of cognitive DT.

Several papers reporting work on state estimation have been published from the work in COGNITWIN:
- Ikonen, E. and I. Selek (2021) Fusing Physical Process Models with Measurement Data Using FIR Calibration, Control Engineering and Applied Informatics, vol 23, nro 2, pp. 67-76.

- Ikonen, E. M. Neuvonen, I. Selek, M. Salo, M. Liukkonen (2022) On-line estimation of circulating fluidized bed boiler fuel composition. 2022 UKACC 13th International Conference on Control (CONTROL 2022), 20-22 April 2022, Plymouth, UK.
- Liukkonen, M., A. Kettunen, J. Miettinen, E. Ikonen, I. Selek, M. Neuvonen, A. Hansen and M. Edelborg (2022). Hybrid Modelling Approach to Optimize Fouling Management in a Circulating Fluidized Bed Boiler. Fluidized bed conversion conference 2022 (FBC24), 8–11 May 2022, Gothenburg.

Video demonstrations are available on the fuel characterization and fouling monitoring

- Estimation of power plant fuel characteristics. Estimation of power plant fuel characteristics - YouTube
- Fouling monitoring demo. Fouling monitor demo - YouTube
- Fouling management demonstration. SUMITOMO Pilot (Final COGNITWIN Demonstrator - D3.4) - YouTube as well as a video on the UOULU COGNITWIN tools, including FUSE/UKF and FouMon/EnKF. UOULU Toolbox components (Final COGNITWIN Demonstrator - D4.4 and D5.4) - YouTube

9.2.2.5   *Hybrid model designer for StreamPipes*

One of the most challenging tasks in the hybrid modelling is enabling an efficient creation of hybrid models, since it requires an efficient orchestration. We argue that StreamPipes is a very suitable framework for such a hybridization due to its pipeline-oriented nature.

This component uses these functionalities to support the creation of hybrid models.

In the following figure we illustrate the integration of two data-driven models (developed for the Sidenor pilot), whereas the output of one model is used as an input for the other model.
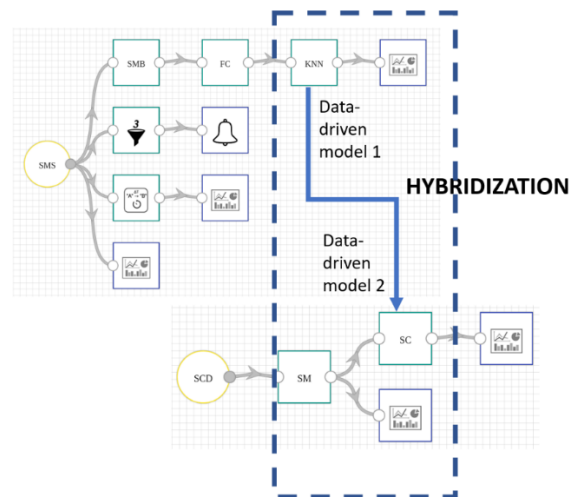

Figure 16: Integration of two data-driven models.

As shown in Figure 16:, the output of one model is used as an input for another model. There can be different ways of connecting and StreamPipes orchestration seems to be suitable for any meaningful combination of models.

9.2.2.6   *TIA DATA-GEN*

By combining two related models - a data driven-model and a (physics)-driven 1st order principal model - a hybrid digital twin has been generated. 1st order physics-driven models can be beneficial to the data-driven ones in many ways including but not limited to:

- Synthetic data generation in case of poor data: An example is training a machine learning pipeline for the predictive maintenance. Generally, when a machine is new, it does not have historical sensor data that can be used to train a data-driven approach. When carefully designed, the virtual physics-based twin can generate the needed supervised training dataset.

- Data-Driven Digital Twin quality control: When operating a critical infrastructure or asset, it is seen as a risky approach to fully rely on data-driven approaches in taking real-time decisions. To mitigate these risks, it is possible to build a control pipeline in which the physics-based model will be used as a controller to the data-driven predictor. A broker needs to be designed to integrate the two approaches in a seamless way.

Data-driven models can be used to continuously calibrate physics-based models. Machine degradation, wearing of parts, environment, and other factors impacts the overall process performance over time. The state of the practice is that an operator will manually recalibrate the control system when a deviation is identified. Such manual operation can be replaced by setting a data-driven model to identify and calibrate critical process variables that will be fed into a physics-based model, which in turn will optimize the control system of the process.

A hybrid digital twin for predictive maintenance of a component which is composed of electrical and mechanical elements has been generated. The hybrid twin includes the sensor installed on the machinery.

TIA DATA-GEN generates synthetic data from the 1st order model elements for common electro-mechanical parts, including an electric DC motor, a gearbox and a hydraulic press. TIA DATA-GEN works with MATLAB Simulink. Random realistic error sources are generated such as degradation of the components and measurement errors. The output of TIA DATA-GEN is a supervised and annotated dataset in .mat format .
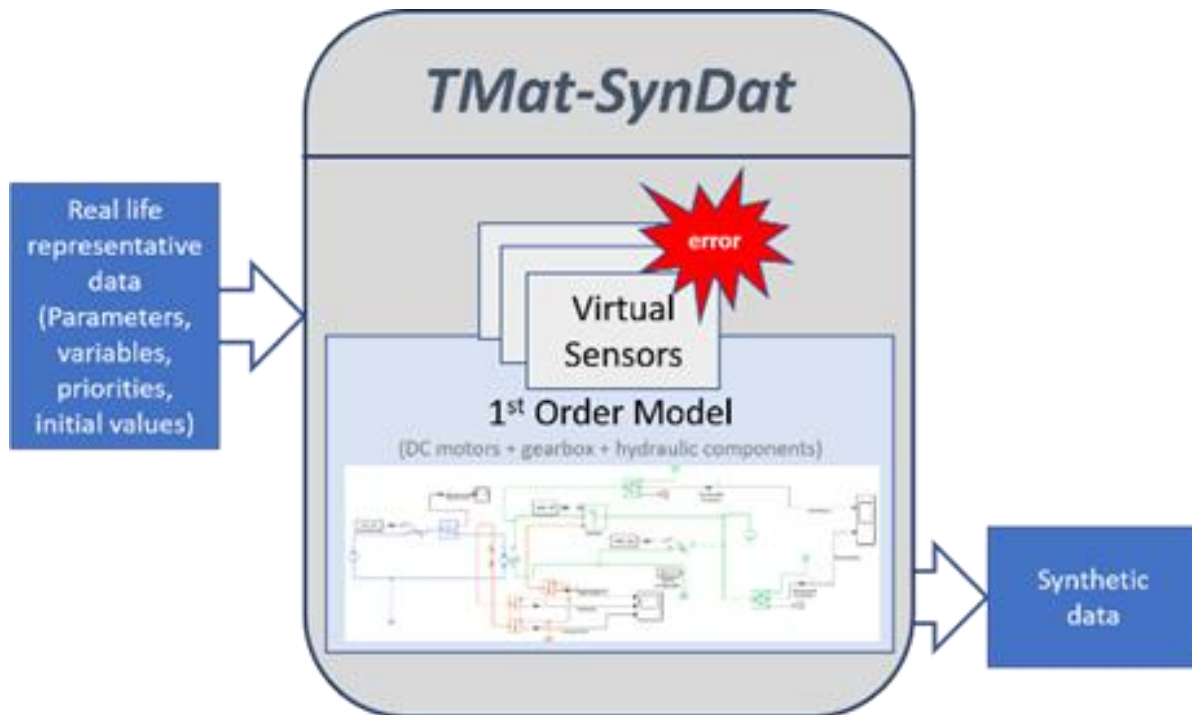
Figure 17: TIA DATA-GEN previously named as TMat-SynDat to generate synthetic data

9.2.2.7   *Hydraulic/Motor/Gearbox Models*

Physical hydraulic/motor/gearbox models for the plant have been developed. The models are developed/implemented using Matlab SimScape with the aim of predictive maintenance purposes. Model parameters have been calibrated and simulated. Potential failure scenarios have been identified and used in generation of synthetic data, used by ML/AI algorithms for predictive maintenance. The model is enriched with data retrieved from the experts.

Since the last milestone, sensors have been added to the 1st order principal models. Current and temperature sensors have been added to the motor and gearbox model, while a hydraulic press sensor has been added to the previously developed hydraulic press model.

Following the sensor implementations for the models, model parameters have been calibrated and the random error sources have been introduced to the model. Thus, the model has been updated to be ready for predictive maintenance algorithms by introducing sources of random errors to be used in predictive maintenance, adding appropriate sensors to observe the effect of these error sources on important variables of the models and calibrating the geometrical, electrical, and hydraulic parameters of components to make the model as applicable and as realistic as possible.

The TIA DATA-GEN, TIA MODEL, TIA PREMA AND TIA ASP are described in the component/tool template in Appendix.

9.3 Progress beyond State of the Art or State of the Practice

Several physical and data-driven models have been developed for the pilot cases.

UOULU has developed state estimation tools for fuel characterization and fouling monitoring (FUSE/UKF, FouMon/EnKF)

TEKNOPAR has created a hybrid digital twin for predictive maintenance, combining a physical model of the process with sensor data and ML/AI algorithms.

Nissatech has developed a hybrid model designer for StreamPipes. It has been applied in the Sidenor pilot to combine two data-driven models. The study have been published in the following journal article: Selcuk, ŞY, Unal, P., Albayrak, Ö, Jomâa, Moez., " A Workflow for Synthetic Data Generation and Predictive Maintenance for Vibration Data", MDPI21.

Important extensions and modifications for the SINTEF Bedrock, SINTEF Pragmatism, and Cybernetica CENIT tools/ platforms have been made that will be used later in the project.

9.4 Summary of the key achievements

Task 5.4 has been involved in the development or extension of the following tools:

- several physics-based process models for the pilots
- improvements to the Bedrock platform
- improvements to the Pragmatism methodology
- input signal and calculation results validation (Cybernetica CENIT extension)
- development of FouMon component tools
- Hybrid model designer for StreamPipes
- Synthetic data generator for DC motor and hydraulic shaft
- Improvements to TIA APPS

9.5 Conclusion

Task 5.4 has focused on creating and improving tools that support the creation, use and exploitation of Hybrid Digital Twins. Early in the project, much work was done on building physics-based models for the various pilots. Later these models were extended with data driven models, thus forming hybrid twins. Several of these twins run in parallel with the process, continuously updating themselves. Finally, generic elements in the twins that are suitable for reuse, have been extracted and made available as tools in the toolbox. All tools have been used in at least one pilot project.

10 Cognitive Digital Twins

10.1 Objectives, challenges and components

The main objective of this task is to design the cognition process as a part of industrial decision making and its realization in Cognitive Twins.

During the 1st year of the project, we reviewed the relevant definitions in the literature and documented the results of this analysis in our paper "Cognitive Digital Twins for the Process Industry" accepted for the Twelfth International Conference on Advanced Cognitive Technologies and Applications (COGNITIVE 2020). We defined the cognitive digital twins as an extension of digital twins with cognitive capabilities in the context of the process industry.

For realizing cognitive digital twins in the process industry, an essential aspect is to devise the architectural building blocks that can serve as a foundation for cognitive systems in this domain. We provided our architectural perspective on the type of cognitive services needed for Cognitive Twins in the context of process industry. The proposed architecture provides a blueprint, supporting a wide range of abilities similarly to human capabilities. In Figure 18: we illustrate the role of knowledge in the Cognitive Twin (Layer in the Toolbox).
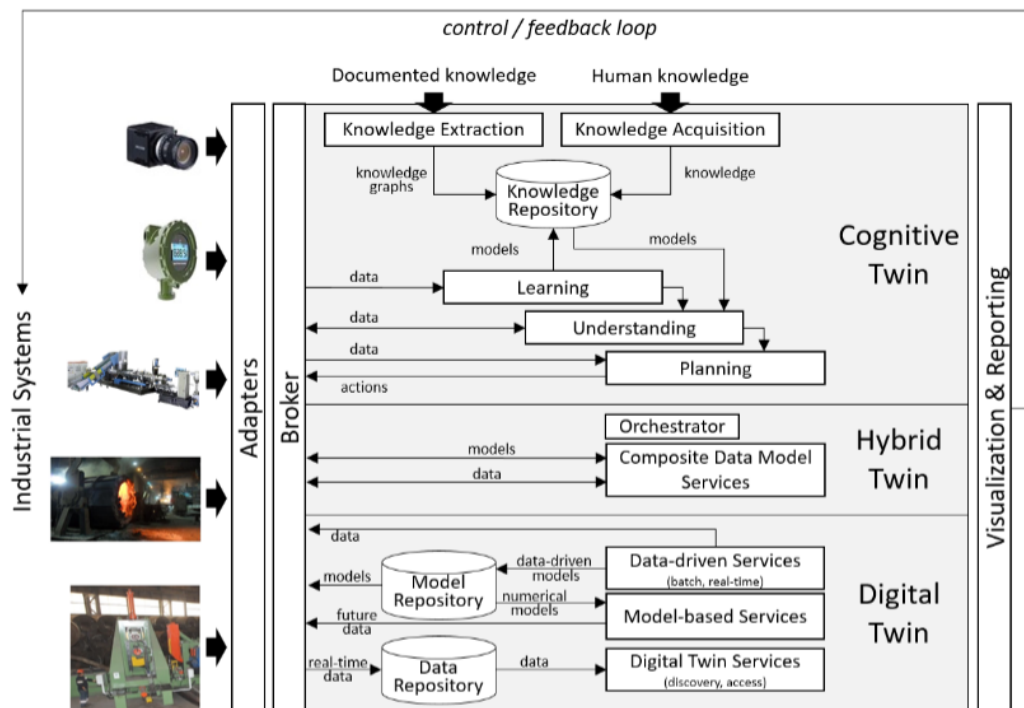

Figure 18: The role of Knowledge in the Cognitive Twin

There are many definitions of the cognition, but for this paper we focus on that derived from the cognitive computing domain, which are related to reasoning and understanding at a higher level, in a manner that is analogous to human cognition. We specialize this view for the complex cases where there is a lot of uncertainties inherent in the available data and models. We expect that a human-cognition-like approach will enable a broader, as well as a more connected view on the data and

models. The key advantage is the introduction of new knowledge that should provide missing insights for resolving original cases, as illustrated in Figure 19:Figure .
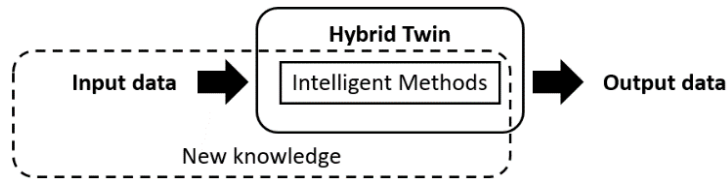

Figure 19: Cognition extending Hybrid Twin solution

As presented in the figure, we assume that "intelligent methods", which can be a part of Hybrid Twin, support the development of a solution that "maps" inputs into outputs. However, the solution might be missing a high accuracy, due to not having enough data in the training set. As illustrated, cognition supports augmenting the input data, as well as intelligent methods with new knowledge (gathered directly from the expert or some other sources), with the goal to generate new outputs (with a higher accuracy). Therefore, we argue that the uncertainty inherited in the problem (e.g., missing data, models) can be resolved by augmenting data and intelligent methods to compensate missing information. Notice that this process is not about getting new data, but rather new insights about existing data (through cognition).

Therefore, the main role of cognition services is to enable understanding the monitored system's behavior under various types of uncertainties/unknowns, to support reliable decision making (by human experts) or control (in autonomous systems). Uncertainties can be of different types, but we focus on the two most important types from the DT point of view: lack of data and unavailability of models regarding the current system behavior. It means that the current system behavior cannot be understood neither a) by analyzing past data, since the relevant data is missing nor b) by the simulations of numerical models, since these do not exist (or are not accurate enough). In such cases, it is important to compensate these unknowns by introducing new processing steps that will gradually improve the understanding of the system behavior, until this understanding is enough for the desired/requested action. This process we consider as cognition, where the processing steps are part of cognition services.

The main challenge is that the real time data is not enough for understanding the current situation (regarding the underlying problem). The main goal of the cognition service is to enable resolution of the original problem by introducing new knowledge which provides new insights for the model learning/creation processes, e.g. introduction of some constraints in the interpretation of originally collected data. Therefore, cognition is working on top of existing models, which can be derived using AI methods, extending the intelligence with the with the deep understanding, and reasoning strategies.

We can materialize this general process by following four steps (cf. Figure): (1) Inserting new knowledge (relevant for the problem) (2) Learning more accurate models, by applying new knowledge (3) Better situational understanding (e.g. lower interpretation uncertainty), by applying new models (4) Planning actions for resolving the problem, based on improved situational understanding.

We describe these steps in the following: **Firstly**, by knowledge extraction and knowledge acquisition, for gathering knowledge from the existing data sources (e.g. unstructured and semi-structured content) and from experts, respectively. The goal is to collect knowledge related to the uncertainties

in data and models. Since the process is related to supporting human-like understanding, it is important that the process is driven by the well-defined knowledge structures (like knowledge graphs) which provide a general description of the domain. Indeed, one of the main characteristics of the human cognition is a very fast discovery of hidden connections between arbitrary information items, which is based on large memory maps. **Secondly**, by learning, which encompasses applying new knowledge to the existing data, models, and methods, with the goal of learning more accurate models (from existing datasets). There are three main activities: transforming existing datasets in the anomaly-free ones, which can be used for learning more accurate models, improving used learning methods by introducing some knowledge-driven constraints in the learning process, and adding new methods which can complement existing ones in the context of the above-mentioned uncertainties. **Thirdly**, understanding, which is related to applying new models on real-time data to get a better interpretation of the situations of interest (e.g. problem/anomaly detection). We assume that, as in the human-like cognition, this process can be iterative, i.e. understanding processes can generate data which can be used for improving the learning process. **Finally**, planning, for defining optimal actions based on system behavior understanding.

There are many challenges to be addressed to realize the vision of the cognitive digital twins. The most important ones are discussed below:

Knowledge representation challenge. The first question to be clarified is how knowledge can be formally represented to enable a digital twin to learn from experience and behave intelligently like a human. All cognitive services mentioned above are heavily dependent on this decision.

The more complex the representation of knowledge is, the more difficult it is to acquire this knowledge automatically. However, more advanced reasoning services can be offered. Our goal is not only to support the decision-making process, but also to increase its accuracy and human-acceptance. Thus, both declarative and procedural knowledge is needed, as questions like 'what?', 'how?', 'when?', 'in what context?', 'what-if?' etc. should be answered.

Several knowledge representation formalisms seem to be suitable for cognitive digital twins. To clearly separate the general knowledge from the specific knowledge, it makes sense to structure the knowledge into two parts: ontologies for representing the domain knowledge and rules for representing the problem-solving knowledge.

To better understand a current situation (i.e. the asset itself, the context in which it is used, its environment, etc.), we consider using ontologies. They are a knowledge representation method that is on one hand expressive enough and on the other hand extensible. They could be used:

- to represent the domain knowledge which includes the vocabulary domain-experts apply (e.g. brick wall: types of bricks - e.g. red shale, clay bricks, etc. - the features of bricks - thermal shock resistance, mechanical strength, etc. - and so on) as well as the constraints (e.g. temperature threshold at which the stone is unusable)

- to take into account existing standards for the domain

- to support collaboration between digital twins, e.g. for cooperative execution of complex tasks.

Although simple constraints (e.g. temperature of a ladle must not exceed a certain threshold) can be modeled by using ontologies, there are many scenarios where complex (functional or behavioral)

constraints should be considered (e.g. calculations including results of different physics-based, AI, statistic-based, etc. models). To mimic the reasoning of a human expert in solving knowledge intensive problems, there is a need to use rules (e.g. event condition action rules). Rules should be used even in the presence of incomplete and/or uncertain information to

(i)   focus the attention to the most important aspects and

(ii)   collect additional, goal-oriented information relevant for a given context. This can be done by mapping raw sensor data and/or outputs of different digital twin models into actions (such as control decisions or recommendations for human operators).

Knowledge acquisition challenge. The second challenge is to collect knowledge which is not only spread in different documents (e.g. excel tables) and software systems (e.g. error reports in MES systems), but could be also implicit as it is based on personal experience which is even more difficult to express. To make the tacit knowledge explicit and machine-understandable as well as -processable, different cognitive technologies could be used, such as NLP, speech recognition, etc. For example, one possibility is to apply a speech-to-knowledge approach, as speech is relevant for the shop floor workers for short information interchange allowing hands-free conversations. Since the multilingual speech functionality in recent years became a commodity available on smart speakers, mobile phones, and computers, the pre-existing solutions could be reused and added to the cognitive digital twin to enable speech communication channels with human operators. Ontologies can help achieving higher accuracy of resulting rules, as synonyms, multilingual aspects, context, etc. can be taken into account. In this way, the domain and problem-solving knowledge will be connected.

Knowledge update challenge. In addition to collecting knowledge, the ability to learn, to unlearn, and to continuously update knowledge is crucial for cognitive digital twins to create competitive advantage. Knowledge update is however a complex process, which includes knowledge extension (e.g. adding a new entity in the ontology for new types of bricks), knowledge forgetting (removing an ontology entity representing material not used anymore for bricks), and knowledge evolution (e.g. changing the maximum temperature of a ladle). Similar strategies can be applied to the problem-solving rules. The challenge lies not only in ensuring the consistency after applying a change, but more importantly in discovering the need for a change. This can be done by applying usage-driven strategies (e.g. by monitoring whether the proposed decisions were accepted by domain experts) or by using structure-driven methods (e.g. by using ontology-based reasoning to discover conflicting rules or generalized/specialized rules).

Table 37 summarizes the challenges, requirements and solutions related to the development of cognitive digital twins for the six pilots. As this is the final goal of the COGNITWIN project, the challenges, requirements and solutions are more individual to each pilot. Since most pilots will utilise some sort of automatic control, the tasks pertaining to that are summarized in Table 38. In Table 39, we show the mapping between the toolbox components and the pilots for task 5.5.

Table 37: Cognitive Digital Twins – challenges, requirements and solutions

Pilots	Cognitive Digital Twins (by task 5.5) – Challenges, Requirements and Solutions

Hydro	• **Challenge**: Self-learning, reactive/smart hybrid digital twins - for cognitive plants. • **Requirement**: Methods for automatically identifying faults in the Hybrid Digital Twins should be developed. • **Solution**: By employing fault detection methods, the system can let the operators know if the results should be discarded or trusted, and automatically suggest suitable actions for fault mitigation.
Elkem	• **Challenge**: Introduce cognition through knowledge and learning from past data and situation in order to provide operator guidance • **Requirement**: Interact in a suitable way with operators to provide guidance and recommendations • **Solution:** Ensure inclusion of operators knowledge combined with system situation understanding.
Saarstahl	• **Challenge**: Support self-learning of the system also after initial machine learning. • **Requirement**: The system should provide alerts and recommendations for operators and be able to learn continuously • **Solution**: Provide interactive operator guidance
Noksel	• • Challenge: Ensure that the predictive maintenance also takes into account operators' knowledge and experiences • Requirement: Combine the Digital Twin based recommendations with the inclusion of operators knowledge. • Solution: Extract the tacit knowledge from experts as a basis for developing the cognition. Partially by applying unusuality detection on past data. These are developed in TIA CONTROL
Sidenor	• **Challenge**: Involve cognition into the pilot - *self learning and reactivity with operator interaction* • **Requirement**: The knowledge of operators must be acknowledged • **Solution**: Train the operators to work with the model and build confidence that the operators, based on model predictions, may make a correct decision.
Sumitomo SHI FW	• **Challenge**: The challenges are in extending from monitoring to prediction, and establishing feasible approaches in optimization • **Requirement**: Cognitive DT requires abilities in human-in-the-loop considerations and feedback of HDT outcomes to the plant/KPI • **Solution**: These are developed in FouCon.

Table 38: Control System Interaction – challenges, requirements and solutions

Pilots	Control – system interaction (related also to autonomous Cognitive Twins) (by task 5.5) – Challenges, Requirements and Solutions
Hydro	• **Challenge**: Optimal control requires characterization of a feasible cost function and efficient tools for finding solutions. The

	involvement of decision maker / user in the loop needs to be addressed. Operations can be partly automated, but only partly. • **Requirement**: Closed-loop control should minimize process disturbances while staying within operating constraints of GTC operation (silo levels, achievable feed rates, feasible recycle rates) • **Solution**: Nonlinear model predictive control is available and implemented as part of Cybernetica Cenit
Elkem	• **Challenge**: Optimal control requires characterization of a feasible cost function and efficient tools for finding solutions. The involvement of decision maker / user in the loop needs to be addressed. Operations can be partly automated, but only partly. • **Requirement**: Closed-loop control should minimize process disturbances while staying within operating constraints • **Solution**: Nonlinear model predictive control is available and implemented as part of Cybernetica Cenit.
Saarstahl	• **Challenge**: interfere in real time if critical situation is detected to prevent damage to billet or the roll stand • **Requirement**: sufficiently short inference time of model and suitable visualization for operator • **Possible Solution**: alert operator with sufficient lead time and provide suggestion for action
NOKSEL	• **Challenge:** Performance of search query s low • **Requirement:** Efficient and fast ontology query result • **Possible Solution:** Save ontology in relational database by means of ON2RDB script.
Sidenor	• **Challenge**: Develop decision support, such that both model predictions and operator's experience can be exploited • **Requirement**: Model predictions must be available at the time when the operator must decide if the ladle must be taken out of production or not • **Solution**: Combine the operator's assessment and the model prediction, to arrive at a safe decision, supervised by the operator.
Sumitomo SHI FW	• Ch: Optimal control requires characterization of a feasible cost function and efficient tools for finding solutions. The involvement of decision maker / user in the loop needs to be addressed. Operations can be partly automated, but only partly. • Req: Solutions must be robust in the industrial environment. • Sol: Suitable solutions will be selected by focusing on formulation of the cost function and feasible optimization techniques. • Toolbox components: FouCon

Table 39: Toolbox components per pilot used by task 5.5 Cognitive Digital Twins

Pilot type	Pilot	Task	DFKI - Generation of photorealistic data	DFKI - Neuroscope	Nissatech: D2Lab-C	Nissatech: StreamPipes Siddhi Processor	SINTEF's BEDROCK	TEKNOPAR: TIA DATA (TIA STREAM, TIA STORAGE, TIA CONTROL)	TEKNOPAR: TIA APPS (TIA MODEL, TIA PREMA)	TEKNOPAR: TIA UX (TIA DASHBOARD, TIA UX)	TEKNOPAR: TIA APPS (TIA ASP)	TEKNOPAR: TIA APPS (TIA DATA-GEN)	SINTEF Open Framework and Tools (SOFT)	Machine learning for hybrid models (SINTEF)	Pragmatic framework for development of hybrid models (SINTEF)	Cybernetica CENIT	Cybernetica Cognitive CENIT	Cybernetica ModelFit	Cybernetica RealSim	Cybernetica Viewer	Cybernetica ProSim	Cybernetica OPC UA Server	Bonzai (Scortex)	Como (Scortex)	Keras / tensorflow (Scortex)	Finite Markov Chains Matlab toolbox (MCPQ) (UOULU)	SpinPro (Fraunhofer)	Weather API interface MAP! (SINTEF)	Correlation Analysis Toolbox (SINTEF)	FUSE Fuel state estimation (UOULU)	SubFUSE Subspace identification and state estimation (UOULU)	FouMon fouling monitoring (UOULU)	FouCon fouling management and control (UOULU)	SINDIT (SINTEF)
	Hydro	Cognitive Digital Twins			(x)	(x)										x	x										(x)							(x)
	Elkem	Cognitive Digital Twins			(x)	(x)										x	x										(x)							(x)
	Saarstahl	Cognitive Digital Twins	x	x																							(x)							(x)
	Sidenor	Cognitive Digital Twins			x	x	(x)									(x)	(x)										(x)							x
	Noksel	Cognitive Digital Twins			(x)	(x)	x		x	x	(x)	(x)															(x)							(x)
	Sumitomo	Cognitive Digital Twins			(x)	(x)	(x)	(x)		(x)						(x)	(x)										(x)					(x)	x	(x)

10.2 Detailed description of the activities performed

10.2.1   Cognition-driven Unusuality detection

As we already described in the previous deliverable, cognition is related to the expert knowledge used in (non-trivial) decision making processes. One such a process is the tool/equipment degradation. In the process industry it is especially important since the equipment is used in a very harsh environment (e.g. high temperature) and even more difficult, data related to the condition of the equipment cannot be regularly collected.

We briefly describe the process how the decision about the usage of ladle (equipment) in the steel production (Sidenor pilot).

At the moment, a human expert is in charge of inspecting the state of bricks after every *heat* process and deciding whether they need to be repaired/replaced. He performs **visual inspection** of the bricks (*since he does not have access to them, unless when being repaired/replaced*) and **checks specific parameters related to a current heat process, as well as several previous ones** (*5 - 10*). If bricks pass visual inspection and parameters have appropriate values current set of bricks is used in the next heat. Otherwise, bricks must be repaired or replaced. Additionally, human expert can see whether he made optimal decision or not, during repairment/replacement when bricks can be closely inspected (*whether he made optimal decision is based on the thickness of the bricks during repairment/replacement*). An **optimal decision to stop further heats** is the one when no further heats are possible. Contrariwise, a **suboptimal decision to stop further heats** is the one when further heats could be done before repairment/replacement.

Based on this discussion we provide a set of constraints which the human decision-making process is exposed to

1   Human decision-making is based on his experience and implicit rules which he cannot make formal. Decision-making process is not well defined.

2   Human decision-making process is based on **univariate analysis**. Expert checks parameter values for last N heats **individually**, which means that he does not take into consideration possible relation between different parameters - it is possible that, when individually checked, parameters have appropriate values, but if jointly analyzed, they can indicate that there is a problem, and that repairment/replacement is needed.

3   Human expert uses a subset of all parameters during his decision-making process. It is possible that analysis of more parameters would result in better decisions.

As a direct result of the previous problems, human decision-making is prone to mistakes. These mistakes refer to situations in which it is decided that the bricks need repairment/replacement, when in fact, those bricks could be used for several more heat processes. This problem leads to suboptimal use of said bricks.

However, such mistakes happen very seldom, which indicates that a human operator uses a very efficient mechanism for this type of judgment. Indeed, human are precise in detecting small changes in the known environment, based on the so-called Fast thinking process. In other words, an unusuality will be discovered precisely. We assume that this capability is activated/used when making also a decision in the above-described process.

Therefore, we propose to use unusuality detection methods for simulating the decision-making process of the human operator, i.e., his cognition process

Experimentation is conducted on following parameters from Sidenor data set – *S vacio*, *Kwh_rr*, *Cal total*, *Tiempo_llena*, *Alumina_rr*, *S al vuelco_rr*, *Tiempo_vacio*, *Gases*, *Caf total*, *Acero_liquido*, *V_desulfuracion*, *T_calentando*, *Escoria_land* and *Mn_vuelco*.
Experimentation is performed on each ladle separately, as well as on joined ladle data.

Even though we are getting strange training loss output (Image 5.3.3.1.), the results are quite good – Depending on the unusuality zone, we get from 15% up to nearly 100% of matching between our model and MEWMA. This result stands both for individual ladle and joined ladle data.
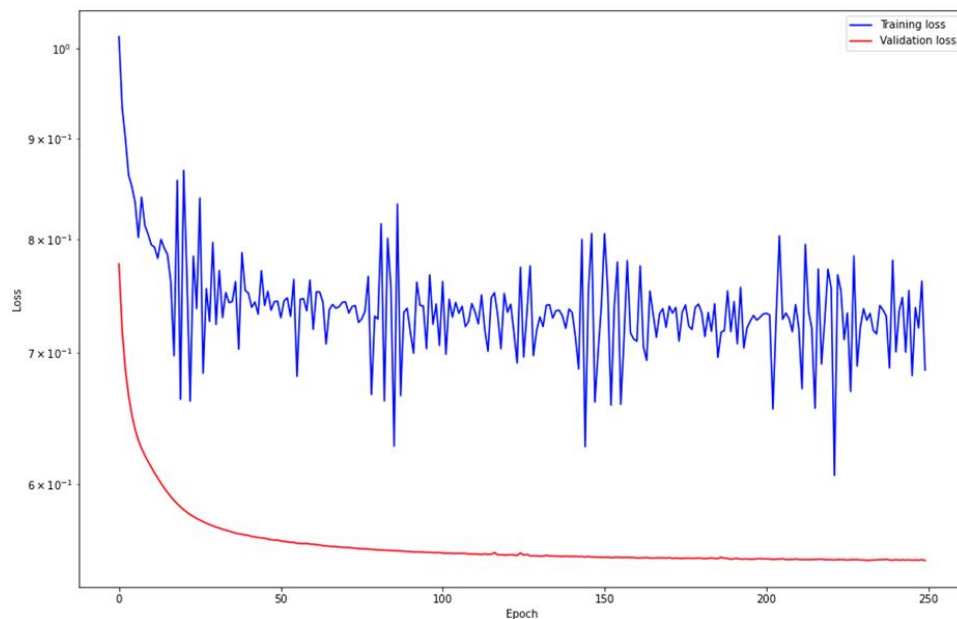
Figure 20: trange zig-zag pattern of training loss (usually indicates that the learning rate is too high, but we did not manage to get appropriate results even with really low values of learning rate)

An example of error curve and unusuality zones (*10, 5, 2.5 and 1 percent of the greatest errors*) for one of the validation parts of data set is presented in Figure 21

Errors
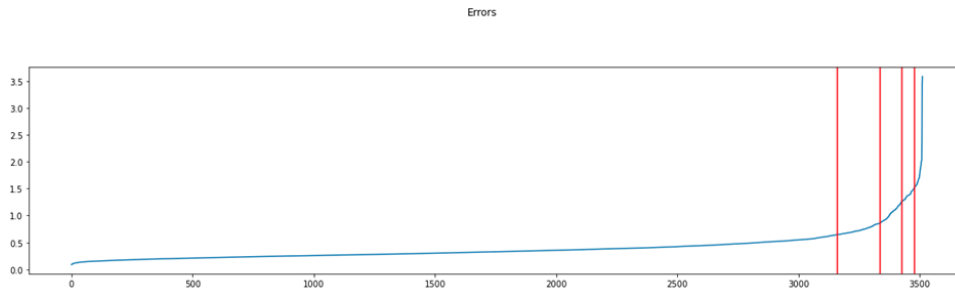
Figure 21: Validation results

10.2.2   Cognitive CENIT

Cybernetica has started the development of an extension to its software product Cybernetica CENIT called Cognitive CENIT, which enables self-diagnosing. A framework for self-monitoring of the model predictive control application via stage cost monitoring has been developed and is currently being evaluated on a simplified and simulated test process. The framework consists of the following steps:

- Estimate the measurement error distribution
- Propagate that noise distribution through the closed-loop model predictive controller via Monte Carlo simulations
- Compare the resulting distribution of the average stage cost from the actual plant. If the average stage cost is significantly off from the theoretical distribution, this indicates an error in the closed-loop model. This is illustrated in Figure 22::
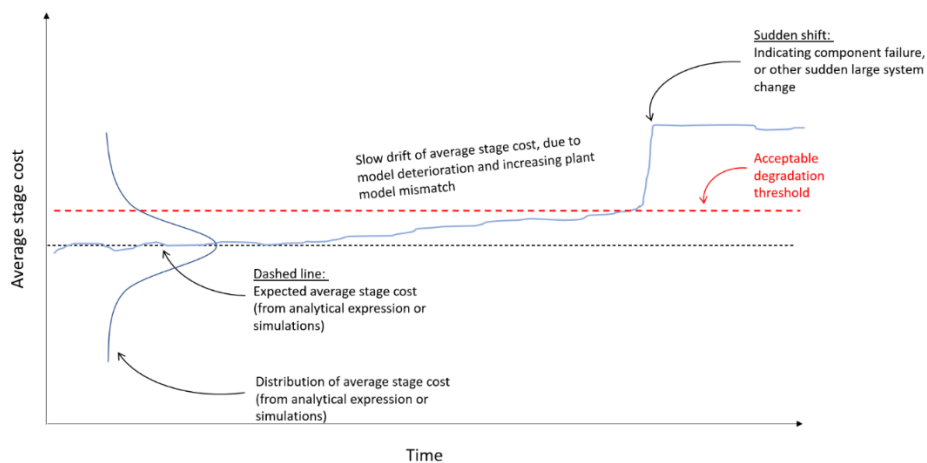
Figure 22: Cognitive CENIT

As shown in Figure 22:, analyzing the average stage cost distribution in closed loop applications can detect anomalies like component failure or model mismatch

10.2.3   FouCon Plant Monitoring and Control

The UOULU (University of Oulu, Intelligent Machines and Systems research unit) work has focused on the development of tools for modelling, monitoring, and control. The work involves modeling and tuning (see WP5 task 1 on plant digital twins with ML/AI, reported in Section 6); state estimation (task

4 on hybrid digital twins, Sec. 9); and extending the hybrid model with adaptive and optimization abilities (task 5 on cognitive digital twins). The driving components towards cognitive digital twins are in exploiting the hybrid model ability to predict to the future, to learn on-line in an automated fashion, to provide optimal solutions to well defined problems, and – with all these – to assist the operator in his/her every day decision making.

The work was driven by the needs for solving the Sumitomo SHI FW pilot problem in Work Package 3. The need for fouling management is due to accumulation of deposit to heat exchanger surfaces at the flue gas path of a combustion plant. To clean the surfaces, the pipes are cleaned by blowing steam at high pressure to detach residues. Typically, this is done at regular intervals. The focus of fouling management was targeted to the soot blowing timing optimization problem, i.e., to finding the optimal start time (and potentially some other adjustable parameters) of a soot blowing sequence.

The FouCon component consists of two main elements: a general-purpose tool for identification, and a specialized optimization and user interface for decision making. A tool that uses subspace identification to extract light-weight approximations of subprocess behaviour, SubFUSE, was originally examined for the fuel characterization problem. As it became apparent that the state estimation (of heat transfer coefficient) relying on physics-based models was reliable but relatively heavy to compute, a light-weight solution was sought when extending from monitoring to on-line optimization. The SubFUSE tool was then further developed for the fouling management problem, by implementation of the Prony method. Subspace identification is a group of modelling methods providing linear state-space approximations from a set of input—output data. It provides means to easily control the dynamic modes of the outcome, the linearity of the model improves the robustness of identification. For the soot blowing problem, the models are repeatedly re-identified after each sootblowing sequence. This helps to keep the models up to date between full maintenances, typically conducted yearly.

The existence of a dynamic model provides means for generating predictions to the future. Given a proper cost function, the predictions can be used to find the decision parameters which minimize the cost / maximize the profits. The optimization problem is highly nontrivial to solve, due to the properties of the problem. In the soot blowing case the problem is mixed-integer, constrained, and nonlinear. It is important to note that the 'optimality' of the solution is only in terms of considered cost function and limited models. In the engineering reality, this optimal solution is entwined with other real-world requirements. The decision maker, the plant operator, is aware of much more details, conditions, and constraints than the automated optimization routine. What the optimization can provide, is a suggestion for a decision. It can also support the decision making by illustrating the impact of alternative decisions to the operator. The conceptual solution to the sootblowing problem of three first superheaters was developed and demonstrated using data from the pilot plant.

Several papers reporting work on subspace identification have been published from the work in COGNITWIN:

- Neuvonen, M., I. Selek and E. Ikonen (2021) Estimating Fuel Characteristics from Simulated Circulating Fluidized Bed Furnace Data. Int. Conf. on Systems and Control (ICSC'21), 24-26 Nov 2021, Caen, France, 2021.
- Neuvonen, M., I. Selek, E. Ikonen and L. Aho (2022) Heat exchanger fouling estimation for combustion–thermal power plants including load level dynamics. IEEE SMC 2022 Prague

A M42 video demonstration is available on fouling management

- Fouling management demonstration. Available at COGNITWIN YouTube channel: [SUMITOMO Pilot (Final COGNITWIN Demonstrator - D3.4) - YouTube](#)

A video on the UOULU COGNITWIN tools, including SubFUSE/MOESP and FouCon/Prony.

- UOULU Guide to COGNITWIN toolbox tools. Available at COGNITWIN YouTube channel: [UOULU Toolbox components (Final COGNITWIN Demonstrator - D4.4 and D5.4) - YouTube](#)

10.2.4   TIA PREMA Predictive Maintenance

Focused on the NOKSEL pilot case of a metal sheet roller system of spiral welded pipes (SWP), TEKNOPAR has worked on related to T5.5. TStreamPipes-ML is developed by TEKNOPAR to apply ML algorithms on the stream and to compare the results of the algorithms. The developed data processor enables users to select the algorithms to be used/compared and the output is displayed on a dashboard.

TEKNOPAR's TMat-PdM component renamed as TIA PREMA, which is under continuous development, can be used for predictive maintenance of the DC motor, gearbox, and hydraulic press. Different ML models have been used by TIA PREMA. TIA PREMA uses MATLAB's Predictive Maintenance toolbox and Classification Learner app. TIA PREMA enables visualization of a confusion matrix for the selected algorithms to present the difference between simulation outputs.

In the related pilot case (the NOKSEL pilot), the cognitive twin will introduce improved decision making by integrating human knowledge into the decision-making process. The anomalies, alarms, and early warnings of machine and system problems will be tackled by the cognitive twin. The decision-making process will emulate the experienced human operator with embedded knowledge base. The cognitive twin will augment expert knowledge for unpredictable cases on the digital and hybrid twins. The human operator's knowledge is reflected to process knowledge and physics-based models with parametric values as well as thresholds and causality relations. Expert knowledge on the causes of breakdowns is collected with the series of the problematic operations and the initial causes which trigger the successive reactions. Cognition will be further integrated by making use of the machine learning algorithms, ontologies, and knowledge graphs to capture background knowledge, entities, and their relationships. Reacting to early warnings, cognitive twins will bring life cycle optimization, and suggesting optimized predictive actions will improve operational performance by optimized operational parameters and it will also decrease energy usage (Figure 23:Figure).

TEKNOPAR's following journal article related to predictive maintenance has been accepted for publication:

Deveci, B.U., Çeltikoğlu, M., Alp, T., Albayrak, Ö., Unal, P., Kırcı, P., (2022), "Transfer Learning Enabled Bearing Fault Detection Methods Based on Image Representations of Single Dimensional Signals" (Information Systems Frontiers).
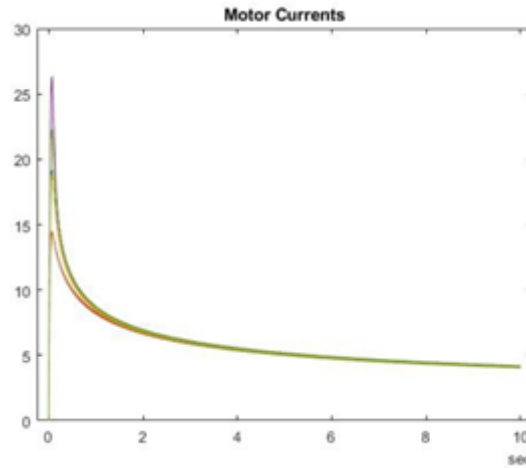
Figure 23: Cognition using StreamPipes Toolbox

10.2.5   Cognition using StreamPipes Toolbox.

StreamPipes Siddhi-Processor (SP). Siddhi-Processor's purpose is to extract information and identify meaningful events (opportunities and threats), such as patterns, relationship between events, etc. It would receive its input from SP element(s), execute written query on received **data, and forward execution result to other SP element(s).**
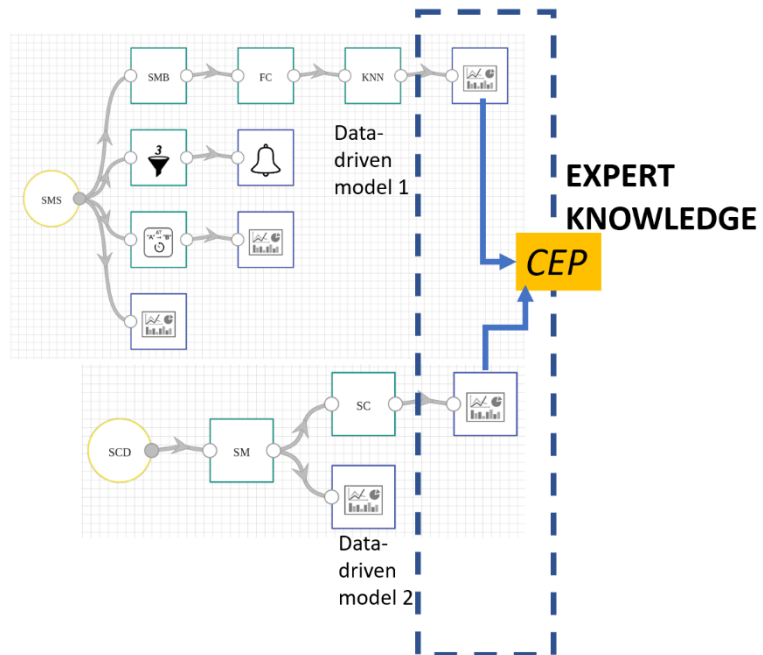

Figure 24: Complex Event Processing (CEP)

The role of Complex Event Processing (CEP) in codifying expert knowledge. Siddhi CEP performs Complex Event Processing using the Siddhi engine. It provides application of complex logic to the "main" outputs of this pipeline (results of various analytical methods). In addition, this element provides points of connection for this and previous pipelines – CEP can be applied on outputs of multiple pipelines connecting them into one complex pipeline (Figure).

Knowledge/Patterns. Regarding outputs from data-driven models, MEWMA, and KNN elements, we singled out the following queries (patterns) that can be applied:

- Test whether there were more than *M* anomalies in a single heat during a time window of length N. For example, if there were more than 10 anomalies in a time window of 5 minutes, raise a warning. (*uses output from MEWMA element*)

- Test whether there were too many anomalies in single heat with the same root-cause. For example, if there were more than 100 anomalies with the same root-cause parameter, this can indicate some sensor or part of a machine is faulty and should be checked. (*uses output from MEWMA element*)

- Test whether during last *N* heats, a cycle is classified as **1** (*indicating that the degradation is greater than given threshold*) with an increasing probability (certainty). This can indicate that the ladle will soon be unusable and should be monitored closely or even repaired/replaced. (*uses output from KNN element*)

- Test whether during the last *N* heats there were more than *M* anomalies and that cycle was classified as **1** (*indicating that the degradation is greater than given threshold*) - *extension to the implemented query in pipeline #2*.

- Test whether during the last *N* heats there were more than *M* anomalies and that cycle was classified as **0** (*indicating that the degradation is lesser than given threshold*) - *extension to the implemented query in pipeline #2*.

10.2.6   Digital Twin extension for time-series data

As Digital Twins (DTs) are a digital representation of a physical (or virtual) asset their primary task is to provide a uniform and standardized way to access all information related to the asset they represent. However, they do not necessarily store all the information itself but rather act as a proxy to existing systems containing the actual information. This includes not only static metadata or simple properties describing the state of the asset/DT but also time series data to keep track of the history of a DT and its state over time.

Unfortunately, current DT standards and specifications do not (yet) properly address the issue of representing time series data within a DT. For the AAS specification, an extension is currently in development that aims to provide a standardized metamodel and API for modelling time series data in the AAS called "SubmodelTemplate Time Series Data" (referred to as SMT Time Series Data in this document)[1].

Our objective was to implement an early version of this specification in the context of our DT implementation FA³ST Service. Besides the fact that the specification is not finished yet and may contain errors and inconsistencies, our main challenge was to implement it in a generic way agnostic to the type of underlying database so that it can potentially be used with any kind of database in the future.

Figure 25 shows a UML class diagram of the SMT Time Series Data metamodel. The general concept of how to model and access time series data in an AAS is as follows: A time series is represented by an AAS submodel which may contain some metadata of the time series as well as a set of so-called segments. Segments can be of one of three types: (1) internal, meaning that all the data is actually contained in the AAS itself, (2) linked, meaning that the data does reside in a database outside the AAS, and (3) external, meaning that the data resides in a file which can be either hosted inside or outside

the AAS. To access the data from different types of segments in a unified way, the time series submodel does offer multiple operations such as *readRecords(…)* or *readSegments(…)*.
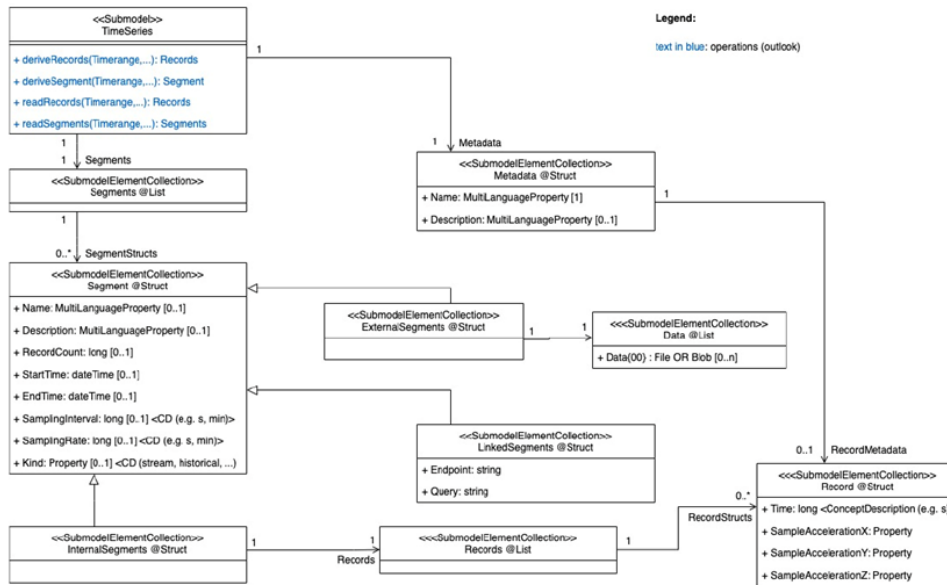

Figure 25: UML class diagram of the SubmodelTemplate Time Series Data metamodel

Extending FA³ST Service to support SMT Time Series Data is tricky, as this requires adding logic to a TimeSeries submodel implementing the required operations like *readSegments(…)*. Figure 2 shows how we extended the architecture to achieve this. First, we introduced the *SubmodelTemplateProcessor* interface, which allows to integrate custom processors for certain kinds of submodel templates which again can alter the processed submodel by e.g. adding operations and underlying logic like needed for SMT Time Series Data. Then we implemented this interface for the Time Series Data submodel template. This implementation again defines an interface called *SegmentProvider* which abstracts from the concrete type of database used to store the data. For this interface we developed an implementation supporting InfluxDB databases as data source.
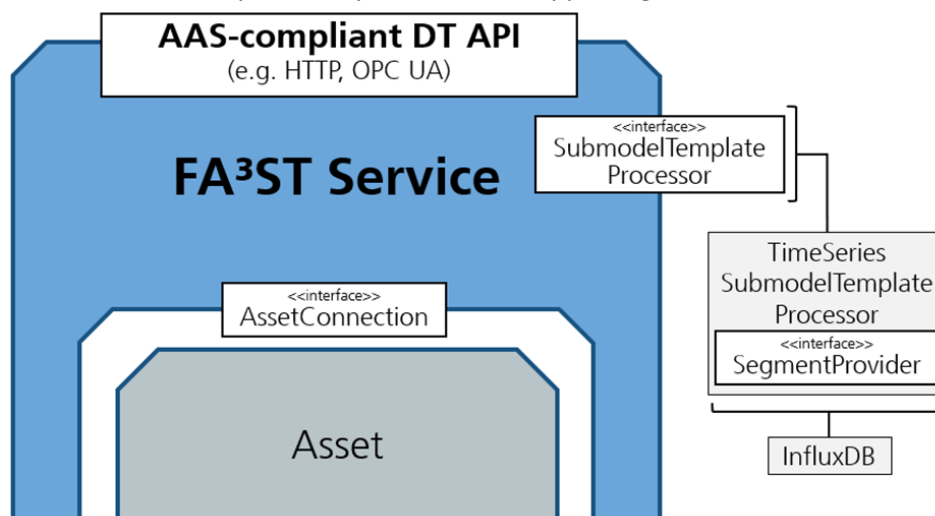
Figure 26: Updated FA³ST Service architecture with SMT Time Series Data support

The implementation is open source and available on Github[2]. When started with a submodel with its semanticId pointing to the SMT Time Series Data it automatically generates the operation to access data in a unified way. However, this currently only works for internal segments and linked segments pointing to InfluxDB databases; external segments are not supported at this point of time. However, to support additional database types besides InfluxDB requires only to implement the *SegmentProvider* interface and can be done with minimum effort.

[1] https://industrialdigitaltwin.org/en/content-hub/submodels
[2] https://github.com/FraunhoferIOSB/FAAAST-Service/pull/256

10.3 Progress beyond State of the Art or State of the Practice

Most related work is dealing with the self-awareness of digital twins. There are several systems which we briefly analyze in the following text.

In (Kapteyn, Knezevic, & Willcox, 2020) a DDDAS system is extended to a self-aware digital twin to support real-time path planning of an unmanned aerial vehicle according to its structural integrity. In this work, stimulus awareness and goal awareness are implicitly involved.

In (Chhetri & Al Faruque, 2020) a dynamic data-driven approach is applied to the digital twin model for 3D printer products. The digital twin is a machine learning model that predicts the surface texture and dimension of the product to be printed by using environmental parameters from sensors as input. Stimulus awareness and time awareness are implicitly involved.

In (Roßmann, et al., 2014) a 3D simulation model is used as the mental model for the path planning of a mobile robot. The robot simulates all the possible future paths resulting from different initial parameters. Stimulus- and time-awareness are implicitly involved, the latter to predict future path trajectories.

In (Zhang, Bahsoon, & Theodoropoulos, 2020) twins that can exhibit a high level of intelligence are described. They can replicate human cognitive processes and execute conscious actions autonomously. The paper brings together the concepts of digital twins and self-awareness and discusses how the different levels of self-awareness can be harnessed for the design of cognitive digital twins.

Regarding the time-series data and their integration with digital twins, our solution offers a standardized (although the specification is only at draft stage) to handle time series data in an AAS which is something that no other AAS implementation can offer so far.

10.4 Summary of the key achievements

There are three key achievements: (1) Initial conceptualization of the cognition, driven by the role of knowledge in the cognitive twin layer (Toolbox) (2) Initial realization of the cognition in two pilots and (3) Conceptual model for the cognition in the StreamPipes toolbox.

Regarding time series data and their integration into digital twins, we implemented most of the SMT Time Series Data specification thus providing a standardized way to integrate time series data with the AAS. As proof-of-concept we implemented a way to connect the AAS to time series data stored in an external InfluxDB. We furthermore designed our solution in such a way that it is easily extendible to other types of databases in the future.

10.5 Conclusion

Since this task is responsible for the realization of the cognitive twins, which are one of the main outcomes of the project, there are several dependencies to other tasks, i.e. the results from these tasks should be fed into this one.

In addition, initial concepts and realizations (as mentioned in previous section) will be further developed and validated.

Integration of time series data in the AAS is essential, especially with the focus on DTs close to production modules and machines as they continuously produce streams of data that need to be captured and made available via DTs. Unfortunately, this aspect of DTs is not well covered by standardization and most of the time neglected by existing implementations. With our solution we try to close this gap and provide an easy-to-use and extendable open-source software addressing this need.

11   Demonstrators

Several videos have been made to demonstrate the use of the COGNITWIN toolbox. These videos are available on the COGNITWIN YouTube channel:

https://www.youtube.com/channel/UCgHunz1V68YGOxaqVkkyN1A

11.1 Demonstrators for D5.4

The following four videos demonstrate novel developments and the state-of-the-art as of this delivery, whereas the remaining videos were made prior and demonstrate the COGNITWIN toolbox components at a somewhat earlier stage.

11.1.1   Hybrid digital twin for the Elkem pilot

A video demonstrating the pipeline for the Elkem pilot is available. It shows how Cybernetica CENIT is used as a basis to build a hybrid digital twin. It shows how data flow from the process, how it is stored and distributed to the different tools, used in calculations and finally presented to the users (operators and process engineers). Name: "Hybrid digital twin for Elkem pilot"

11.1.2   Hybrid digital twin for the Hydro pilot

A video demonstrating the use of the model and how Cybernetica CENIT is used to build a hybrid digital twin in the Hydro pilot case is available: "CogniTwin Hydro".

11.1.3   Hybrid digital twin for the Sidenor pilot

The Pragmatism-based model for the Sidenor pilot is predicting ladle refractory erosion. Predictions of steel, slag and ladle wall temperatures are an integral part of the model as temperatures control thermodynamics. A video demonstrating the PPBM-based development and use of the model is available: "Pragmatism in physics-based modelling (PPBM), applied to the COGNITWIN Sidenor use case on ladle erosion".

11.1.4   FUSE, FouMon and FouCon for Sumitomo SHI FW pilot

Three video demonstrations on developments for solving the Sumitomo SHI FW pilot problem are available. The latest (M42) demonstration video illustrates the fouling management digital twin service tool. In addition, a quick user's guide on the general-purpose, application independent tools, derived based on the pilot-driven work, is provided in a fourth video (M42). All videos are be available via the YouTube COGNITWIN channel. COGNITWIN - YouTube

11.1.5   TIA APPS

Video demonstrations for the WP5 related tools (i.e. TIA PREMA, TIA MODEL, TIA ASP, TIA DATA-GEN, TIA OEE, TIA STATISTICS) of TIA APPS are/will be available in the YouTube COGNITIWIN channel. The link is also available on: TIA Monitoring TEKNOPAR (Final COGNITWIN Demonstrator - D5.4) - YouTube

11.1.6   FA3ST Demonstrator

This demonstrator shows how time series data can be integrated into a digital twin.

12   Conclusion

In this deliverable D5.4 we report the methods and technologies developed in the "COGNITWIN Hybrid and Cognitive Twin Toolbox", as well as how they were applied in the six industrial pilots. The report takes the form of an updated version of the previous deliverable D5.3, such that all the previous developments are included for the sake of continuity.

The overall goal of the COGNITWIN project is to support European heavy industries through digitalization, with the aim to significantly improve operation. To realize the COGNITWIN vision, various tools for combining data-driven, physics-based, and machine learning methods are developed.

As of this deliverable, the toolbox consists of components developed to satisfy the specific pilot challenges. Since technical details are best presented on a per-component-basis, and our presentation on the individual tasks focuses on more abstract insights. The bulk of technical details and development status of the individual toolbox components is additionally reported as Appendix 1 and referred to in this document.

Progress has been made since the previous deliverable, and most toolbox components have now been applied to the pilots. Furthermore, many of the components are interacting in a unified manner as part of pipelines. The components and the pipelines are a step towards full-fledged cognitive digital twins for the process industry.

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14   Appendix 1. Toolbox components

As described in the high-level overview from deliverable D4.2, the COGNITWIN vision can only be achieved if interoperability between the heterogeneous components is supported. To this end, it was chosen to define standardized interfaces for each component and define pipelines. Figure 27:Figure illustrates the approach.

Heterogeneous components

Integrated components in a Toolbox (engineering phase)

Integrated pipelines with DTs (operational phase)
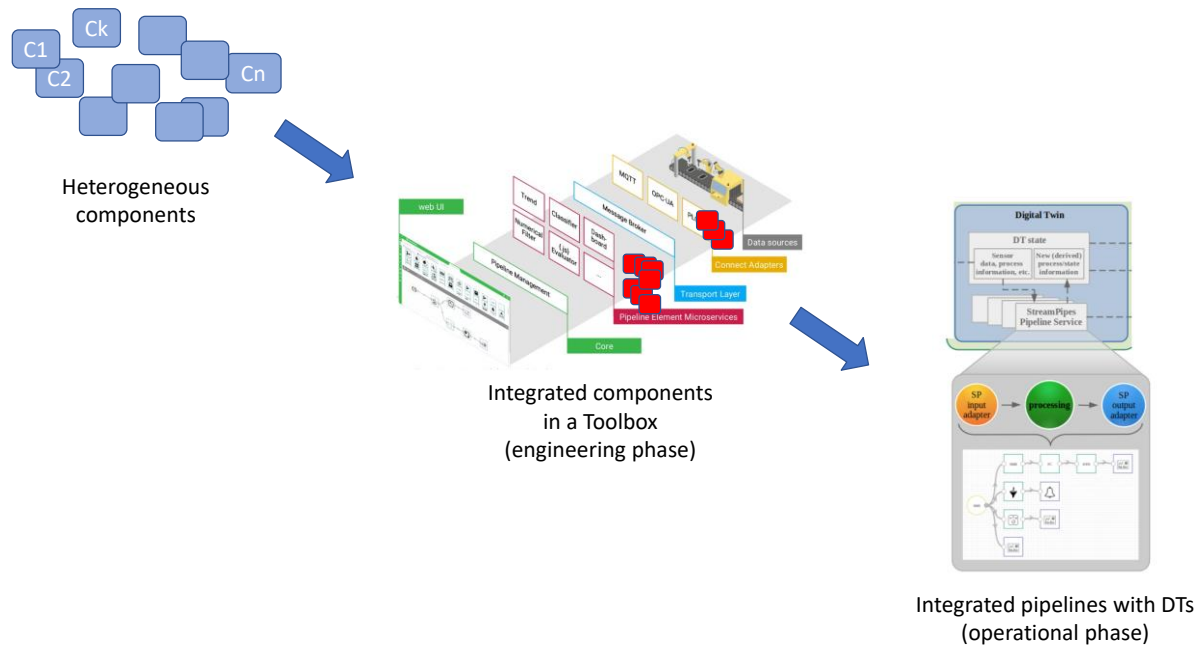
Figure 27: CogniTwin approach for digital twins

In this Appendix, the various toolbox components are described.

14.1 TIA UX: Industrial Control and Visualization Panel

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA UX: Industrial Control and Visualization Panel
Defined in Task
T5.1, T5.2
Short Description – incl. Purpose
TIA UX supports the digital twin by means of visual components presenting the generated data which is retrieved from, and processed within other STEEL4.0 components.
The purpose of TIA UX is to visualize the digital twin. TIA UX visualizes the historical, real time data as trend graphs and status reports by means of different types of graphical elements. Both real-time and processed information that are used for condition monitoring and predictive maintenance of SWP are visualized by TIA UX. TIA UX contains TIA DASHBOARD and TIA 3D applications. TIA 3D is used for 3D visualisation of data, where TIA DASHBOARD generates and displayes Dashboards to the usets.
Progress since delivery D5.1
Visual components of all of the SWP machinery parts were prepared.
GUI designs (including the icons, graph types, dashboard elements, etc.) for the display screens were updated, graphical elements to display real-time and calculated fields have been changed.
AI/ML related elements are visualized on GUIs of TIA UX.
Accepted Proceeding Paper including STEEL4.0 Digital Twin (related to TIA UX elements):
Albayrak, Ö., P. Unal "Smart Steel Pipe Production Plant via Cognitive Digital Twins: A Case Study on Digitalization of Spiral Welded Pipe Machinery" has been accepted for publication in the Proceedings of the ESTEP Workshop on Impact and opportunities of AI in the Steel Industry.
Progress since delivery D5.2
• **Customization for the visual components, such as light, background color, foreground color, constrast level etc. have been added.** • **Model explosion has been added.** • Overall equipment efficiency and energy consumption is displayed
Progress since delivery D5.3
• Verification and validation have been completed.
Examples of usage / illustrations

Figure 28: TIA UX Sample GUI for External Welding of SWP displaying Real-Time sensor Data.
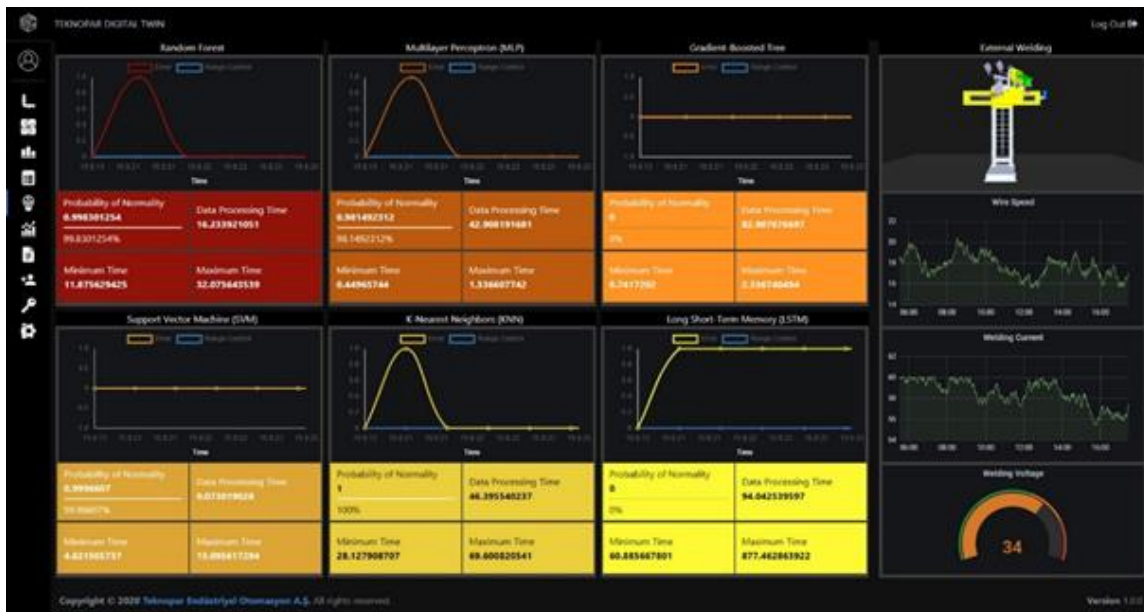
Figure 29: Real-Time ML Sample GUI visualized by TIA UX.

Interfaces (in/out) – system/user

TIA UX uses real time sensor data and predictions as input and displays them in the forms of visual elements to the users.

Subordinates and platform dependencies

Being a web application, ICPV is platform independent, it can run on many different types of browsers including Google Chrome, Safari, Microsoft Edge, Mozilla, Opera, etc.

Licenses, etc. (free for use in the project)
Proprietary/ Subject to license

TRL for overall component/tool and any parts/subordinates
The current TRL is 7 as targeted..

References – incl. web etc.
https://tia-platform.com/module/tia-ux.html

To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.2 MAI - Collection of weather data

Component/Tool description
Component/Tool/Method/Framework/Service Name
MAI - Collection of weather data
Defined in Task
Task 5.1: Plant Digital Twins with ML/AI
Short Description – incl. Purpose
The MET API Interface (MAI for short) is a user interface to FROST, the API developed by the Norwegian Meteorological Institute (MET), which enables public access to weather data. MAI is a software bundle written in Python and is intended to be used as a standard Python module. The purpose of MAI is to simplify data retrieval from FROST by providing a streamlined user interface. A user can select a location, a time interval, and a series of measurements, then MAI takes care of contacting the correct access point in FROST, submitting a properly composed request, as well as receiving and handling the response. MAI allows querying FROST for three main purposes: 1) Retrieve all available weather-station names in a given area (at municipality level); 2) retrieve a list of all available measurements at a selected location or municipality; 3) retrieve all data available for the selected measurements at a chosen location and time interval. The weather data is collected in a properly formatted Pandas DataFrame for ease of use. The modularity of MAI allows for flexible development and extension of its features.
Progress since delivery D5.1
N/A
Progress since delivery D5.2
N/A
Examples of usage / illustrations
To allow MAI to access FROST, a user must first register and receive its client ID. This is done by visiting https://frost.met.no/auth/requestCredentials.html and registering with an email address. MET's API terms of use as well the privacy statement hold in this step. After registration, weather data can be retrieved by the user in one simple call to MAI. The figure below illustrates a minimal usage example.

```
# Author: Filippo Remonato

import met_api_interface as mai


# Insert your own client ID here
client_id = '<your_personal_id_here>' # Personal ID

location_name = 'oslo - blindern' # list of location names. Can use municipality='<municipality_name>' instead
measurements = 'air_temperature' # list of measurement quantities to retrieve
time_period = '2020-01-01/2020-01-02' # requested time period

df = mai.get_weather_data(client_id, time_period , name=location_name, measurements=measurements)
```

Figure 30: Minimal usage example for retrieving weather data using MAI

Interfaces (in/out) – system/user
The software is intended to be run as a standard Python module, imported in a script and run either in terminal or in a notebook. Most functions contained in MAI accept as input location names, list of measurements, and time intervals (or a combination of those). The returned output can be either messages on the screen containing the requested information, or a Pandas

DataFrame containing the weather data, formatted with timestamps in rows and the different measurements in columns. Errors are handled through descriptive explanations and suggestions to the user.
Subordinates and platform dependencies
MAI is available on any platform that can run Python 3.x.
Licenses, etc. (free for use in the project)
none
TRL for overall component/tool and any parts/subordinates
none
References – incl. web etc.
none
To be considered in particular for the following COGNITWIN pilots
Hydro.

14.3 FUSE

Component/Tool description
Component/Tool/Method/Framework/Service Name
FUSE
Defined in task
5.1 (5.4)
Short Description – incl. Purpose
FUSE is a tool for process input and state estimation, fusing plant physical model predictions with process measurements. The model and measurements are fused in nonlinear state estimation using an unscented Kalman filtering (UKF)-based approach.   In particular, the tool is developed for estimation of combustion boiler input fuel composition characteristics. The tool uses a physical model of the CFB boiler hotloop (fluidization and combustion) as well as on-line measurements from the process (flue gas, furnace temperatures, etc). The approach can be applied for alternative state estimation purposes, given that a suitable plant model and measurements are provided. A generalized version is under development.   The UKF algorithm is well known and many implementations are available (e.g. in Matlab Control System Toolbox and Matlab Central open exchange). The FUSE tool focuses on practical aspects: enabling the selection of states/inputs to estimate, measurement selection, data validation and reconciliation, physical model tuning, UKF tuning, and reduction of computational load, so as to support exploitation of computationally heavy physical models in plant operation and control.
Progress since delivery D5.1
The tool has been developed (designed, implemented, and verified) after the last milestone in 2/2020. A paper has been published on the physical model tuning, available in IEEE Xplore (see References).
Progress since delivery D5.2
N/A
Examples of usage / illustrations
The tool originates from solving the WP3 pilot problem on fuel characterization, as a part of the heat exchanger fouling monitoring problem. The tool was tuned and tested using real full scale boiler plant design and measurement data.   Figure 1 illustrates the estimation filter outcomes during fuel test experiments.

Figure 31: FUSE fuel characterization during one-week CFB operation

The top left picture shows the estimated fuel characteristics as a function of time. The coloured lines show the mass flow feed for pure forest wood chips, design fuel mix, and moisture. The black lines show the estimated and measured total fuel feed (indistinguishable). The bottom left picture illustrates the elementary composition of the estimated fuel feed. The right plots show the measured and predicted flue gas oxygen and sulfur dioxide concentrations and furnace temperatures during an eight-day plant operation period. The estimated fuel feeds match with the feeds during five known test setup periods (3 to 8 hours), also performance outside of test periods appears feasible.

Interfaces (in/out) – system/user

The physical model and measurements are set up in the Matlab m-files. Input data (measurements) are provided as numerical vectors. Interactive tuning is enabled by Matlab interface/graphics. Estimation outcomes are provided as numerical vectors.

A link with StreamPipes is enabled by an OPC-UA client/server component (see FUSE OPC-UA tool).

Subordinates and platform dependencies

The tool is implemented using Matlab language (m-files). Matlab from the Mathworks is required (FUSE has been tested on Matlab 2020b).

Matlab (2020b) is available on all major operating systems, including Windows 7, Ubuntu 16, Debian 9, MacOS 10 and newer. No particular Matlab Toolboxes are required. Open software such as Octave is known to be able to interpret m-files, but FUSE-codes have not been tested with Octave.

Licenses, etc. (free for use in the project)

The FUSE code is free for use in the project (contact Enso.Ikonen@oulu.fi). ▯ The CFB hotloop physical model is Sumitomo SHI FW Energia Oy proprietary. The plant measurement data in its unprocessed form is proprietary of the pilot plant.

TRL for overall component/tool and any parts/subordinates
Current state is TRL 5 (validated in a relevant environment) currently being raised to TRL 6 (demonstrated in a relevant environment).

References – incl. web etc.
Ikonen & Selek (2020) Calibration of Physical Models with Process Data Using FIR filtering. Australian and New Zealand Control Conference, Gold Coast, pp-143-148. **(Ikonen & Selek, 2020)**   The generalized Matlab-tool is available at http://cc.oulu.fi/~iko/COGNITWIN/

To be considered in particular for the following COGNITWIN pilots
Sumitomo SHI FW Energia Oy

14.4 SubFUSE

Component/Tool description
Component/Tool/Method/Framework/Service Name
SubFUSE
Defined in Task
5.1 / 5.4
Short Description – incl. Purpose
SubFUSE is a state estimation (soft-sensory) tool which fuses subspace methods for system identification with Kalman filtering. The tool is solely data-driven, it requires IO data (measurements) as input. In particular, the tool is developed for the estimation of input fuel characteristics of combustion-thermal power plants. Relying on regular process data including flue gas composition measurements, an estimate of the chemical structure of the fuel fed to the furnace of a CFB boiler is provided. The approach can be applied for alternative state estimation purposes as well, given that a suitable plant model can be generated and proper measurements are provided. The tool has been tested in a simulated environment which aims to replicate the dynamics of the pilot problem. Validation of the tool using data from pilot will be conducted in 2021, a generalized version will be developed based on validation results. The tool has been implemented in MATLAB, and is available in script format.
Progress since delivery D5.1
The tool has been developed (designed, implemented, and verified) after the last milestone in 2/2020.
Progress since delivery D5.2
N/A
Examples of usage / illustrations
The tool target is solving the WP3 pilot problem on fuel characterization, as a part of the heat exchanger fouling monitoring problem. Using IO data pairs of the process of interest, the tool proceeds in two steps: first, a sufficient Linear Time-Invariant approximation of the governing dynamics is conducted utilizing subspace identification. Once the approximate dynamics is available, a standard Kalman filter is used for state estimation. For example, Figures 1 and 2 illustrate the performance of the tool in soft-sensing the chemical composition of the fuel fed to a CFB boiler. In the learning phase (figure 1) the tool learns to mimic the dynamics of combustion.
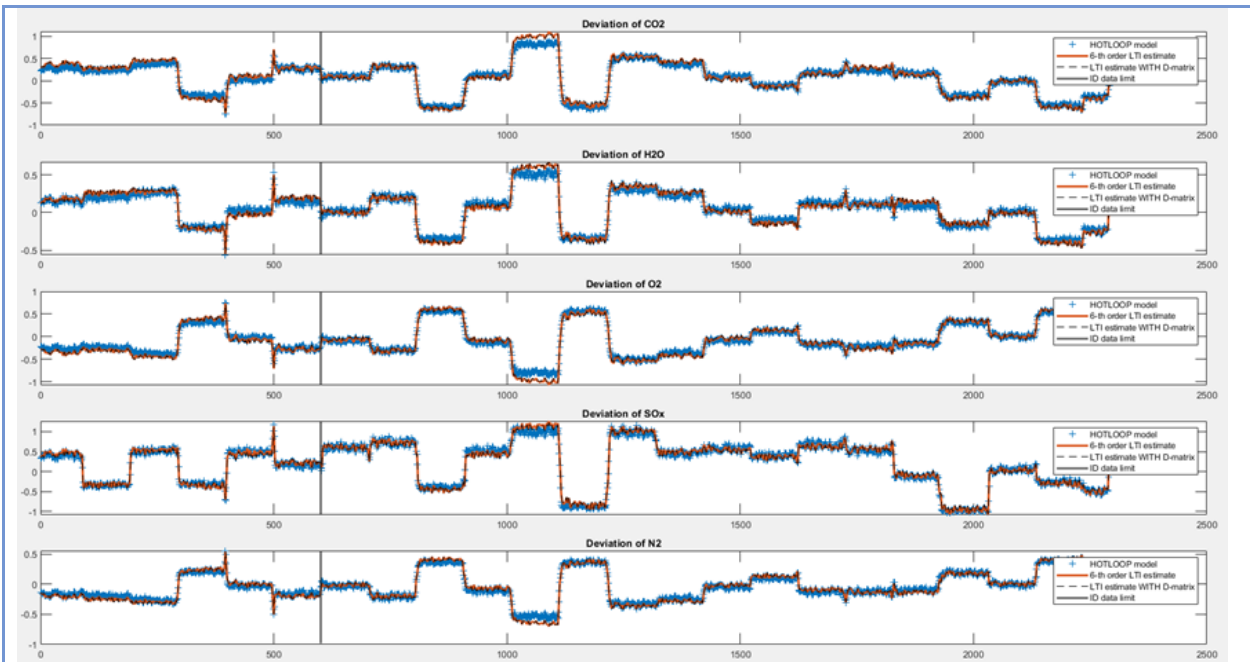
Figure 32: The identified Linear Time Invariant model (red) of a nonlinear combustion dynamic using IO measurement pairs (blue). Training data (left) are separated from the validation data (right) by a black line located at timestep 600.

Based on the IO relationship identified from data, the tool estimates (soft-senses) the chemical composition of the fuel using standard flue gas measurement data available at the power plant of interest (figure 2).
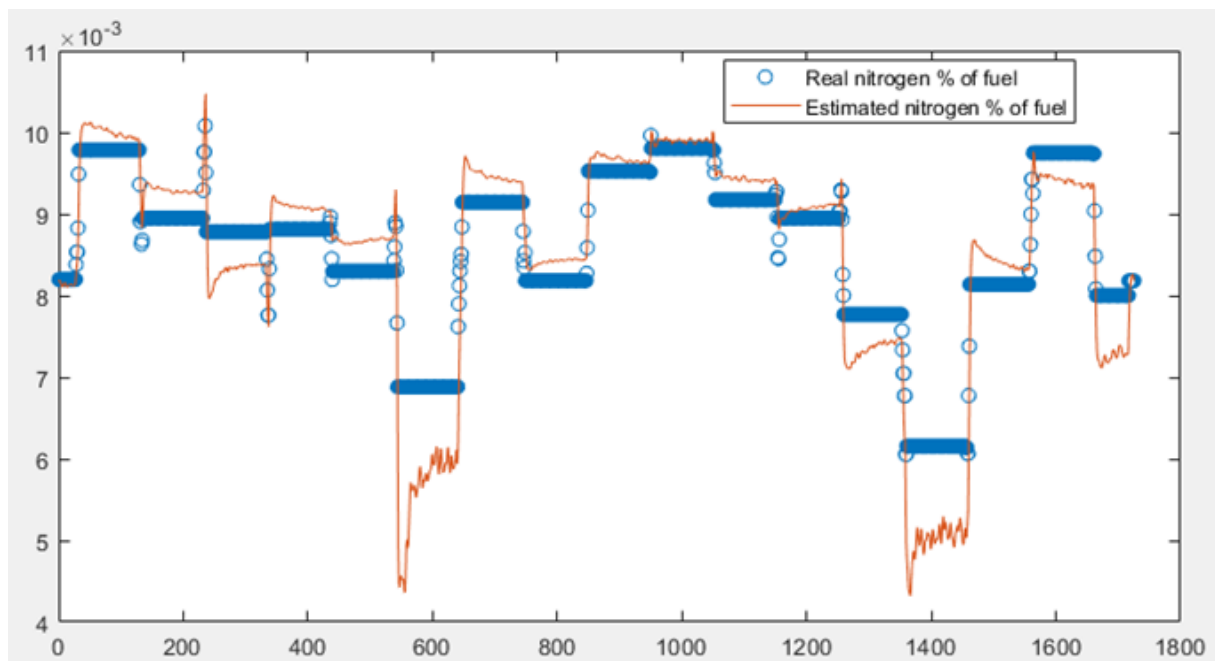

Figure 33: Actual (blue) and estimated (red) nitrogen content of the fuel used for heat generation in the combustion-thermal power plant of interest

Interfaces (in/out) – system/user

The tool is implemented in MATLAB script (.m file). Input data (measurements) are provided as numerical vectors (matrices). Estimation outcomes are provided as numerical vectors (matrices).

A link with StreamPipes is enabled by an OPC-UA client/server component (see FUSE OPC-UA tool).

Subordinates and platform dependencies

The tool is implemented in MATLAB script (.m file). MATLAB, a product Mathworks is required to run the application. (SubFUSE has been tested on MATLAB version 2020b).

MATLAB (2020b) is available on all major operating systems, including Windows, Unix/Linux and MacOS. The tool uses the MATLAB core, additional toolboxes are not required. Open software such as Octave is known to be able to interpret m-files, but FUSE-codes have not been tested with Octave.

Licenses, etc. (free for use in the project)

The SubFUSE code is free for use in the project (contact Istvan.Selek@oulu.fi).

TRL for overall component/tool and any parts/subordinates

Current state is TRL 4 (validated in lab) currently being raised to TRL 5 (validated in a relevant environment).

References – incl. web etc.

Istvan Selek (Istvan.Selek@oulu.fi)
Markus Neuvonen (Markus.Neuvonen@oulu.fi)

To be considered in particular for the following COGNITWIN pilots

Sumitomo SHI FW Energia Oy

14.5 TIA MODEL

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA MODEL
Defined in task
T5.1, T5.2
Short Description – incl. Purpose
TIA AIprovides and enables the application of machine learning algorithms and needed to perform smart predictive maintenance for the SWP machinery. TIA MODEL utilizes supervised, unsupervised, multidimensional scaling, and reinforcement learning algorithms as needed. To compare ML models used for predictive analysis, GUIs have been developed.
Progress since delivery D5.1
Since the last milestone, frontend and backend software of TIA MODEL were developed. Multiple machine learning algorithms have been applied to the data passing through the incremental PCA stage to detect anomalies. RF, Gradient boosted tree, LSTM, SVM, KNN, and MLP algorithms have been used. Unal, P., et.al*. (2021) "Data-driven Artificial Intelligence and Predictive Analytics for the Maintenance of Industrial Machinery Based on an Event Processing Platform"*
Progress since delivery D5.2
- Data labelling and data cleaning have been performed.   - ML/DL prototypes have been completed for LSTM, SVM, KNN and MLP.   - Results obtained by trained and tested models have been discussed with the experts.   - Improvements of the algorithms and features are in progress.
Progress since delivery D5.3
Verification and validation have been completed.
Examples of usage / illustrations
For predictive maintenance purposes the tool is being utilized.
Interfaces (in/out) – system/user
TIA DATA data is used by TIA MODELas input. TIA MODEL output is visualized by TIA UX.
Subordinates and platform dependencies
None (platform independent web application)
Licenses, etc. (free for use in the project)
Proprietary/ Subject to license
TRL for overall component/tool and any parts/subordinates

The current TRL is6 as targeted.

References – incl. web etc.
https://tia-platform.com/module/tia-apps.html
To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.6 Neuroscope

Component/Tool description
Component/Tool/Method/Framework/Service Name
Neuroscope

Defined in Task
Task 5.2: Multi-variate Sensor analytics with Deep Learning

Short Description – incl. Purpose
Neuroscope is a visual debugger for convolutional neural networks. The software is an interactive tool with a graphical user interface intended for interactive use by data scientists on the application level. The purpose of the Neuroscope software is to allow data scientists to gain insight into the inner workings of a neural network, in the case of a system malfunction or misbehavior. The approach taken by Neuroscope is a network visualization approach, which means that the weights of the inner layers are visualized in a human-interpretable way, which is helpful for understanding why a certain misbehavior occurred. In the context of COGNITWIN, the Neuroscope software will be useful as part of a software toolbox to make machine learning technology practically useable. The software supports the following major features: (1) visualization of network architectures loaded from PyTorch or TensorFlow files as graph representation, visualization of trained weights by means of (2) activation maps, (3) saliency map, (4) guided back propagation, (5) grad-CAM, (6) guided Grad-CAM, and (7) grad-CAM plus. The software supports arbitrary networks architectures for classification and semantic segmentation of image-like data and is currently being extended to multi-object detection and localization architectures. Neuroscope is comparable to systems like Tensorboard. The major difference is the support of exchangeable machine learning backends (TensorFlow and PyTorch), and the interactive use via a graphical user interface.

Progress since delivery D5.1
Since the last milestone, we added the following features to the project: (1) support for semantic segmentation network architectures, and (2) support for guided Grad-CAM. We are currently raising the technology readiness level to TL 7 by bug fixing and implementing smaller improvements. We are currently implementing (3) support for multi-object detection and localization architectures. **We are currently writing a publication concerning the software (Schorr, Godarzi, Chen, & Dahmen, 2021)**

Progress since delivery D5.2
Since the last milestone, we had to cancel a technical attempt to integrate multi object detection and localization architectures via the Explain-to-fix method in Neuroscope. The integration turned out to be technically infeasible for principal reasons. We reconsidered our efforts and are now starting to integrate a method called D-RISE. We published the following paper (Schorr, Luschkova, & Dahmen, Automatic detection of billets in rolling mills using convolutional neural networks with synthetic data, 2021)

Examples of usage / illustrations

The example synthetic image of billet rolling process illustrates the capability of Neuroscope to analyze a given neural network (top left). The task is to segment the image regarding the class "billet" as a component of automatic optical detection and tracking process. Using a saliency metric, a diffuse image of pixels sensitive to the class "billet" is computed (top right). The second visualization method called guided Grad-CAM shows clear regions of high activation in places of billets, as well as some localized areas of low activation (bottom left). The activation map computed by Guided Backpropagation method (bottom right) highlights pixels of high activation exactly at billet locations. The analysis of these 3 types of visualization maps raises the question of why the activation maps do not show high activated pixels monotonously within the bounds of billets. This observation could be the indicator of a poorly trained deep learning model or scarce training data.
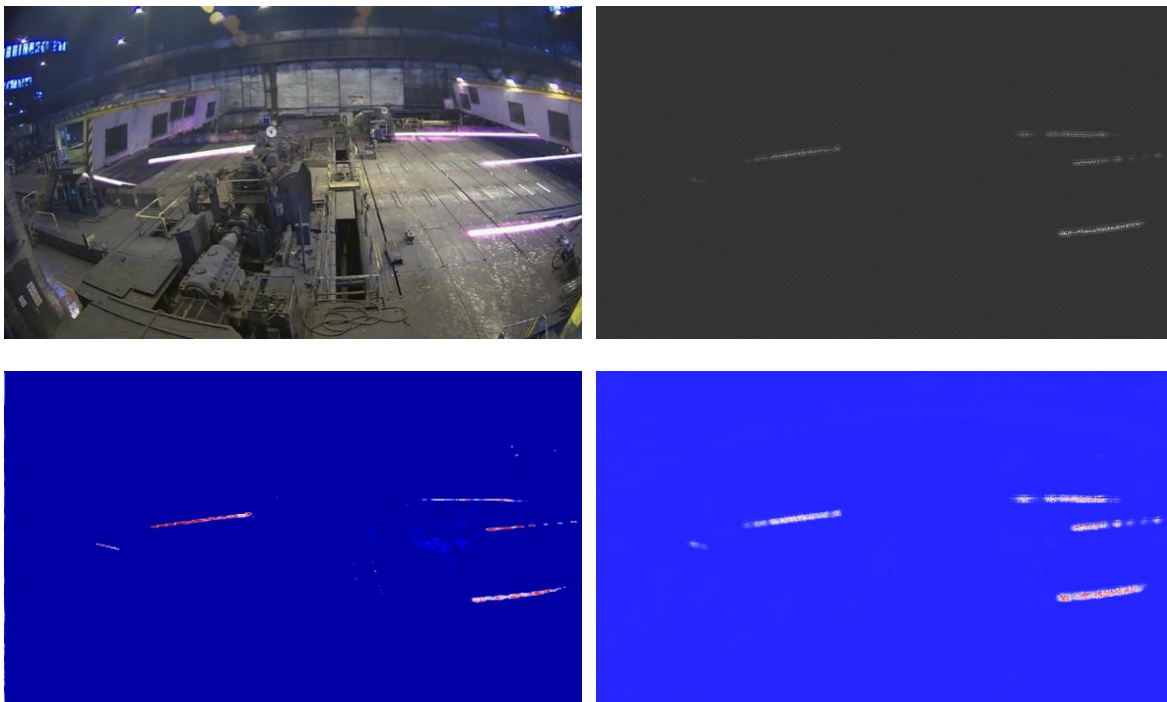
Figure 34: Visualization of the class "billet" using Neuroscope: top left: original image, top right: saliency map, bottom left: guided Grad-CAM, bottom right: guided backpropagation.

Interfaces (in/out) – system/user

The system features a graphical user interface and is intended for interactive use only. The system can load network architectures and weights in TensorFlow and PyTorch format. It is able to export visualization results in common image formats.

Subordinates and platform dependencies

Neuroscope is available for Linux and Windows. It supports PyTorch and TensorFlow as backends.

Licenses, etc. (free for use in the project)

We provide a community version under GPL. For commercial licenses, contact DFKI directly (Tim.Dahmen@dfki.de).
TRL for overall component/tool and any parts/subordinates
6, currently being raised to 7
References – incl. web etc.
https://github.com/c3di/neuroscope
To be considered in particular for the following COGNITWIN pilots
Saarstahl.

14.7 Aerial Photogrammetry

Component/Tool description
Component/Tool/Method/Framework/Service Name
Aerial Photogrammetry
Defined in Task
Task 5.2: Multi-variate Sensor analytics with Deep Learning
Short Description – incl. Purpose
Photogrammetry is a technique for the capturing of three-dimensional (3D) models from real world environments. The technique works by taking images from manually selected positions and reconstructing a 3D model from the images. As the camera parameters (position and orientation) are unknown, the most important step is to computationally determine position and orientation of each image.
Photogrammetry has a reduced surface precision compared to laser-based surface scanners, but has the immense advantage that it generates textured models in a single step, i.e. the generated models can immediately be used for photorealistic rendering. Another advantage is that photogrammetry is applicable to a wide range of length scales. If combined with macro photography, photogrammetry can capture details on the micrometer scale, if combined with handheld cameras it can produce centimeter scale objects, and combined with drones (aerial photogrammetry), the capture area can extend over several square kilometers.
In the course of this project, we will provide a process for aerial photogrammetry which allows the capturing of entire sections of production plants, such as the Saarstahl milling plant. This workflow will be assembled from commercially available components but adapted to the specific needs if being used in a large indoor-environment with harsh production conditions. The purpose of the captured 3D models is the generation of training data for machine learning applications.
Progress since delivery D5.1
A number of datasets was captured using different flight patterns from a drone and using a handheld and tripod-mounted camera system. Reconstruction results were compared to determine the optimal capturing mode.
A commercially available photogrammetry software (Agisoft Metashape) was purchased, installed on suitable server hardware, and reconstruction settings were optimized to work with the available datasets.
Progress since delivery D5.2
The pipeline for synthetic data generation was improved by increasing flexibility (exposing additional parameters) and by improving usability. The documentation was improved considerable. The technical dependencies were consolidated and documented. A controlled installation procedure was developed, documented and partially automated. Several instances of the data generation pipeline from different projects were re-integrated and consolidated on the source-code level, concerning data organization (folder structure) and concerning the version control system.
Interfaces (in/out) – system/user
Agisoft Metashape software is a stand-along software that performs photogrammetric processing of digital photographs. It loads arbitrary number of unpreprocessed images in common formats and generates a 3D model of a scenery. Here it is important to capture high-quality and highly

overlapping images of the setting to compute the best quality model. It is recommended to employ a camera with 5Mpx resolution at least and to shoot photographs with 80% overlap.

Subordinates and platform dependencies
Recommended configurations for Agisoft Metashape: • Windows 7 SP 1 or later (64 bit), Mac OS X Mountain Lion or later, Debian/Ubuntu with GLIBC 2.13+(64 bit) • Intel Core i7 or AMD Ryzen 7 processor • Discrete NVIDIA or AMD GPU • 32 GB of RAM
Licenses, etc. (free for use in the project)
The component is realized as a non-disclosed inhouse workflow.
TRL for overall component/tool and any parts/subordinates
7
References – incl. web etc.
https://www.software3d.de/agisoft-metashape-pro
To be considered in particular for the following COGNITWIN pilots
Saarstahl.

14.8 Bonzai

Component/Tool description
Component/Tool/Method/Framework/Service Name
Bonzai
Defined in Task
Task 5.3: Deep Learning Performance
Short Description – incl. Purpose
Bonzai is Scortex python library handling everything related to deep learning on images. Bonzai is built on top of Keras / Tensorflow. It uses as input a connection to a mongo database for annotations and meta-information (dates, part reference, acquisition system version, ...), as well as an azure filesystem for image storage. The main output is the production of deep learning model in tf.keras format (topology in .json and weights in .h5). With this library, Scortex engineers manipulate and clean images and their metadata. They use it to train deep learning models and properly evaluate these models.
Progress since delivery D5.1
Scortex has greatly improved its machine learning library. A large focus was put on the maintainability and traceability of the deployed systems. From any deployed model, Scortex is able to retrace which images, metadata, and preprocessing was used to train it. Scortex extended its library to user use cases as well. Previously, only defect detection was supported. Now, the library can handle part detection/segmentation as well as anomaly detection. Related to inference speed: Scortex worked on a way to improve all models inference time and published a blog post about it: https://scortex.io/batch-norm-folding-an-easy-way-to-improve-your-network-speed/. This technology is now deployed at some of Scortex' clients. Scortex worked on improving the architecture speed of the network they are using at their clients. Typically using a smaller / shallower network. The difficulty of this is to maintain good robustness (mostly for repeatability. See this other blog post: https://scortex.io/robustness-and-repeatability-of-modern-deep-neural-networks-a-review/). Scortex devised real time / light architectures for the task of detection / semantic segmentation as well as anomaly detection. Scortex has investigated pruning networks but that did not provide good results for inference time, as most software / hardware (example: GPU + TensorFlow) do not support leverage sparsity. It is our hope FPGA technology will be able to do so. "Distillation": Scortex successfully managed to transfer knowledge from a large network to a smaller one. The performance is not as good as the large model but better than the performance of the smaller model trained on its own.

By combining, Scortex managed to deploy a station capable of a complex inspection of rotating parts. The Scortex box handles the inspection of 3 parts per second, which requires inference of 300 (3 x 100) 1280x640 grayscale images per second. To the best of our knowledge, Scortex is the only company able to achieve such performances in a real-life deployment.

Some experiments such as "Pruning "or "distillation" are not yet in production as the benefits did not outweigh the implementation cost as of today.

Scortex is also working on improving training speed as shown by this blog post: https://scortex.io/extending-selective-back-propagation-to-segmentation-focus-biggest-losers/.

Its new unsupervised demonstrator allows one second training for a very constrained set up.

Progress since delivery D5.2
N/A
Examples of usage / illustrations

Below is an example image from our unsupervised anomaly detection demonstrator.

The user can train a model with a few un-annotated images and the model will detect anomalies.

The result shows the original image with a defect score and a defect localization. Here is detects a tiny pen mark on the business card the model was trained on.
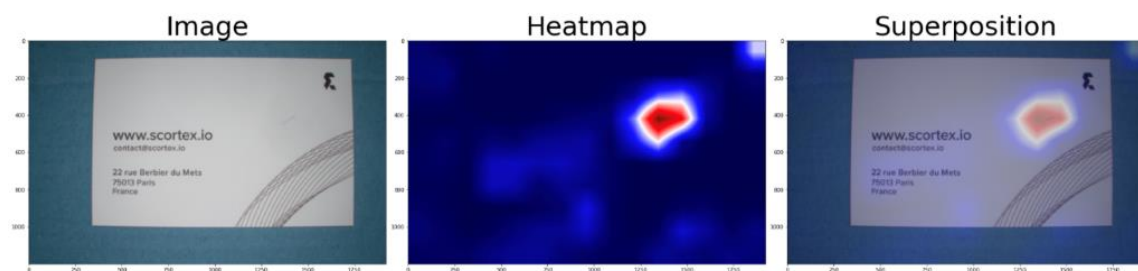
Figure 35: Example image from our unsupervised anomaly detection demonstrator

Example of detections on our supervised demonstrator (less constrained). The part goes on the conveyor belt. Inside the Scortex dark "box" there are 2 cameras filming continuously 1920x1200 colored images. One report is created per part. The (defect) detection is shown with closeups on the bottom of the screen.
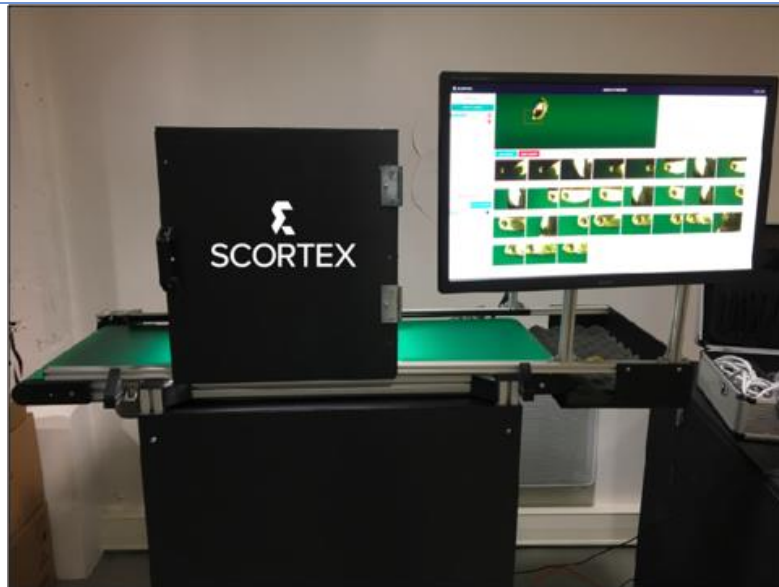
Figure 36: Scortex Bonzai software in action

There is currently no frontend to train supervised models using only the mouse but we are hoping to be able to work on this in 2021.

Interfaces (in/out) – system/user
Bonzai connects to mongodb and other database systems to get images and meta-data (e.g.: annotations). Outputs are deep learning Keras/Tensorflow models and pipelines to be used in productions.
Subordinates and platform dependencies
keras/tensorflow, mongodb.
Licenses, etc. (free for use in the project)
Proprietary. In development, remains the property of Scortex. Will be used by Scortex exclusively.
TRL for overall component/tool and any parts/subordinates
TRL 7
References – incl. web etc.
https://scortex.io/batch-norm-folding-an-easy-way-to-improve-your-network-speed/ https://scortex.io/robustness-and-repeatability-of-modern-deep-neural-networks-a-review/ https://scortex.io/extending-selective-back-propagation-to-segmentation-focus-biggest-losers/
To be considered in particular for the following COGNITWIN pilots
Saarstahl, Sumitomo SHI FW

14.9 Machine learning to FPGA conversion: Keras2RTL

Component/Tool description
Component/Tool/Method/Framework/Service Name
Machine learning to FPGA conversion: Keras2RTL
Defined in Task
Task 5.3: Deep learning performance
Short Description – incl. Purpose
This tool allows to fill the gap between machine / deep learning development environments and FPGA development environments. Machine learning development environments are typically based on the python programming language and libraries such as Keras and Tensorflow (or pytorch) relying on the Nvidia low level computing library named CUDA. Meanwhile, FPGA developments are based on VHDL programming language and integrated development environments (IDE) provided by the company providing the FPGA component. For a Xilinx Virtex Ultrascale+ VU9P, the IDE is named Vivado. Keras2RTL takes as input a tf.keras model that is a file with .h5 extension which contains the topology of the machine learning neural network and the weights. At Scortex, the Keras model is generated using the bonzai library (see other 5.3 components). Keras2RTL converts the topology from the .h5 file and generates the VHDL configuration files. These files will be used by Vivado to generate Honir.
Progress since delivery D5.1
This task is currently handled manually by following a defined process to verify the corner cases and technically cover 100% of the scope to unlock the automation of this process. Its 100% automation will be part of the next steps.
Progress since delivery D5.2
N/A
Examples of usage / illustrations
The overall usage flow is: - Train a tf.keras / keras model (typically using bonzai). - Quantize the model (or train it in a quantized way immediately). - Convert it using keras2RTL. Use this model to run inference on images using the Honir component.

Figure 37: Overall usage flow of Keras model

As a demonstrator, Scortex trained a Keras model on data from one of its demonstrators. The model allows defect detection on common goods parts, such as Lego bricks, electrical switches and door handles.

This deep learning model was quantized using the bonzai tool (see other component) and then processed by Keras2RTL process manually. The VHDL files produced was used for the configuration of the inference engine (Honir: in task 4.4).

In a more general manner, the tool should be used to allow automatic and fast conversion from a Keras machine learning model to a VHDL config file that can be used for Honir creation.

Interfaces (in/out) – system/user
At a user level (a command line tool) IN : keras .h5 file (topology + weights) OUT : VHDL config file (for Honir tool build in T4.4)
Subordinates and platform dependencies
This module can work in standalone. It is, however, necessary for Honir (inference engine) to work properly. Today the tool will support only keras models.
Licenses, etc.
In development, remains the property of Scortex. Will be used by Scortex exclusively.
TRL for overall component/tool and any parts/subordinates
TRL5
References – incl. web etc.
- https://www.h5py.org/ - https://www.tensorflow.org/guide/keras/save_and_serialize - https://github.com/keras-team/keras
To be considered in particular for the following COGNITWIN pilots
- The Honir platform will be considered as a way to run the tracking system for the Saarstahl use case. In which case, keras2TL will be used to generate Honir configuration.

- But it could be extended to any other pilots running deep learning on images.

14.10   TIA DATA-GEN MATLAB Synthetic Data Generator

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA DATA-GEN MATLAB Synthetic Data Generator
Defined in task
T5.4
Short Description – incl. Purpose
TIA DATA-GEN (MATLAB Synthetic Data Generator for Electro Mechanical parts) is a synthetic data generator for common electro-mechanical parts, including electric DC motors and a hydraulic shaft. The purpose of TIA DATA-GEN is to generate synthetic of fault data from the model elements. Hence, the generation of such data enables users to have a model-driven digital twin for a common DC motor, gearbox, and hydraulic shaft and their associated components. TIA DATA-GEN utilizes several 1st order models: DC motor and gearbox models, and a hydraulic press model. For both of these models, random sources of errors (degradation of the components) are introduced. A load representative to what they may experience in the real world is then applied. Virtual sensors will collect data for several specific degradation scenarios. The outcome is a supervised and annotated dataset. The latter will be used in training a ML classifier. The classifier will be used to monitor the condition of the machine in operation and provide early warning for potential fault. In the context of COGNITWIN, the TIA DATA-GEN output will be useful in conducting the predictive maintenance of the modelled elements.
Progress since delivery D5.1
Since the last milestone, sensors have been added to the 1st order principal models. Current and temperature sensors have been added to the motor and gearbox model, while a hydraulic press sensor has been added to the previously developed hydraulic press model. Following the sensor implementations for the models, model parameters have been calibrated and the random error sources have been introduced to the model. Thus, the model has been updated to be ready for predictive maintenance algorithms by introducing sources of random errors to be used in predictive maintenance, adding appropriate sensors to observe the effect of these error sources on important variables of the models and calibrating the geometrical, electrical, and hydraulic parameters of components to make the model as applicable and as realistic as possible.
Progress since delivery D5.2
N/A
Progress since delivery D5.3
• Verification and validation have been completed.
Examples of usage / illustrations

MATLAB Simulink is used to develop and update the models.

Interfaces (in/out) – system/user

TIA DATA-GEN generates output data in .mat format and/or .csv format.

Subordinates and platform dependencies

TIA DATA-GEN works with MATLAB Simulink and it converted to operate a standalone executable program.

Licenses, etc. (free for use in the project)

TBD

TRL for overall component/tool and any parts/subordinates

The current TRL is 5 as targeted. The laboratory integrated system testing has been conducted..

References – incl. web etc.

https://tia-platform.com/module/tia-apps.html

To be considered in particular for the following COGNITWIN pilots

NOKSEL

14.11   Pragmatism in physics-based modeling (PPBM)

Component/Tool description
Component/Tool/Method/Framework/Service Name
Pragmatism in physics-based modeling (PPBM)

Defined in Task
Task 5.4: Hybrid Digital Twins

Short Description – incl. Purpose
"Pragmatism in physics-based modeling" (PPBM) is a method/framework for developing physics-based mathematical models. Such models may serve as a digital twin alone or as companion with data-based AI/ML methods, to form hybrid digital twins to exploit the combination of data and physics-based modeling. The purpose of PPBM is to devise a generic methodology for development of physics-based models for application in digital twins. The PPBM provides a recipe for attacking a digital twin development, starting out from problem definition, information collection, including exact definitions of the output requirements for the model, assembling a system architects team, model specification, use of sub-level empirical or computed data, model building and application. The PPBM can only be developed further through application in industrial cases, like the Sidenor pilot case. The physics, chemistry, and numerical methods to be used may differ between applications, but PPBM should help the developers (system architects) to run through a set of well-defined steps on the way from problem definition to final application. For each new application using the PPBM, new learning must be extracted and reported (published). In the Sidenor pilot case offline data is used. Tuning of the model was done by help of operational data from the industrial partner. This alone is a hybrid approach. The data has multiple challenges. We extended the PPBM to clean the available data, but also to provide additional simulated data. These combined data has been, and will be further explored in a extended hybrid approach.

Progress since delivery D5.3
During the last period, we finalized the method/framework through the development of the physics-based model for the Sidenor pilot. Following elements were in focus:

- i)   Adding more iterations to the method. During visit to Sidenor in Bilbao it became clear that vacuum treatment has very strong effects of surface flow and splashing. The flow in the ladles had to be re-simulated, accounting for vacuum effects. Relations obtained from curve fitting of the simulated results was plugged into the code. This modified the heat transfer coefficients and erosion speed.

- ii)   Tuning methods were developed and applied to the model. This resulted in very good temperature predictions.

- iii)   *Updating the pragmatism work steps*

  - a.   **Problem and Context Identification**

    - i.   Define the problem in a problem document. Consolidation with the industrial partner. Defining and collecting the needed information

ii.   Process to agree on model requirements,

b.   **Analytical Strategy and Plan**

i.   Writing (here updating) model specification

c.   **Architecture of the Analytical Framework**

d.   **Execution**

e.   **Evaluation of the Solution**

f.   **Conclusion and Communication**

i.   Result communicated through two papers:

1.   "**Pragmatism in industrial modelling, applied to "ladle lifetime in the steel industry"**", dealing with the PPBM

2.   "Pragmatism based model for ladle lifetime prediction", explaining the physics model

iv)   **Model was submitted to https://github.com/SINTEF/refractorywear**

The Sidenor pilot has been a good case for further development of the pragmatism method. The models were defined to explain the thermal evolution of a steel ladle during its lifetime and predict the refractory erosion from heat to heat. In order to handle the major and complex physics and thermodynamics (multiphase flows, slag heater, radiation, thermal stress erosion, interface waves, local heat and mass transfer, chemical equilibrium of complex metal-slag systems, dissolution of refractory components) several simplifications are introduced, some based on using Computational Fluid Dynamics (CFD) to create data that can be applied in the simpler and faster model.

In this pilot we applied and extended the PPBM, to be implemented in the Python framework where many tools available for Python may be explored for various types of hybridization.

The work, involving extensions of the PPBM, will be published under "Pragmatism in industrial modeling, applied to ladle lifetime in the steel industry"[JOH+23]. A particularly important contribution is to show how such a model can reveal the goodness of the industrial data. This is critical as industrial data, for many good reasons, may be completely incorrect, and it may in some cases be impossible to build automated filters that can fix the problem.

Progress since delivery D5.2

The PPBM method has now been extended by more strict checks on the data as we have learned that some data cannot be trusted before being checked for consistency. A main learning is that consistency is hard to evaluate without some physics-based model.
The model must be checked against the data and improved and tuned, exploiting alle available data. Methods for learning from the data and tuning have been developed. Here we use residual-based methods and fractional factorial design.

Examples of usage / illustrations

In the Sidenor pilot, applying and extending the PPBM method, we are developing a model for the ladle refractory erosion. The model can predict the thermal evolution in the refractory and shell. The change of erosion pattern, from heat to heat is predicted. An example is shown below.

We can see that the steel in this case was rather high (position of slag line). Use of the model has indicated that steel may penetrate in between refractory bricks. This will significantly impact the temperature of the steel shell, but also ladle life. In this manner, combining the PPBM-based model, thermal imaging and ML/AI a route to keep track on ladle life is possible.
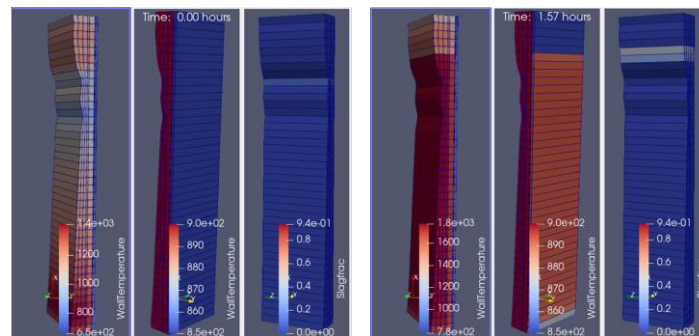
Figure 38: Left: We see the refractory and outer surface temperature at time metal was filled into the ladle. The ladle was initially eroded. Right: Same case as on the left, but now the erosion pattern has changed since previous heat. In the right subplot we see where the slag is located (slag fraction), on top of the metal.
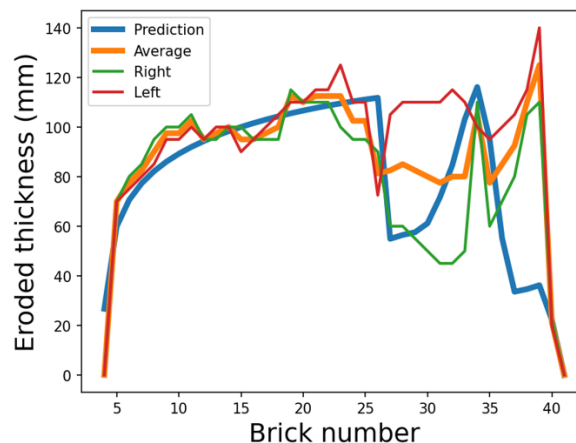
Figure 39: Comparison between predicted and measured erosion profile, taken at the end-of-life for a Sidenor ladle. The deviations above brick number 35 is above melt level and is not included in the model.

Interfaces (in/out) – system/user

The Sidenor application of the PPBM is currently reading data in ascii format (*.csv, *.xls) and output is saved as files in similar formats. In addition, data can be saved in the VTK *.vts format. These files can be loaded into the Paraview (https://www.paraview.org/) tool for 3D visualization of the results.

Subordinates and platform dependencies

The Sidenor model is using Python 3 and standard Python libraries. It can be run on both Windows and Linux systems.

Licenses, etc. (free for use in the project)
The model will be open (free of use)**,** and **is** published at **https://github.com/SINTEF/refractorywear** **, using the MIT open source** license**.**

TRL for overall component/tool and any parts/subordinates
Currently it is TRL-3. As this belongs to the class of methods it may be developed into a technical standard at a later stage. https://en.wikipedia.org/wiki/Technical_standard

References – incl. web etc.	
[ZOR+15]	J. Zoric, S. T. Johansen, K. E. Einarsrud, and A. Solheim, 'ON PRAGMATISM IN INDUSTRIAL MODELING', Progress in Applied CFD, Selected papers from 10th International Conference on Computational Fluid Dynamics in the Oil & Gas, Metallurgical and Process Industries, vol. 1, pp. 9–24, 2015. Available: https://www.sintefbok.no/book/download/1038
[ZOR+15b]	J. Zoric et al., 'On Pragmatism in industrial modeling - Part II: Workflows and associated data and metadata', Melbourne, Australia, 7-9 December, 2015, 2015, p. 7 pages, [Online]. Available: http://www.cfd.com.au/cfd_conf15/PDFs/032JOH.pdf .
[JOH+17]	S. T. Johansen, E. A. Meese, J. Zoric, A. Islam, and D. W. Martins, 'On Pragmatism in Industrial Modeling, Part III: Application to Operational Drilling', in Progress in Applied CFD – CFD2017 Selected papers from 12th International Conference on Computational Fluid Dynamics in the Oil & Gas, Metallurgical and Process Industries, Trondheim, 2017, p. 11, [Online]. Available: http://hdl.handle.net/11250/2465068 .
[JOH+22]	S. T. Johansen, K. E. Einarsrud, A. Solheim, and K. J. Vachaparambil, 'A Pragmatic Model for Alumina Feeding', in Light Metals 2022, D. Eskin, Ed. Cham: Springer International Publishing, 2022, pp. 503–511. doi: 10.1007/978-3-030-92529-1_67.
[JOH+23]	Stein Tore Johansen, Bjørn Tore Løvfall, Tamara Rodriguez Duran and Josip Zoric, 'Pragmatism in industrial modelling, applied to "ladle lifetime in the steel industry"', paper ready for submission, 2023.

Was applied in the following COGNITWIN pilots
Sidenor. However, PPBM could have been applied in the Sumitomo SHI FW (fouling), as well as the Hydro and Elkem pilots. In addition, the Sidenor application may later be exploited by COGNITWIN partners Elkem and Saarstahl.

14.12   Cybernetica CENIT

Component/Tool description
Component/Tool/Method/Framework/Service Name
Cybernetica CENIT
Defined in Task
5.4 Hybrid Digital Twins
Short Description – incl. Purpose
Cybernetica CENIT is a tool for online estimation and nonlinear model predictive control. It can be used as both a soft sensing application and a control application. Model Predictive control is an advanced control method where a mathematical model of the process is used to predict future behavior. The predictions from the model are used in a mathematical optimization algorithm that calculates the optimal process inputs in order to achieve optimal future behavior of selected variables in the process. Constraints and setpoints may be imposed both on the manipulated process inputs variables and the controlled process output variables. Model predictive control also has the advantage that couplings between variables in the process are taken into account.
Progress since delivery D5.1
Cybernetica CENIT has been extended with application modules for the Elkem and Hydro pilot processes. These modules contain physics-based models of the processes and make it possible to run online state and parameter estimation, as well as implement soft sensing and nonlinear model predictive control applications. Cybernetica CENIT has further been extended with routines for validation of the input data and its own calculation results. This includes new interface routines for the application components. This extension forms a basis for the development of the proposed "Cognitive CENIT" tool.
Progress since delivery D5.2
The validation routines added in D5.1 have been improved and the application component interface has been standardized.
Progress since delivery D5.3
The error validation routines has been further improved.
Examples of usage / illustrations

Figure 40: Main components of Cybernetica CENIT

Cybernetica CENIT consists of a generic part and an application-specific part, namely the process model. A Cybernetica CENIT application is defined as Cybernetica CENIT and some process model together.

The following table describes the main components of a Cybernetica CENIT application:

Component	Purpose
CenitKernel	This is the main component of Cybernetica CENIT. It implements communication with the process control system and the calculation algorithms (estimator and nonlinear model predictive controller).
CenitMMI	This is an engineering interface used to configure and supervise CenitKernel, mainly during the engineering phase of the project. The operators interface is normally integrated in the existing DCS interface.
Process model	This is the application-specific part of a Cybernetica CENIT application. It implements a mathematical representation of the process that is controlled.
Database	An optional database for logging parameters and calculated data from CenitKernel. The data is used both by CenitMMI and for offline data analysis, and can be used to trend inputs, states and other calculated values.
Control system	This is the process control system (DCS/ PLC), which handles the low-level communication with the process. This system is not a part of Cybernetica CENIT and should implement an OPC server on a standard form to handle the communication with CenitKernel. Both OPC Classic and OPC UA interfaces are supported by Cenit. The communication includes process measurements, manipulated variables and possibly other variables as well.

The model component is implemented as a Microsoft Windows dynamic link library (DLL). One or more model interfaces can be implemented in such a DLL, depending on which calculation modules shall be used. It is not necessary to implement unused interfaces.

The interfaces do not depend on each other, and it is possible to implement different models for each interface, i.e., a complex model for the simulator interface and a simpler model for the controller. However, it is quite common to implement the same model for

all the interfaces. The figure below shows how to do this. In this figure, there is a common inner model code base for all the interfaces:
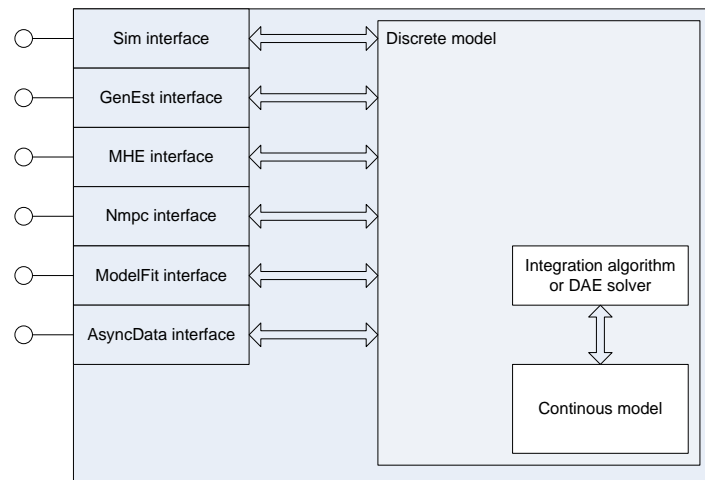

Figure 41: Cybernetica CENIT interfaces

The available interfaces are:

- **Sim interface: Used to simulate the process.**
- **GenEst interface: Used by the Kalman Filter.**
- **MHE interface: Used by the Moving Horizon Estimator.**
- **Nmpc interface: Used by the non-linear predictive controller**
- **ModelFit interface: Used by Cybernetica ModelFit.**
- **AsyncData interface: Used by Cybernetica Cenit to handle input data that requires special handling; e.g. registration of process event data.**

Interfaces (in/out) – system/user

Data can be presented to the user by using Cybernetica CenitMMI, or extracted from the database using the included tool getdbdata.

Example of CenitMMI displaying some historical trend and prediction plots for some manipulated variables:
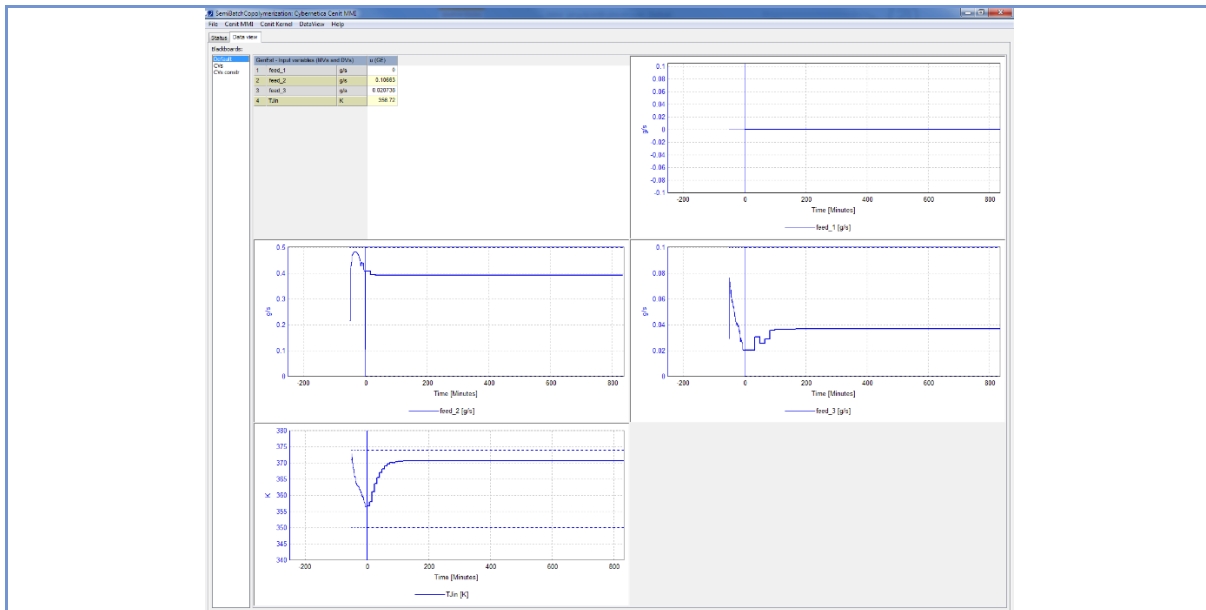
Figure 42: Cybernetica CENIT MMI

Subordinates and platform dependencies
May use PostgreSQL database.

Licenses, etc. (free for use in the project)
Cybernetica Cenit licenses are provided free of charge for the duration of the CogniTwin-project for project partners who need such license to execute their work in the project. Should the project result be taken into permanent use after the end of the project, licenses are provided on fair and reasonable terms as stated in the Grant Agreement.

TRL for overall component/tool and any parts/subordinates
9 - Commercial product.

References – incl. web etc.
http://cybernetica.no/technology/model-predictive-control/

To be considered in particular for the following COGNITWIN pilots
Hydro, Elkem.

14.13   Cybernetica ProXim

Component/Tool description
Component/Tool/Method/Framework/Service Name
Cybernetica ProXim
Defined in Task
5.4 Hybrid Digital Twins
Short Description – incl. Purpose
Cybernetica ProXim is a software platform for building tailor-made process simulators using the same kind of process models as Cybernetica CENIT.   The platform includes components for simulation and data visualisation.
Progress since delivery D5.1
This product has not been updated since last milestone, but the description is included as it will be used at a later stage in the Elkem and Hydro pilots.
Progress since delivery D5.2
N/A
Progress since delivery D5.3
N/A
Examples of usage / illustrations
Example of the user interface of a process simulator:

Figure 43: *Cybernetica ProXim*

Interfaces (in/out) – system/user
Subordinates and platform dependencies
Licenses, etc. (free for use in the project)
Cybernetica ProXim licenses are provided free of charge for the duration of the COGNITWIN-project for project partners who need such license to execute their work in the project. Should the project result be taken into permanent use after the end of the project, licenses are provided on fair and reasonable terms as stated in the Grant Agreement.
TRL for overall component/tool and any parts/subordinates
8
References – incl. web etc.
http://cybernetica.no/technology/model-predictive-control/
To be considered in particular for the following COGNITWIN pilots
Hydro, Elkem.

14.14   Cybernetica RealSim

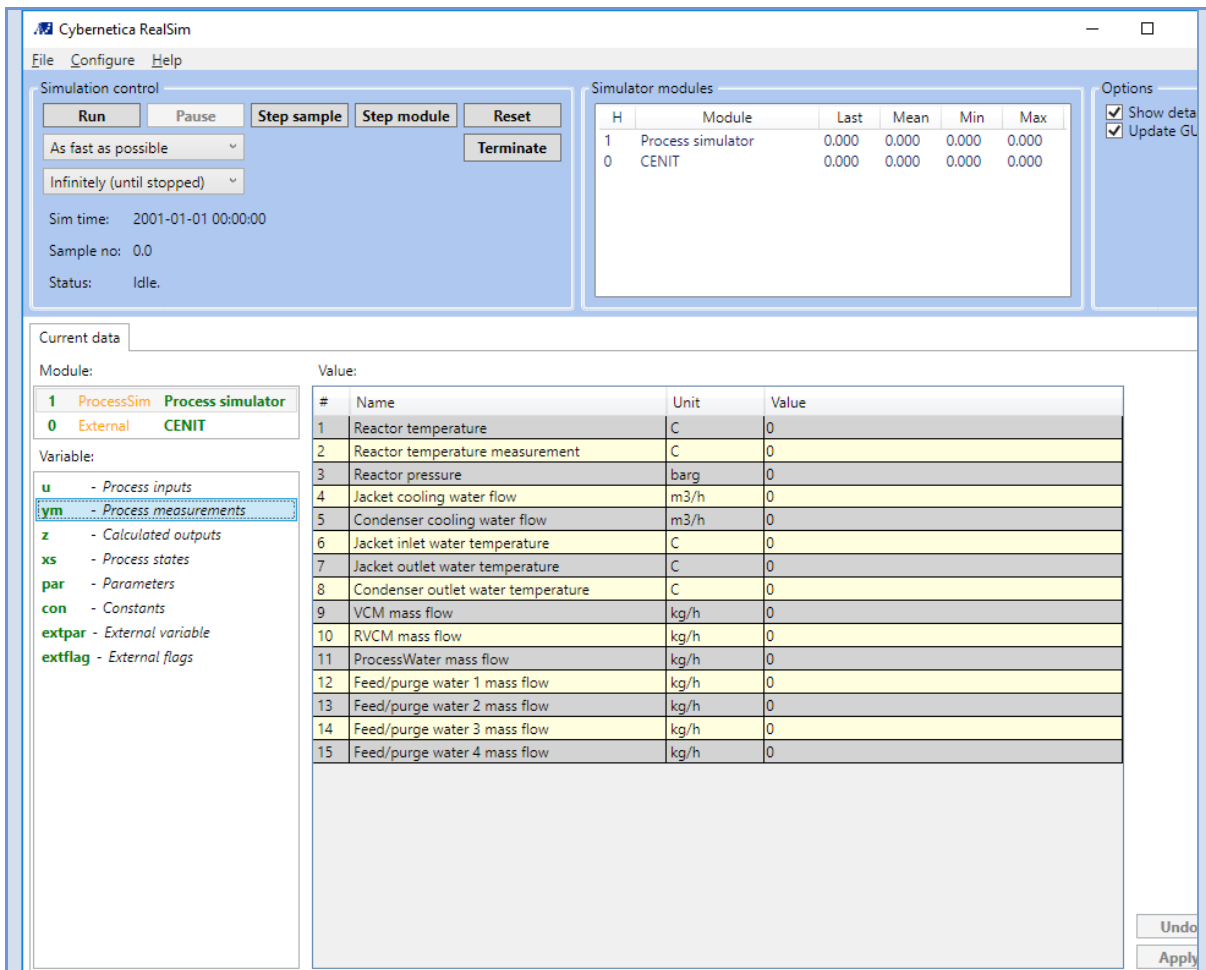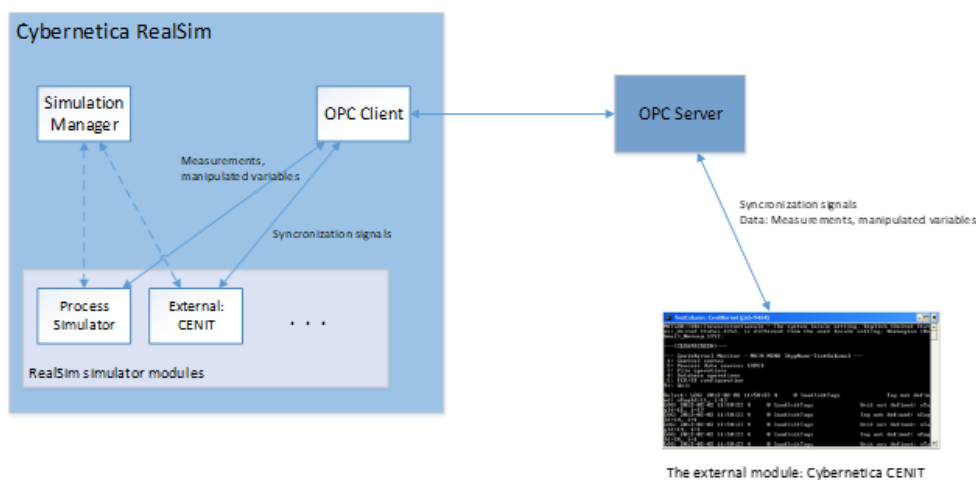| Component/Tool description |
|---|
| **Component/Tool/Method/Framework/Service Name** |
| Cybernetica RealSim |
| **Defined in Task** |
| 5.4 Hybrid Digital Twins |
| **Short Description – incl. Purpose** |
| Cybernetica RealSim is a plant replacement process simulator used for testing of CENIT or other control applications. It communicates over the OPC protocol in order to replicate the interface to the DCS at the plant as closely as possible. It interfaces to Cybernetica Model and Application Components. The plant replacement model might be the same as the model used in CENIT or it might be a different one in order to evaluate how the controller responds to model uncertainty and unknown process disturbances. Cybernetica RealSim is typically used during application development and for factory acceptance tests. |
| **Progress since delivery D5.1** |
| Cybernetica RealSim has been extended with application modules for the Elkem and Hydro pilot processes. These modules contain physics-based models of the processes and make it possible to run online state and parameter estimation, as well as implement soft sensing and nonlinear model predictive control applications.

Support for using OPC UA servers for data exchange has been added. |
| **Progress since delivery D5.2** |
| Functionality for using OPC UA server has been improved.
Support for using text data (strings) as input and output data has been added. |
| **Progress since delivery D5.3** |
| N/A |
| **Examples of usage / illustrations** |
| Example of Cybernetica RealSim user interface: |

Figure 44: Cybernetica RealSim

Overall architecture / pipeline / workflow (incl. figure – elements according to BDVA)

The following figure shows how Cybernetica RealSim works as a plant replacement tool for Cybernetica CENIT:

Figure 45: Cybernetica RealSim as a plant replacement tool for Cybernetica CENIT

Interfaces (in/out) – system/user

Subordinates and platform dependencies

Licenses, etc. (free for use in the project)
Cybernetica RealSim licenses are provided free of charge for the duration of the COGNITWIN-project for project partners who need such license to execute their work in the project. Should the project result be taken into permanent use after the end of the project, licenses are provided on fair and reasonable terms as stated in the Grant Agreement.

TRL for overall component/tool and any parts/subordinates
8

References – incl. web etc.
http://cybernetica.no/technology/model-predictive-control/

To be considered in particular for the following COGNITWIN pilots
Hydro, Elkem.

14.15   Cybernetica Modelfit

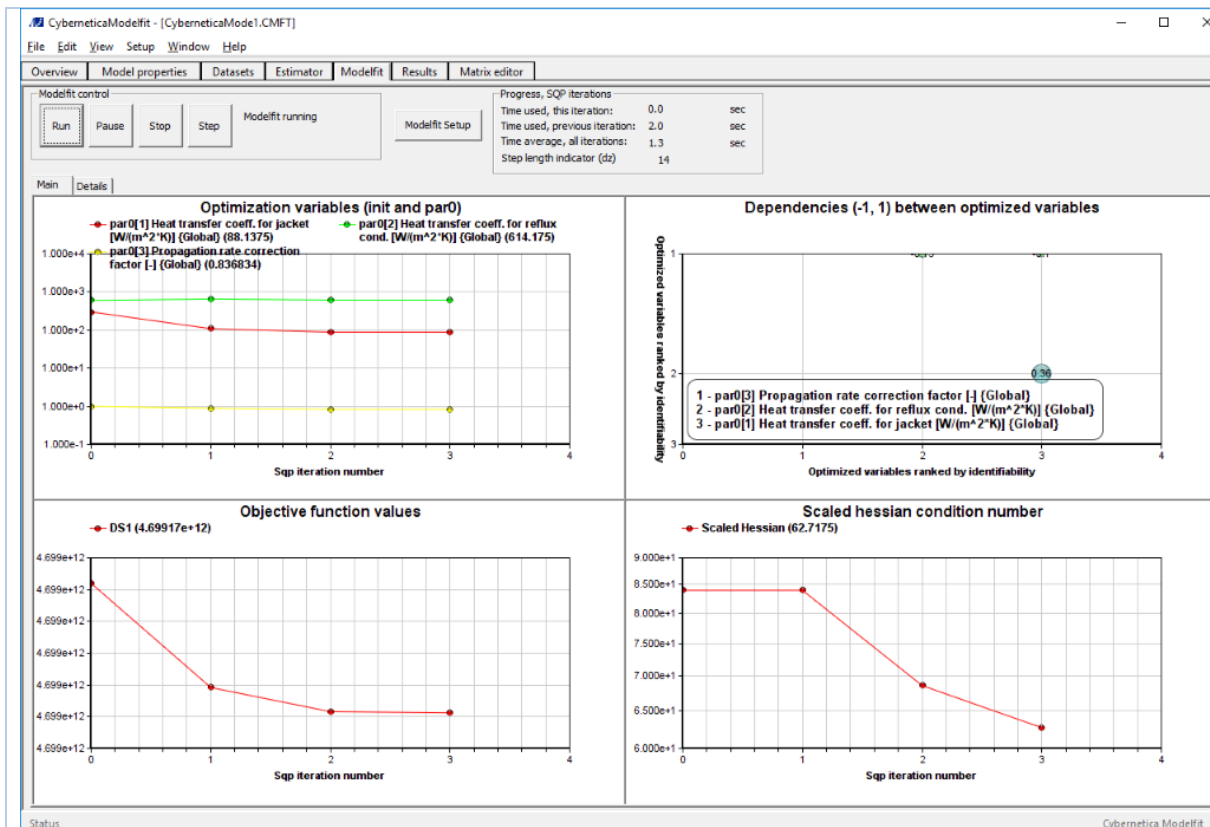| Component/Tool description |
| --- |
| **Component/Tool/Method/Framework/Service Name** |
| Cybernetica Modelfit |
| **Defined in Task** |
| 5.4 Hybrid Digital Twins |
| **Short Description – incl. Purpose** |
| Cybernetica ModelFit is a tool used for off-line estimation of model states and parameters, for model validation, and for design of the on-line estimation part of Cybernetica CENIT applications. ModelFit is used to decide which model parameters should be estimated on-line, to design the on-line estimators, and to estimate the parameters that are considered constant. ModelFit interfaces to Cybernetica Model and Application Components, and it supports the same model formats as CENIT. |
| **Progress since delivery D5.1** |
| Cybernetica Modelfit has been extended with application modules for the Elkem and Hydro pilot processes. These modules contain physics-based models of the processes and make it possible to run online state and parameter estimation, as well as implement soft sensing and nonlinear model predictive control applications. |
| **Progress since delivery D5.2** |
| Support for text data input has been added. |
| **Progress since delivery D5.3** |
| N/A |
| **Examples of usage / illustrations** |
| **Cybernetica ModelFit user interface:** |

Figure 46: Cybernetica ModelFit

The features of Cybernetica ModelFit include:
 Design and tuning of on-line estimators in CENIT applications.
- **Estimation of constant or time varying model parameters.**
- **Estimation of initial states.**
- **Simultaneous use of multiple data sets.**
- **Parameter identifiability analysis.**

Cybernetica ModelFit is flexible with respect to configuration of the parameter estimation. Parameters can be time varying or constant. Multiple data sets from different operating conditions may be used to find the best parameter fit taken all data sets into account.

Interfaces (in/out) – system/user

Subordinates and platform dependencies

Licenses, etc. (free for use in the project)
Cybernetica ModelFit licenses are provided free of charge for the duration of the COGNITWIN-project for project partners who need such license to execute their work in the project. Should the project result be taken into permanent use after the end of the project, licenses are provided on fair and reasonable terms as stated in the Grant Agreement.

TRL for overall component/tool and any parts/subordinates
9 – Commercial product.

References – incl. web etc.
http://cybernetica.no/technology/model-predictive-control/

To be considered in particular for the following COGNITWIN pilots
Hydro, Elkem.

14.16   Cybernetica Viewer

Component/Tool description
Component/Tool/Method/Framework/Service Name
Cybernetica Viewer
Defined in Task
5.4 Hybrid Digital Twins
Short Description – incl. Purpose
Cybernetica Viewer is a tool for creating user interfaces to display and manipulate data from an OPC server in various ways.
Progress since delivery D5.1
This product has not been updated since last milestone, but the description is included as it will be used at a later stage in the Elkem and Hydro pilots.
Progress since delivery D5.2
No updates.
Progress since delivery D5.3
A REST interface has been implemented, such that the Viewer application can be displayed in a web browser.
Examples of usage / illustrations
The following figure shows an example of Cybernetica Viewer. The user interface is tailor made for the specific application:

Figure 47: Cybernetica Viewer

Interfaces (in/out) – system/user

OPC classic + OPC UA
Subordinates and platform dependencies
Licenses, etc. (free for use in the project)
Cybernetica Viewer licenses are provided free of charge for the duration of the COGNITWIN-project for project partners who need such license to execute their work in the project. Should the project result be taken into permanent use after the end of the project, licenses are provided on fair and reasonable terms as stated in the Grant Agreement.
TRL for overall component/tool and any parts/subordinates
9
References – incl. web etc.
http://cybernetica.no/technology/model-predictive-control/
To be considered in particular for the following COGNITWIN pilots
Hydro, Elkem.

14.17   Cybernetica Cognitive CENIT

Component/Tool description
Component/Tool/Method/Framework/Service Name
Cybernetica Cognitive CENIT
Defined in Task
5.5 Cognitive Digital Twins
Short Description – incl. Purpose

This is an experimental extension of the existing Cybernetica CENIT that adds cognition to the application.

The goals of the extension are to:
- Add self-diagnosing capability to CENIT by use of data analysis

The generic functionality has been added. The cognitive extension runs in parallel with the current estimator (digital twin).

Cybernetica CENIT already implements adaption in the form of parameter estimation.
In addition we have developed and implemented a simple method for real-time and offline analysis of the estimator (digital twin) performance related to process data.

For future extensions, we want to further develop Cybernetica Cognitive CENIT to include advanced AI-based identification and classification methods. In this way it should be possible to automatically classify types of errors: sensor failure, input error or model error. Ultimately, the goal will be to suggest model improvements based on this analysis.

Progress since delivery D5.1

The development of an extension of Cybernetica CENIT that enables self-diagnosing has been started. A framework for self-monitoring of the MPC application via stage-cost monitoring has been developed. The framework consists of the following steps:
- Estimate the measurement error distribution.
- Propagate that noise distribution through the closed-loop MPC model via Monte Carlo simulations
- Compare the resulting distribution of the average stage cost to the actual average stage cost from the actual plant. If average stage cost is significantly off from the theoretical distribution, this indicates an error in the closed-loop model.

After monitoring and error detection, the next step is to develop error classification and correction routines.

Progress since delivery D5.2

A rudimentary implementation of the described framework has been implemented, using Python for the statistical analysis, as a proof of concept. Although it was found that the crude Monte Carlo implementation was prohibitively slow, it showed that it is possible to detect controller degradation.
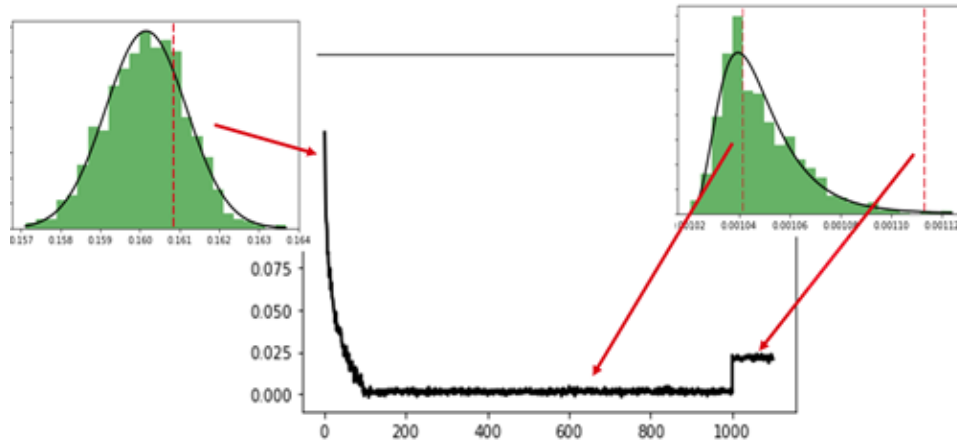
Figure 48: Cybernetica Cognitive CENIT

Progress since delivery D5.3

No significant updates to Cybernetica Cognitive CENIT since D5.3

Examples of usage / illustrations

Example 1: Error detection (Current capabilities)
The performance of the MPC system will eventually degrade over time due to changing plant conditions, i.e. increased plant-model-mismatch. To prevent poor controller performance, the error/performance degradation first must be detected. There are currently no self-diagnosing capabilities in CENIT. An important part of Cognitive CENIT will be the ability to perform self-diagnosis and detect when the controller performance is unsatisfactory. In the case where unacceptable levels of control performance degradation has been found, further action (such as error classification and error correction) is needed.

Example 2: Error classification (Future capabilities)
Estimators are generally unable to distinguish between prediction deviations resulting from the following errors:
- Faulty input data (requires correction or scepticism)
- Faulty model (suggest adaption)

Being able to distinguish between these errors is important because the required response is very different:
In the case of input error, the appropriate response is some combination of correcting the faulty input signal and minimizing the faulty signal's impact on the model-predictive control.
This can include:
- Using a default signal instead of the faulty signal,
- Ignoring model state variables that are highly correlated with the faulty signal, and
- Altogether turning off estimation for the affected data points.

In the case of model error, the appropriate response is to try to adapt the model to most accurately reproduce the process data.

An important goal for Cognitive CENIT will be to distinguish between these cases based on an offline training of a classification algorithm.

Example 3:　(Future capabilities)

Situations where the model structure is incomplete or wrong may be identified using an automated analysis of the prediction error distributions. Currently Cybernetica CENIT estimators assume that the model structure is correct, and that the prediction error is normally distributed around a mean value, which the estimator tries to centre at zero. In many cases this is not true, and significant deviation from normally distributed error may imply error in the model structure. Identifying this error is non-trivial and may be a well-suited task for an AI extension.

Interfaces　(in/out) – system/user
CENIT controller and estimator data + process data in via OPC (UA). Performance data + CENIT controller and estimator parameter suggestions out.
Subordinates and platform dependencies
CENIT, OPC (UA), python
Licenses, etc.　(free for use in the project)
Cybernetica Cenit licenses are provided free of charge for the duration of the CogniTwin-project for project partners who need such license to execute their work in the project. Should the project result be taken into permanent use after the end of the project, licenses are provided on fair and reasonable terms as stated in the Grant Agreement.
TRL for overall component/tool and any parts/subordinates
Cybernetica CENIT: TRL 9 Cybernetica Cognitive CENIT: TRL 1-2
References – incl. web etc.
To be considered in particular for the following COGNITWIN pilots
Hydro, Elkem.

14.18   TIA MONITORING

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA MONITORING
Defined in task
T5.1, T5.2
Short Description – incl. Purpose
TIA MONITORING is an application, that enables users to monitor condition of a system The data can be gathered from multiple different sources. **TIA MONIT**O**RING**
Progress since delivery D5.3
The application has been tuned and named after D5.3. Validation and verifications have been completed.
Examples of usage / illustrations
Data coming from multiple sources are being monitored.
Interfaces (in/out) – system/user
Data streams to be monitored are input, where as generated charts and notifications are output.
Subordinates and platform dependencies
None
Licenses, etc. (free for use in the project)
Proprietary/ Subject to License
TRL for overall component/tool and any parts/subordinates
The current TRL is 6.
References – incl. web etc.
https://tia-platform.com/module/tia-apps.html
To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.19   TIA STATISTICS

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA STATISTICS
Defined in task
T5.1
Short Description – incl. Purpose
TIA STATISTICS is a software module created to perform statistical analyzes on the data.

The tool has an easy-to-use user interface. Different data sources can be used as inputs.
Progress since delivery D5.3
The module is created and named. Verification and validation have been completed.
Examples of usage / illustrations
Data of different sources are statistically analyzed.
Interfaces (in/out) – system/user
Input are data output is statistical results of performed statical data analysis.
Subordinates and platform dependencies
None
Licenses, etc. (free for use in the project)
Proprietary/ Subject to License
TRL for overall component/tool and any parts/subordinates
The current TRL is 6.
References – incl. web etc.
https://tia-platform.com/module/tia-apps.html
To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.20   TIA METRICS

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA ASP METRICS
Defined in task
T5.1
Short Description – incl. Purpose
TIA METRICS enable the users to calculate defined criteria for any process, production unit, or product.
Progress since delivery D5.3
Created, named, and deployed. Validation and verification have been completed.
Examples of usage / illustrations
Different metrics can be defined by means of the application. For example a threshold value is set as a criteria to pass or fail.
Interfaces (in/out) – system/user
Data in and parameters are input, defined metric is output. When data and metric are selected by the user at the same time, the selected metric type is calculated and the result is compared with the metric value.

Non
Apache StreamPipes, Apache Kafka, Fiware

Licenses, etc. (free for use in the project)
Proprietary/ Subject to License

TRL for overall component/tool and any parts/subordinates
The current TRL is 6.

References – incl. web etc.
https://tia-platform.com/module/tia-apps.html

To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.21   TIA OEE

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA OEE
Defined in task
T5.1
Short Description – incl. Purpose
TIA OEE is a software module created to calculate overall equipment effectiveness (OEE) of the process and/or machine The tool has an easy-to-use user interface. Validation and verification have been completed.
Progress since delivery D5.3
Created, named and deployed.
Examples of usage / illustrations
OEE is calculated based on its formula using the input data.
Interfaces (in/out) – system/user
Subordinates and platform dependencies
None
Licenses, etc. (free for use in the project)
Proprietary/ Subject to License
TRL for overall component/tool and any parts/subordinates
The current TRL is 6 as targeted.
References – incl. web etc.
https://tia-platform.com/module/tia-apps.html

To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.22   TIA ASP

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA ASP Teknopar Machine Learning on StreamPipes as a Data Processor
Defined in task
T5.5
Short Description – incl. Purpose
TIA ASP is an Apache StreamPipes based tool, it enables none technical users to select and execute machine learning algorithms for predictive maintenance purposes. The performances and the results obtained by the executed Machine Learning algorithms are presented in forms of graphs.   The tool has an easy-to-use, drag and drop user interface. Different data sources can be used as inputs to the ML algorithms of TIA ASP, including data from Kafka, and .csv files. The ML algorithms are MLP, GBT, LSTM, RF, SVM, and KNN.
Progress since delivery D5.1
Since the last milestone a data processor to conduct an ML application has been developed.
Progress since delivery D5.2
A new model addition to the executable ML/DL model list has been implemented.   Displaying invalid mode message is realized, in cases where invalid ML/DL models are to be included.
Progress since delivery D5.3
Verification and validation have been completed. The component has been renamed.
Examples of usage / illustrations
Data coming from Kafka or .csv files can be used by the user selected machine learning algorithms, and the results of the predictive maintenance applied by the selected algorithms are displayed on the presented GUI above.
Interfaces (in/out) – system/user
User selected set of ML algorithms are executed on the stream and the results of the algorithms can be compared and graphically presented. Stream data contains sensor data in vector form.
Subordinates and platform dependencies
Apache StreamPipes, Apache Kafka, Fiware
Licenses, etc. (free for use in the project)
Proprietary/ Subject to License
TRL for overall component/tool and any parts/subordinates
The current TRL is 6 as targeted.

References – incl. web etc.
https://tia-platform.com/module/tia-apps.html

To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.23   TIA PREMA

Component/Tool description
Component/Tool/Method/Framework/Service Name
TIA PREMA
Defined in task
T5.5
Short Description – incl. Purpose
TIA PREMA (MATLAB Predictive Maintenance for Electro Mechanical Components) is a model used for predictive maintenance of DC motor, gearbox and hydraulic press. By studying random scenarios, due to the changes in gearbox efficiency, resistance and damping coefficient values multiple random scenarios can be generated. Using the data fault code, labeling is performed. TIA PREMA uses different ML Models.
Progress since delivery D5.1
All of the related work related to TIA PREMA is conducted after the last milestone.
Progress since delivery D5.2
Early detection of bearing faults have been studied by developed additions that are utilizing vibration signals. Transfer learnings on pre-trained networks such as AlexNet, GoogLeNet and ResNet-50 has been applied ater saving spectograms. For the studies MATLAB's spectogram function is used.
Progress since delivery D5.3
New models have been trained.
Subordinates and platform dependencies
TIA PREMA uses Predictive Maintenance Toolbox of MATLAB and Classification Learner App.
Licenses, etc. (free for use in the project)
TRL for overall component/tool and any parts/subordinates
The current TRL is 5 as targeted.
References – incl. web etc.
https://tia-platform.com/module/tia-apps.html
To be considered in particular for the following COGNITWIN pilots
NOKSEL

14.24   SpinPro

Component/Tool description
Component/Tool/Method/Framework/Service Name
SpinPro – Speech support in Production
Defined in Task
Task 5.5
Short Description – incl. Purpose
The goal of this component is to formalize human tacit knowledge and make it available to other software components. This will be done by generating machine-processable rules based on spoken input. In addition, the knowledge base will be extended by the "discovered" rules, while at the same time ensuring the consistency of the knowledge base (e.g., avoiding contradictory rules).   -
Progress since delivery D5.1
During the reporting period, we have defined the conceptual architecture (see below) and performed detailed analysis of the existing speech recognition frameworks. **Today, many speech recognition frameworks archive good accuracies on given test sets like LibriSpeech (Panayotov, Chen, Povey, & Khudanpur, 2015). However, these results often are not applicable to an industrial and commercial usage. Consequently, we focus on making these techniques more robust to their respective environments. Moreover, domain specific language must be recognized as well. Therefore, possibilities for efficient addition of vocabulary to existing frameworks needs to be found. As a first step, we made an overview on some speech recognition frameworks available now and evaluates a subset of them. Additionally, we discuss the possibility to use multiple speech recognition frameworks and evaluate the margin for improvement by using the proposed technique. Moreover, possibilities to add vocabulary by using the proposed technique are presented.** **Recently several frameworks for speech recognition were published. Some of them are compared in** **. The data for the comparison is obtained from the linked repositories and connected websites. The word error rate (WER) is obtained from the papers describing the approaches. Most of the frameworks are written either in C++ or Python. In order to evaluate the performance of a framework, the WER on the LibriSpeech test-clean dataset (Panayotov, Chen, Povey, & Khudanpur, 2015) is used. Comparing the WERs, RETURNN (Zeyer, Alkhouli, & Ney, 2018) and Espresso (Wang, et al., 2019) archive the best performance with 2.3 % and 2.8 % WER respectively. Kaldi (Povey, 2020) archived 3.76 % WER and therefore archives the best performance of the C++ frameworks. Even though Kaldi is only the third best performing framework of the compared ones, it is the most important one. Many frameworks are based on Kaldi, for example Vosk (Inc., 2020) and Espresso. The frameworks differ in their approaches. DeepSpeech, Espresso, Eesen, RETRUNN, wav2letter++ and NVIDIA NeMo utilize machine learning approaches. Vosk uses a database to minimize training time and utilize a bigger pool of audio transcripts. In the following the project descriptions of some frameworks are gathered.**

Table 40: Comparison of speech recognition frameworks

Framework	Binding for JAVA	Primary Programming Language	Offline	Open-Source	Best model accuracy on LibriSpeech clean-test (WER in %)	Repository
Sphinx-4	Yes	JAVA	Yes	Yes		https://github.com/cmusphinx/sphinx4
DeepSpeech	No	C++	Yes	Yes		https://github.com/mozilla/DeepSpeech
Kaldi	Unofficial	C++	Yes	Yes	3.76	https://github.com/kaldi-asr/kaldi
Vosk	Yes	C++	Yes	Yes		https://github.com/alphacep/vosk-api
Eessen	No	C++	Yes	Yes		https://github.com/srvk/eesen
Wav2letter++	No	C++	Yes	Yes	7.2	https://github.com/facebookresearch/wav2letter
HTK3	No	C	Yes	No		-
RETURNN	No	Python	Yes	Yes	2.3	https://github.com/rwth-i6/returnn
Espresso	No	Python	Yes	Yes	2.8	https://github.com/freewym/espresso
Nvidia NeMo	No	Python	Yes	Yes		https://github.com/NVIDIA/NeMo
Google Speech-To-Text	Yes	-	No	No		-

In the following we will focus on:

- **Sphinx-4, because it has a native JAVA binding that we needed at the time we first experimented with the frameworks**

- **DeepSpeech, because it offers one of the best trained open-source models, and**

- **Vosk, because it uses an alternative approach.**

All of them are easy to use, offline and open source and therefore fulfil our most basic requirements. Sphinx-4 slowed down the evaluation process significantly. As seen in Figure 49, Sphinx-4s performance is significantly worse. The recognition time takes about 1.8 times the length of the audio part to recognize. In contrast DeepSpeech only takes about 0.68 and Vosk only 0.15 times the audio length. Since also the accuracy of Sphinx-4 is twice as bad as the accuracy of the other ones, the usage of Sphinx-4 is impractical.

Another observation out of Figure 49 is, that Vosk (vosk-model-small-en-us-0.3) needs only about half the time to recognize long audio samples than DeepSpeech (deepspeech-0.8.1-models.pbmm). If Vosk and DeepSpeech are used in parallel, this difference is utilizable by reducing the resources for Vosk. Therefore, the recognition is less expensive. Another possibility is using the additional time to improve the accuracy of the result. One facility is to additionally preprocess the audio sample and run the original as well as the preprocessed sample through the recognition process. Thereafter an algorithm combines the two results into one result by utilizing the differences in the recognition results.
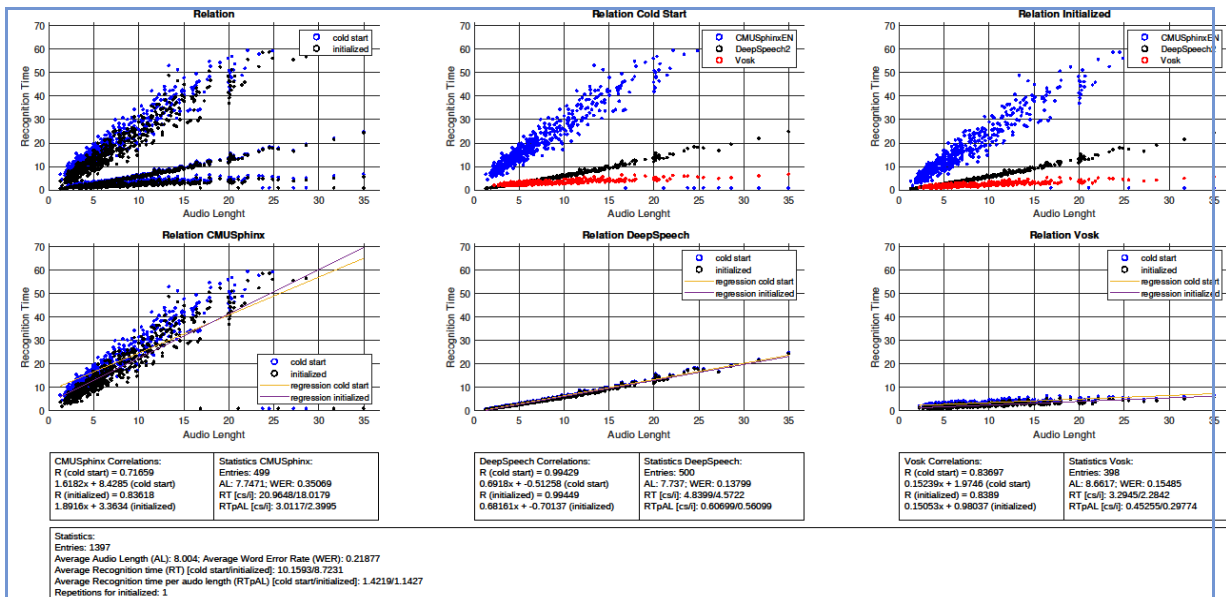
CMUSphinx Correlations:
R (cold start) = 0.71659
1.6182x + 8.4285 (cold start)
R (initialized) = 0.83618
1.8916x + 3.3634 (initialized)

Statistics CMUSphinx:
Entries: 499
AL: 7.7471; WER: 0.35069
RT [cs/i]: 20.9648/18.0179
RTpAL [cs/i]: 3.0117/2.3995

DeepSpeech Correlations:
R (cold start) = 0.99429
0.6918x + -0.51258 (cold start)
R (initialized) = 0.99449
0.68161x + -0.70137 (initialized)

Statistics DeepSpeech:
Entries: 500
AL: 7.737; WER: 0.13799
RT [cs/i]: 4.8399/4.5722
RTpAL [cs/i]: 0.60699/0.56099

Vosk Correlations:
R (cold start) = 0.83697
0.15239x + 1.9746 (cold start)
R (initialized) = 0.8389
0.15053x + 0.98037 (initialized)

Statistics Vosk:
Entries: 398
AL: 8.6617; WER: 0.15485
RT [cs/i]: 3.2945/2.2842
RTpAL [cs/i]: 0.45255/0.29774

Statistics:
Entries: 1397
Average Audio Length (AL): 8.004; Average Word Error Rate (WER): 0.21877
Average Recognition time (RT) [cold start/initialized]: 10.1593/8.7231
Average Recognition time per audo length (RTpAL) [cold start/initialized]: 1.4219/1.1427
Repetitions for initialized: 1

Figure 49: A performance comparison of CMUSphinx, DeepSpeech and Vosk

Figure 49 shows performance comparison of CMUSphinx, DeepSpeech (deepspeech-0.8.1-models.pbmm) and Vosk (vosk-model-smallen-us-0.3) on a randomly chosen subset of LibriSpeech's test-clean. On the x-axis the duration of the given audio segment to recognize is given. On the y-axis the needed time to recognize the audio is described. The results are divided by cold start and initialized. Cold start times include the time needed for preparation when initializing a framework. Initialized times do not include any file independent preparation time, like model loading.

In order to evaluate the potential of such an algorithm, the impact of preprocessing on the recognition results must be estimated first. Therefore, three preprocessings were chosen and the differences in the WERs per audio sample compared. For each of the two LibriSpeech test sets (test-clean/test-other) three additional test sets were created. In the *-normalized test sets, the volume of the audio samples is raised to a threshold of −1.0 decibel. In the *-compressed test sets, a compressor was used to reduce dynamic in the audio samples and afterwards normalize them. For the *-equalized test sets, the intensity of very high and low frequencies was reduced.

Figure 50 shows the fraction of audio samples with an improvement and a debasement. Files with no change are not shown. On average over all test-other test sets and tested framework model combinations about 28% of the entries changed with a maximum of 54.6% for vosk-model-small-en-us-0.3 at test-other-compressed. About half of them improved the WER. If the algorithm is capable to distinguish between improvements and debasements, the WER on about 14% (average) of the audio samples is improvable. Consequently, these variabilities lead to a margin for improvement of speech recognition frameworks.

Moreover, a combination algorithm could use specialized frameworks for recognizing domain specific language. Those frameworks only need to recognize a few words similar to finding keywords for speech assistants. This task is significantly easier than a complete speech recognition and therefore allows for smaller models that are trained more easily. This method can also be applied to recognize words that are important for the later use of the recognition result. This use may be the control of a machine or similar tasks. Those tasks usually use a rather limited vocabulary, and it may increase the accuracy if the words are recognized by specialized frameworks. It is important to note that the framework is still usable for the general case even if

it uses specialized frameworks, because the general tasks are still done by generic speech recognition frameworks. The specialized frameworks only improve accuracy where possible.

For the purpose of developing an algorithm that combines the result of different preprocessing for an audio sample recognized by different frameworks with different models, more research has to be done. Most likely an evaluation of the results on word level is needed to be able to distinct features, that give hints over the accuracy of a recognized audio sample. Ideally generic relations between the preprocessing framework model combination and the accuracy of the recognition of special kinds of words or auditory events are found. However, it is likely, that such generic rules do not exist or lead to bad results due to the complexity of the underlaying recognition process. Nonetheless it may be interesting to try using machine learning approaches for the algorithm. We will try to combine several recognitions of an audio sample into one sentence the reduction of post recognition error (RPRE) and will continue to research in this topic.
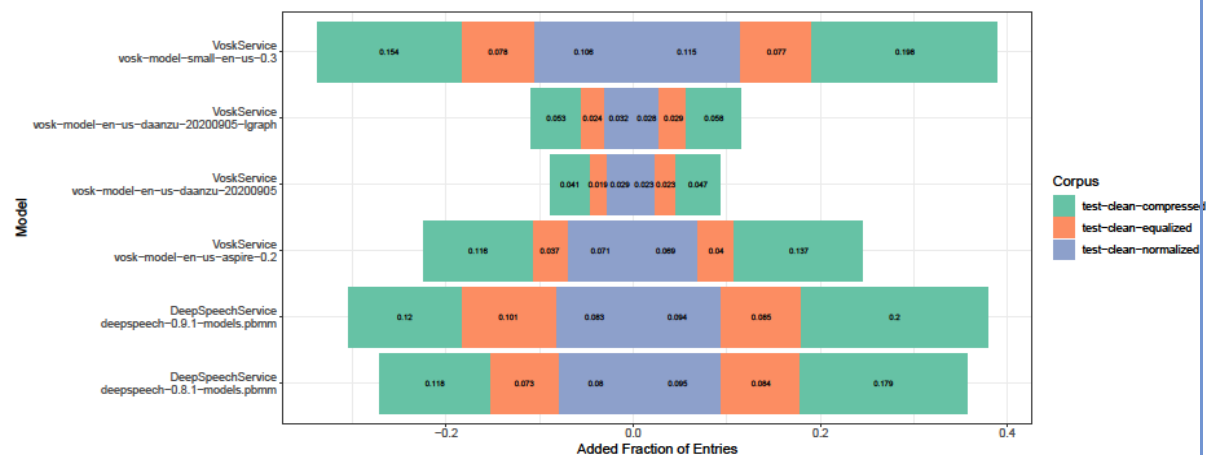
Figure 50: An illustration of changes in accuracy per preprocessed file with respect to the original file on LibriSpeech test-clean.

Figure 50 shows an illustration of changes in accuracy per preprocessed file with respect to the original file on LibriSpeech test-clean. Positive entries signalize an improvement in WER and negative entries signalize a debasement. The original test-clean LibriSpeech corpus contains 2620 entries. The other corpi were created by applying an audio effect to each file. Consequently, each of the corpi contains 2620 entries.
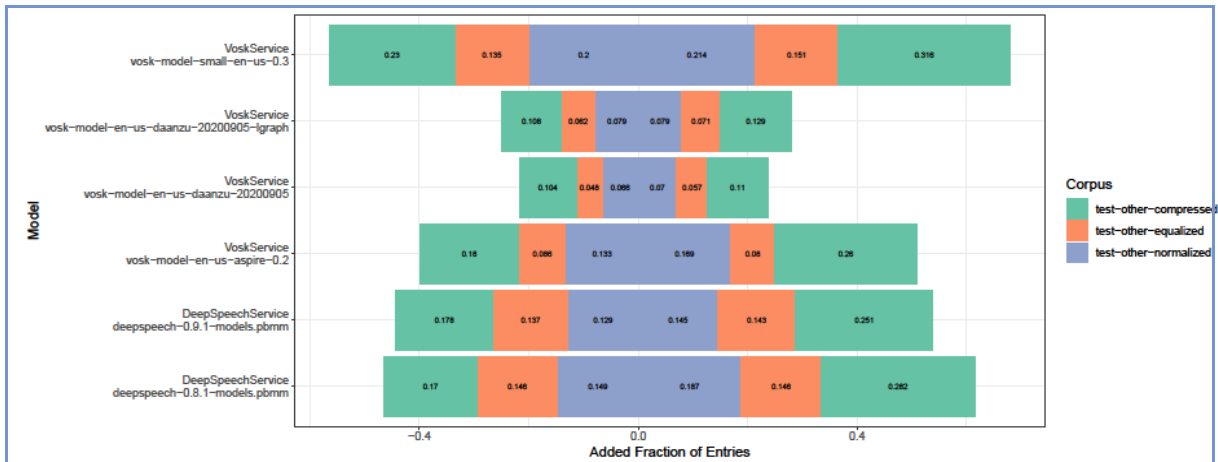
Figure 51: An illustration of changes in accuracy per preprocessed file with respect to the original file on LibriSpeech test-other

Figure 51 shows an illustration of changes in accuracy per preprocessed file with respect to the original file on LibriSpeech test-other. Positive entries signalize an improvement in WER and negative entries signalize a debasement. The original test-other LibriSpeech corpus contains 2939 entries. The other corpi were created by applying an audio effect to each file. Consequently, each of the corpi contains 2939 entries.

Progress since delivery D5.2

Speech recognition systems differ in their quality. By combining several speech-to-text frameworks, the quality of speech recognition can be increased. During the 2nd reporting period, we worked on a distributed speech recognition system that can be used and deployed in many scenarios. Special attention was paid to the interchangeability of the individual components and the adaptability to a given situation.

In this context, SpinPro was extended by a framework for Distributed Automatic Speech Recognition (DARS). This is shown in Figure 52 below.
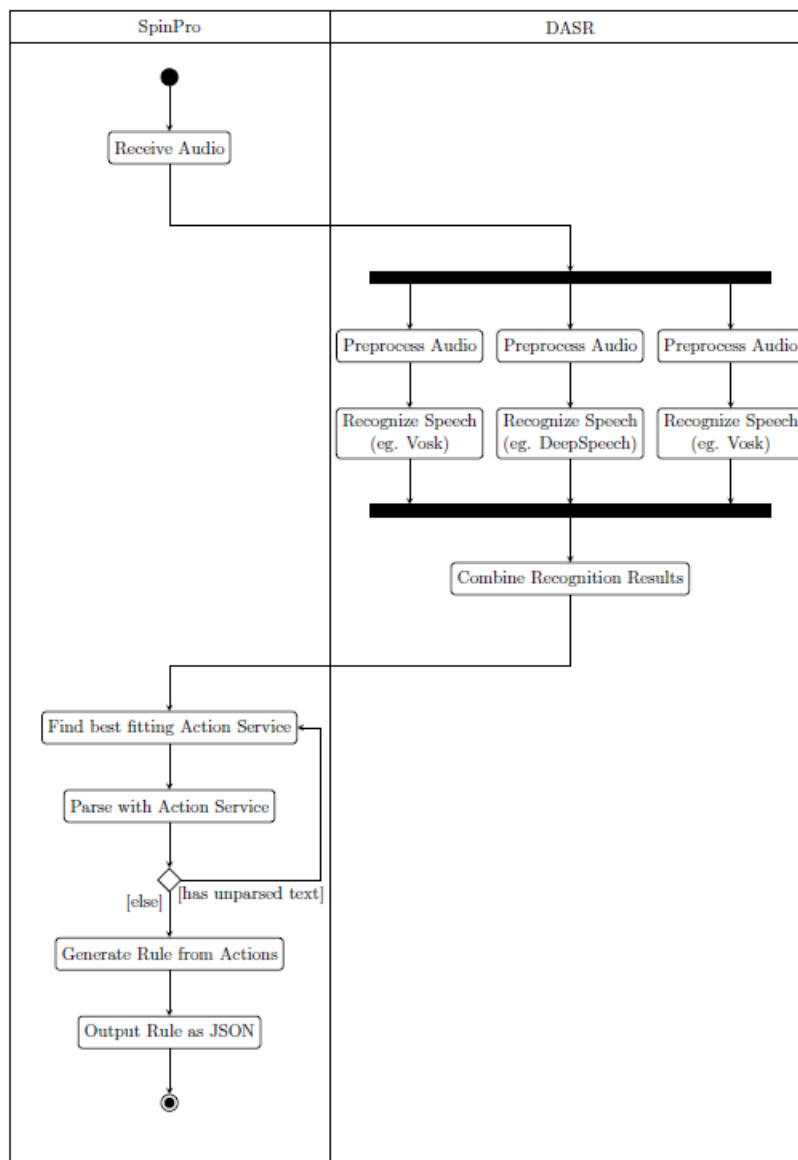
Figure 52: SpinPro extension with DASR

Nowadays, speech recognition systems differ in many aspects, especially in their API. They also require more and more resources to perform inference. To use them jointly, the solution can only be to distribute speech recognition. Due to the long inference and the large size of the audio files, this is a challenge all its own. DASR is a system we have developed to overcome this challenge. It is a tool for exploring combination techniques for multi-system speech recognition using distribution techniques for faster evaluation.

At the highest architectural design level, DASR uses a source-worker architecture. DASR has a source component that is responsible for handling jobs, distributing them to workers, combining recognition results and producing the result for a request. The source component of DASR is called the core. The DASR workers are responsible for pre-processing the audio samples and recognition by an ASR algorithm, i.e. for handling a worker request. The core and the workers communicate via a network. In addition, DASR introduces another component called Dev. Dev provides access to

additional functionality that is mainly used when designing a DASR instance for a specific use case. An overview on the components of DASR is shown below.
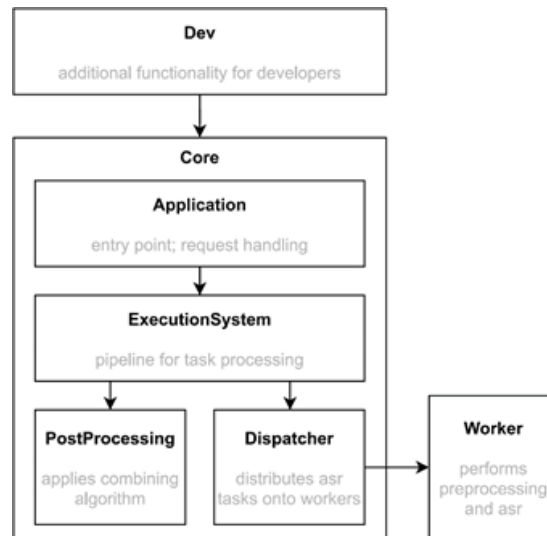
Figure 53: Overview of the DASR components

Whenever a task reaches DASR, it is first checked whether all desired ASR algorithm combinations are available for preprocessing. For each work request, the audio material is preprocessed and then speech recognition is performed with the desired ASR algorithm. The results are collected and forwarded to the combination algorithm. The combination algorithm takes all the recognition results and creates a new combined output. This output is stored with the original recognition results in the corresponding job. When all the jobs in a task are completed, the task is returned with all the results it contains. The entire process is shown below.
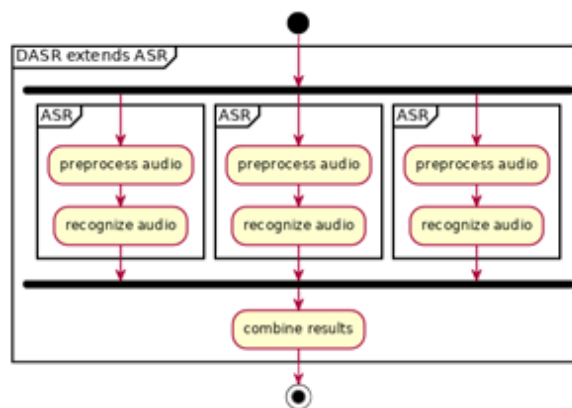
Figure 54: Activity diagram of the general process for distributed speech recognition used by DASR

Examples of usage / illustrations

SpinPro receives the audio data and triggers DARS. DASR itself forwards the audio data to so-called recognisers. Each of these recognisers performs automatic speech recognition using a predefined speech recognition framework and model.

In addition, the recognisers can perform pre-processing of the audio data. For example, one could use a compressor effect to reduce the dynamics of the audio input. After all the recognisers have finished, the results are collected on the main server.

There, a combination algorithm is used to combine the recognised transcripts into one. The combination algorithm itself is interchangeable.

A typical example is a two-step process in which the transcripts are first matched with a progressive multiple sequence alignment algorithm and then a vote is taken per word. The voting can be done by a neural network, but also by a simple majority vote. After the combination, DASR returns the final transcript to SpinPro.

The next step in the SpinPro pipeline is the so-called release step.

In this step, the user is asked whether the recognised transcript is correct. The user can choose whether to cancel the request or continue with the next step.

The third step is the actual rule creation. It can be very frustrating for a user to receive a rule created by non-deterministic algorithms. The user might get a different result each time. We aim for consistent and deterministic rule creation.

SpinPro has a list of keywords. A heuristic based on the occurrence of these keywords chooses a regex pattern. SpinPro checks whether the regex pattern matches the transcript and, if it does, forwards the match to a so-called service. A service contains the keywords, the regex pattern and the parsing logic. Services are developed independently of SpinPro and loaded as needed.

Since the service must know which inputs and outputs are available, SpinPro manages all inputs and outputs and provides them to the services. Services have also a Callback to SpinPro for parsing a specific string within a pattern. This is useful for actions that contain different actions. A simple example is an IF-THEN rule that contains actions in the THEN part. In addition, SpinPro provides useful parsers for arithmetic expressions and conditions.

When SpinPro has successfully created a rule, the final step is to store the rule in a JSON syntax. The JSON syntax used is an intermediate format that contains more meta-information than necessary. Part of the meta-information serves only statistical and identifying purposes, another part can be used to check the compatibility of the services used to create the rules with the interpreters of these services. Of course, they also contain the actual rule actions in the format defined by the services. Some action formats such as IF and WHILE are predefined.

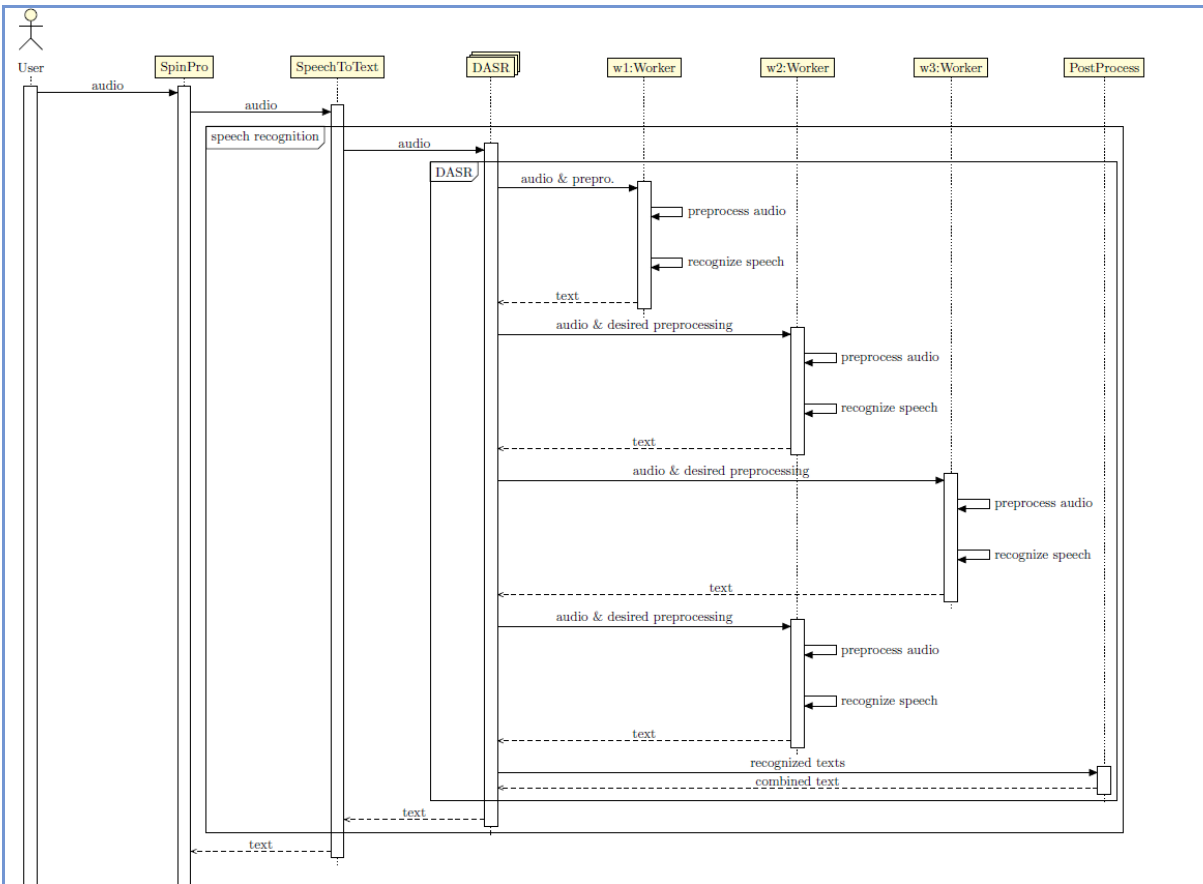The resulting rule is stored in a predefined directory and sent to the client.
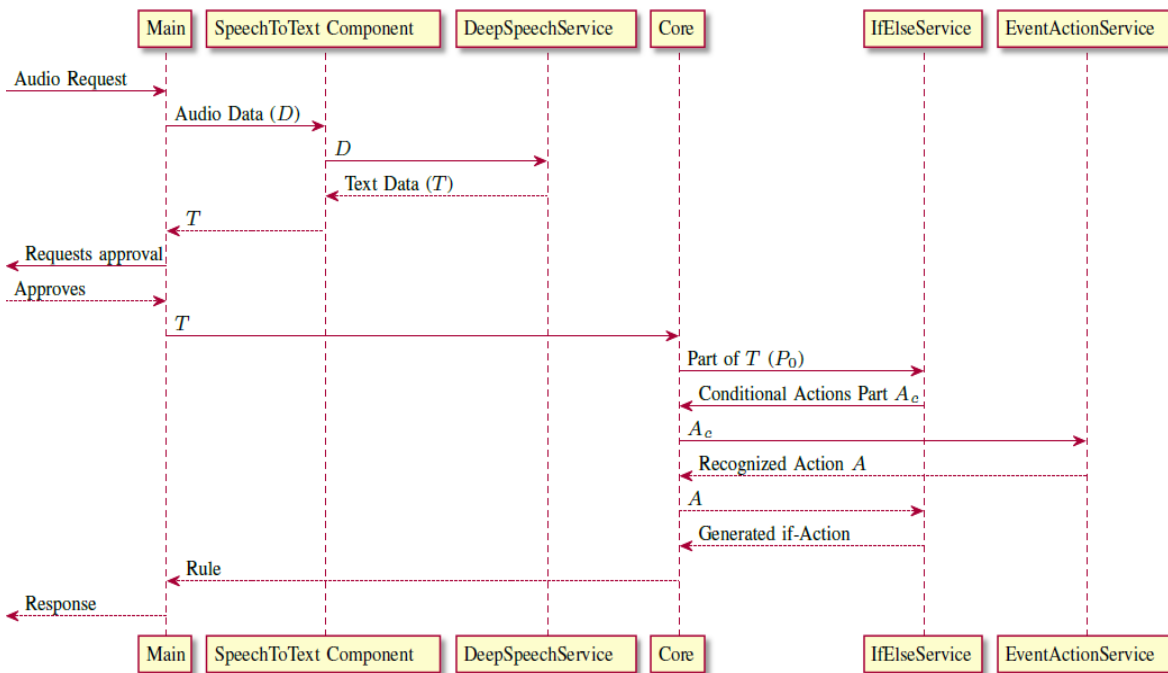
Figure 55: SpinPro

Figure 56: SpinPro

Interfaces (in/out) – system/user

In – spoken text

Out -rule(s)

Subordinates and platform dependencies

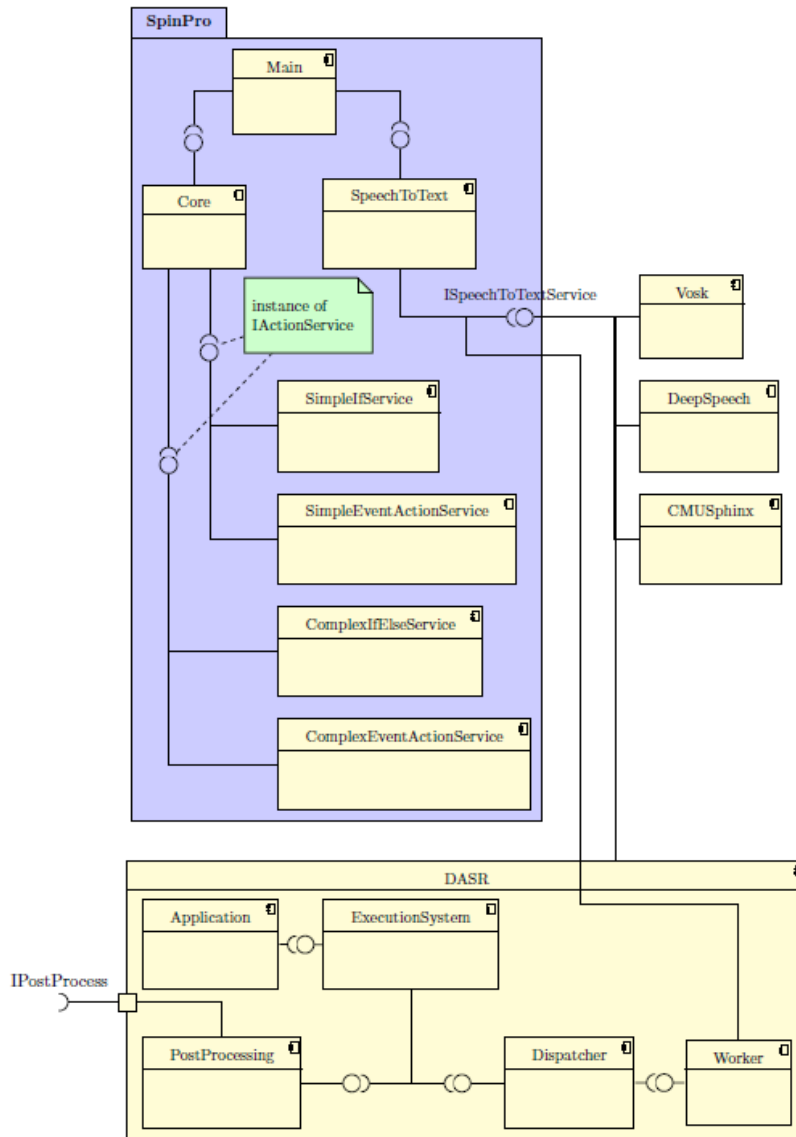The extension of SpinPro with DASR is shown in Figure below.

Figure 57: The extension of SpinPro with DASR

Licenses, etc. (free for use in the project)

License will be defined when the component is ready.

TRL for overall component/tool and any parts/subordinates

TR4

References – incl. web etc.

Frameworks
- Sphinx-4 - https://github.com/cmusphinx/sphinx4
- DeepSpeech - https://github.com/mozilla/DeepSpeech
- Kaldi - http://kaldi-asr.org/doc/about.html
- **VOSK - https://github.com/alphacep/vos**

https://github.com/c3di/neuroscope

To be considered in particular for the following COGNITWIN pilots

TBD - Relevant in consideration for Cognitive services.

14.25   FouMon

Component/Tool description
Component/Tool/Method/Framework/Service Name
FouMon (Fouling Monitoring)
Defined in task
T5.4 (T5.1)
Short Description – incl. Purpose

FouMon is a fouling monitoring component. The component aims at monitoring on-line the state of fouling at heat exchange surfaces, using various alternative and redundant approaches. The approaches include direct calculations using on-line process measurements and laws of physics, a model-based approach using state estimation of uncertain fouling-related parameters, and indexes computed from therein. For model-based state estimation approaches, a heat exchanger model (HE-model) has been derived and the ensemble Kalman filter (EnKF) implemented to fuse the model with on-line data.

In particular, the FouMon component is developed for estimation of combustion boiler superheater heat exchanger surfaces loaceted in the flue gas path. Both short-term (between soot blowings) and long-term (between maintenances) fouling and smoothing can be monitored, but main focus has been set on short term sootblowing.

The FouMon component uses a physical simulation model of a heat exchanger. For this purpose, a physical model for main phenomena between fluegas and the water-steam system has been derived, guided by availability to validate the model using on-line measurements from the process (steam and flue gas temperatures, flows, etc.). The **HE-model** (heat exchanger model) can be used for simulation of other heat exchangers as well. The model is available for download.
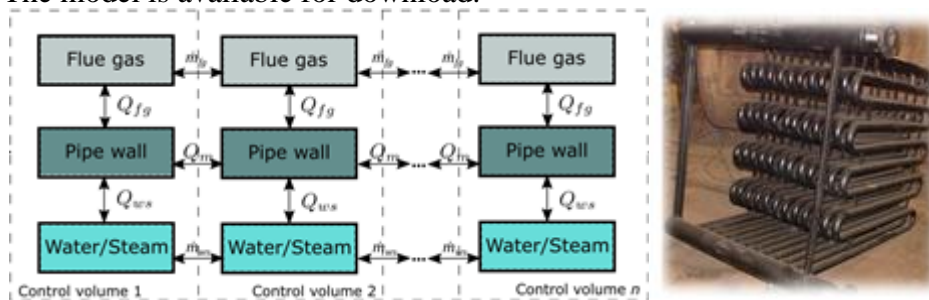

Figure 1. Modeling and simulation of a heat exchanger. Model structure (left) and a typical tube rack setup (right).

The chosen **EnKF** (Ensemble Kalman filtering) state estimation technique can be applied for alternative state estimation purposes, given that a suitable plant model and measurements are provided. The EnKF algorithm is well known in the academia. However, as no CST/SYSID toobox Matlab implementation is yet available, a Matlab tool has been coded. The COGNITWIN Matlab EnKF tool is available for download.

To support data driven modeling of system dynamics, a general purpose data quality tool (**ODtool**) focusing on detection of outliers has been developed and applied in the context of fouling monitoring. Creation of a purely data-driven model requires good quality data. Plant measurements tend to have occasional errors that must be taken into consideration for the self-learning digital twin to be robust. Therefore, in addition to standard measurement

verification by detecting sensor faults (1) and frozen values etc. (2), an additional outlier detection (3) method is implemented for this application. Identifying the nontrivial outliers from a batch of multidimensional measurement vectors supports the process of finding a valid digital twin model, thus enhancing the cognitive capabilities of the approach. The tool is available for download.

Progress since delivery D5.1

N/A.

Progress since delivery D5.2

The tool has been developed (designed, implemented, and verified) after the milestone in 2/2021.

Examples of usage / illustrations

The FouMon component originates from solving the WP3 pilot problem on fouling monitoring, and has been tuned and tested using real full scale boiler plant design and measurement data (WP3 pilot). The basic approach is illustrated in Figure 2.
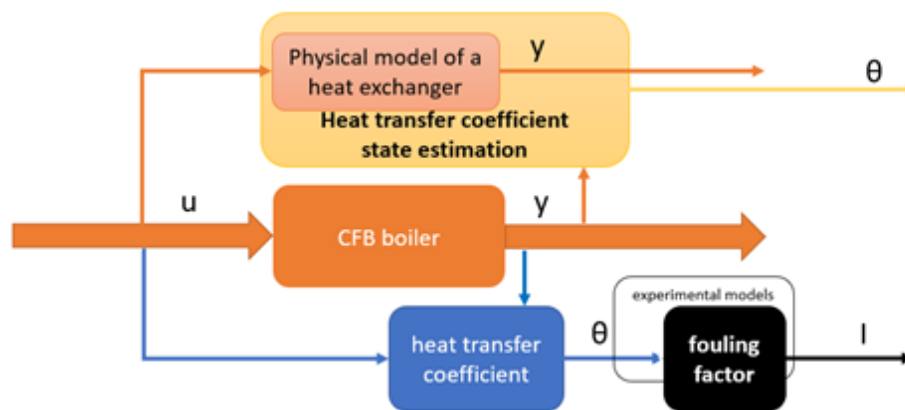

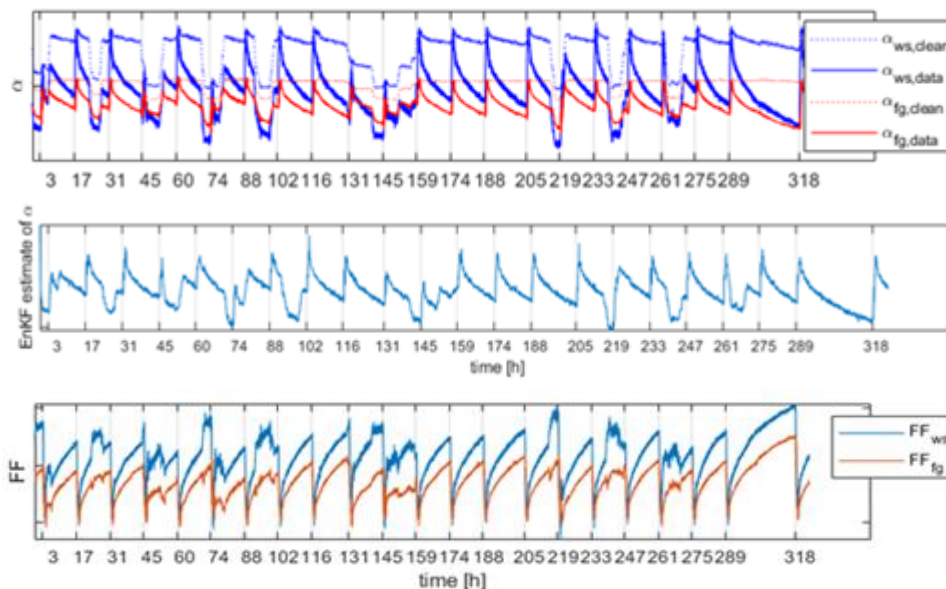Figure 2. State estimation applied to monitoring of fouling.

Figure 3. Data-driven FouMon heat transfer estimate from pilot during Nov 2021 (top plot), a corresponding model-based EnKF estimate (middle plot), and dimensionless adaptive fouling factor indexes. Subscript 'ws' refers to water-steam side, 'fg' to flue gas side.

Figure 3 shows a demonstration of the on-line estimated heat transfer coefficients for a superheater in the flue gas path. The data-driven estimate for heat transfer in a clean (after sootblowing) pipe is also illustrated. The estimates are constructed in two alternative ways. Estimates of the heat transfer coefficient in a physical model can be computed by data assimilation. Dimensionless indexes (FF) can be generated for providing process state independent indication of the state of fouling. Figure 3 illustrates these using pilot data.
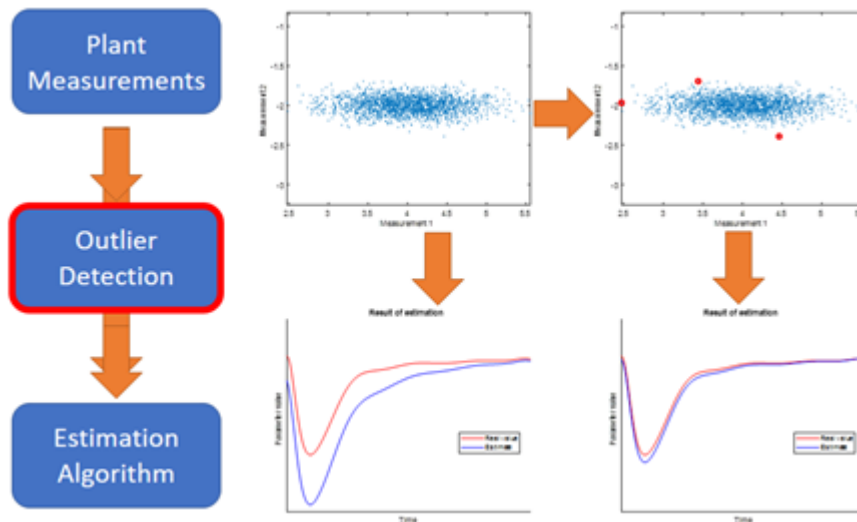

Figure 4. Basic principle of ellipsoidal peeling. Removal of few outliers can improve the performance of identification significantly.

Interfaces (in/out) – system/user

The physical model and measurements are set up in the Matlab m-files. Input data (measurements) are provided as numerical vectors. Interactive tuning is enabled by Matlab interface/graphics. Estimation outcomes are provided as numerical vectors.

A link with StreamPipes is enabled by an OPC-UA client/server component (see FUSE OPC-UA tool).

Subordinates and platform dependencies

The tool is implemented using Matlab language (m-files). Matlab from the Mathworks is required (FouMon has been tested on Matlab 2020b).

Matlab (2020b) is available on all major operating systems, including Windows 7, Ubuntu 16, Debian 9, MacOS 10 and newer. No particular Matlab Toolboxes are required. Open software Octave is known to be able to interpret m-files, but FUSE-codes have not been tested with Octave.

Licenses, etc. (free for use in the project)

The HE-model, the EnKF-tool and ODtool are free for use (contact Istvan.Selek@oulu.fi, Enso.Ikonen@oulu.fi or Markus.Neuvonen@oulu.fi, respectively). The CFB boiler design data and plant measurement data are Sumitomo SHI FW and pilot plant proprietary.

TRL for overall component/tool and any parts/subordinates

TRL 6 (demonstrated in a relevant environment).

References – incl. web etc.

Liukkonen, M., A. Kettunen, J. Miettinen, E. Ikonen, I. Selek, M. Neuvonen, A. Hansen and M. Edelborg (2022). Hybrid Modelling Approach to Optimize Fouling Management in a Circulating Fluidized Bed Boiler. Fluidized bed conversion conference 2022 (FBC24), 8–11 May 2022, Gothenburg.
The EnKF Matlab-tool is available at http://cc.oulu.fi/~iko/COGNITWIN/
The HE-model and ODtool are available for download.

To be considered in particular for the following COGNITWIN pilots

Sumitomo SHI FW Energia Oy

14.26   FouCon

Component/Tool description
Component/Tool/Method/Framework/Service Name
FouCon T5.5, (T5.4, T5.1)
Short Description – incl. Purpose
FouCon is a component for active control/prescriptive maintenance of process, derived based on the needs from the WP3 fouling control pilot problem. Potential specific problems include soot blowing automation and prescriptive maintenance actions. The component includes data-driven modeling tool for predicting the impact of fouling and soot blowing on heat exchange performance, and optimization algorithm to determine how the system should be operated. The identified model is used to compute the optimal soot blowing interval for selected set of heat exchangers. The physical modeling (from FouMon) is replaced by novel data-driven tools based on the Prony approach. The optimal intervals for soot blowing actions are derived using mixed-integer programming (MIP/sb). The cognitive learning aspects are emphasized by on-line model parameter update and support of human decision making. The applied data-driven modeling tool separates the effect of plant load level from fouling estimation. The **Prony** approach in model identification is closely related to other subspace identification methods, resulting in an LTI model of the system. This method enables discarding undesired/unstable modes from the identification results. It is also computationally light, and identification is performed on-line. Model update always takes the most recent measurement data into consideration when creating the model. Therefore, the application is inherently capable of adjusting to changes in the process. The identified LTI-model is used as a basis for soot blowing optimization. The cost function is constructed from gains (improved heat transfer) and losses (steam consumed in soot blowing) so that total power from fuel to steam is maximized. Interactions between individual heat exchangers are also considered in the formulation of the cost function. The optimization problem is solved using Matlab's built-in mixed integer programming -tool. As a result from optimization, **MIP/sb** provides a suggestion of the optimal starting time of soot blowing sequence to operator. The Prony tool is application independent and can be used in various modeling problems. The MIP/sb tool is problem spesific, and provides a solution for the sootblowing operational optimization problem at the pilot site. It is expected that the same principles can be applied at other installations.
Progress since delivery D5.1
FouCon has been developed during M31-M42
Examples of usage / illustrations

The FouCon component originates from solving the WP3 pilot problem on boiler fouling management, and has been tuned and tested using real full scale boiler plant design and measurement data (WP3 pilot).
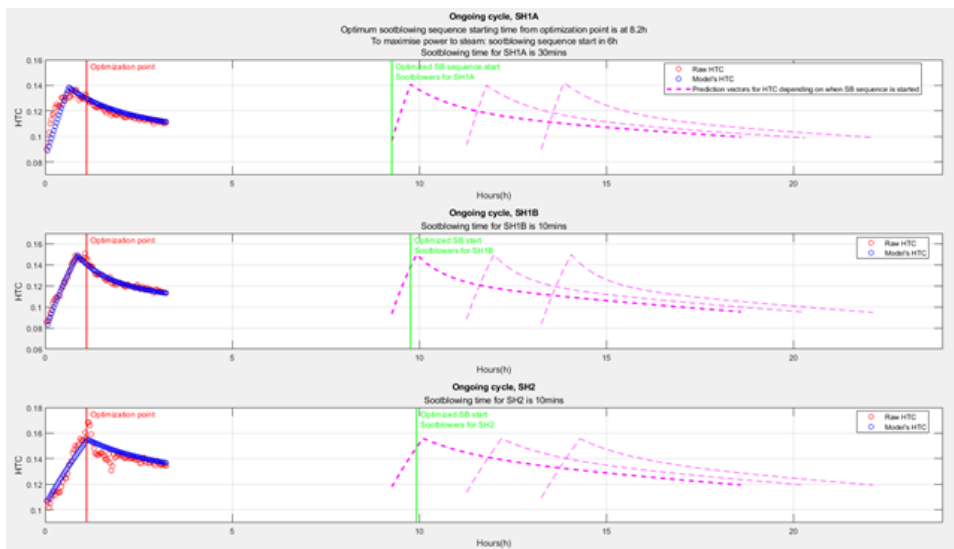

Figure 1. Soot blowing optimization for three consequtive superheaters (SH1A, SH1B and SH2).

The MPI/sb optimization cost function is constructed from the gains and losses associated with a soot blowing sequence (improved heat transfer, steam losses), under constraints (e.g., limited actions). The primary target was set to find the start time and/or length of the sootblowing sequence for individual heat exchangers.

Figure 1 illustrates the approach in simulations on three superheaters. The measured and estimated heat transfer coefficients are displayed, a decrease in HTC indicates fouling of surfaces. The tool provides an optimal sootblowing sequence, and illustrates also the predicted performance (in terms of HTC) if alternative decisions are made.

Interfaces (in/out) – system/user

The physical model and measurements are set up in the Matlab m-files. Input data (measurements) are provided as numerical vectors. Interactive tuning is enabled by Matlab interface/graphics. Estimation outcomes are provided as numerical vectors.

A link with StreamPipes is enabled by an OPC-UA client/server component (see FUSE OPC-UA tool).

Subordinates and platform dependencies

The tool is implemented using Matlab language (m-files). Matlab from the Mathworks is required (FouCon has been tested on Matlab 2020b).

Matlab (2020b) is available on all major operating systems, including Windows 7, Ubuntu 16, Debian 9, MacOS 10 and newer. No particular Matlab Toolboxes are required. Open

software Octave is known to be able to interpret m-files, but FouCon-codes have not been tested with Octave.

Licenses, etc. (free for use in the project)
Matlab (commercial), SmartBoiler (proprietary), StreamPipes (open) The Prony-tool is free for use (contact Markus.Neuvonen@oulu.fi). The CFB boiler design data and plant measurement data are Sumitomo SHI FW and pilot plant proprietary.

TRL for overall component/tool and any parts/subordinates
To be validated in a relevant environment (TRL 5)

References – incl. web etc.
Neuvonen, M., I. Selek, E. Ikonen and L. Aho. Heat exchanger fouling estimation for combustion–thermal power plants including load level dynamics. IEEE International Conference on Systems, Man, and Cybernetics, 9–12 Oct 2022, Prague. Aho, L. Mallipohjainen on-line estimaattori polttovoimalan lämmönvaihtimien likaantumiselle (*Model-based on-line estimator for combustion plant heat exchanger fouling*, in Finnish). 2022. University of Oulu, Master's Thesis. contact: Enso.Ikonen@oulu.fi Markus.Neuvonen@oulu.fi

To be considered in particular for the following COGNITWIN pilots
WP3/Sumitomo SHI FW Energia Oy engineering pilot