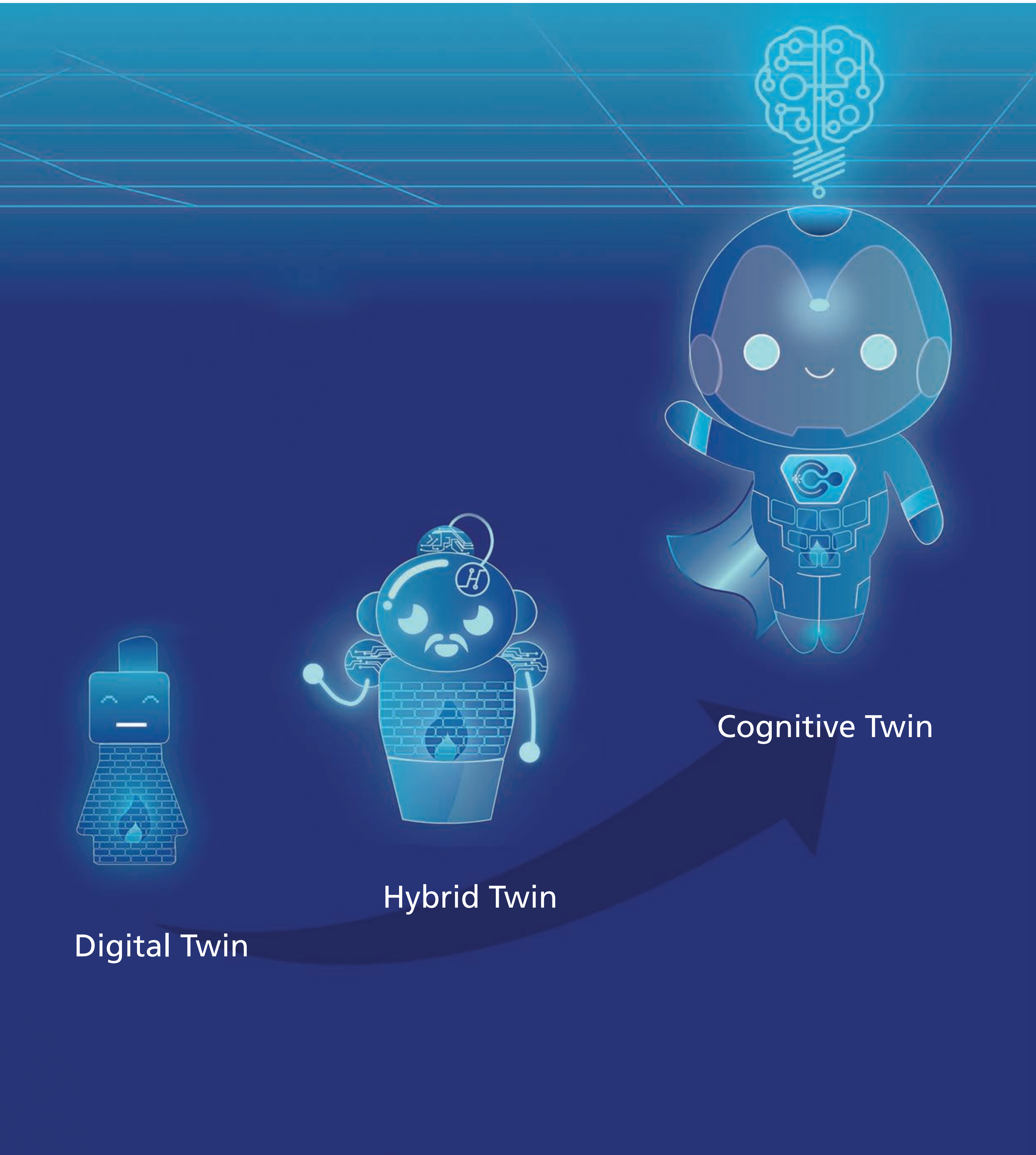
COGNITWIN



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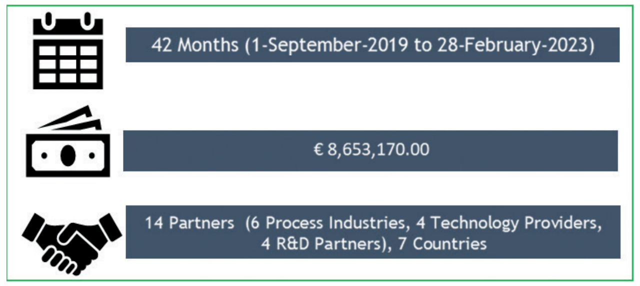
COGNITWIN Project Information



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European Commission

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Dear readers,

We are pleased to share with you the 2nd COGNITWIN newsletter.

Our vision is to cognify the process industry. We want to enhance the potential of the process industry in Europe by creating and validating a new approach for cognitive digital twins affordable for all process industries.

This very challenging transformation to cognitive plants will be realized step by step. The first step in this direction was done from M13 to M18 of the project by defining the digital twin pipeline steps, by implementing the COGNITWIN components and by mapping the different COGNITWIN components into the pipeline steps. The results achieved so far are tangible, described in detail (e.g. in the COGNITWIN Toolbox Portal) and demonstrable!

In this second newsletter, we highlight the most important technical results we have realized in the last 6 months of the project. We present several software components that have a great potential for exploitation, as they can be used in more than one use case. For each component, we provide a brief description, illustrate its relevance to the COGNITWIN vision, discuss the key research and technical challenges we have addressed, describe the typical use cases, and outline the next steps we plan to take. To make the newsletter more attractive and draw the attention of a wider audience, we include many pictures showing the architecture or user interface of the selected COGNITWIN components.

After the first 18 months of activity, we are now entering a new phase in which the components will be generalized to be used not only in at least two COGNITWIN use cases, but also to make them available to other plants in the same sector or even to transfer them in other process industries.

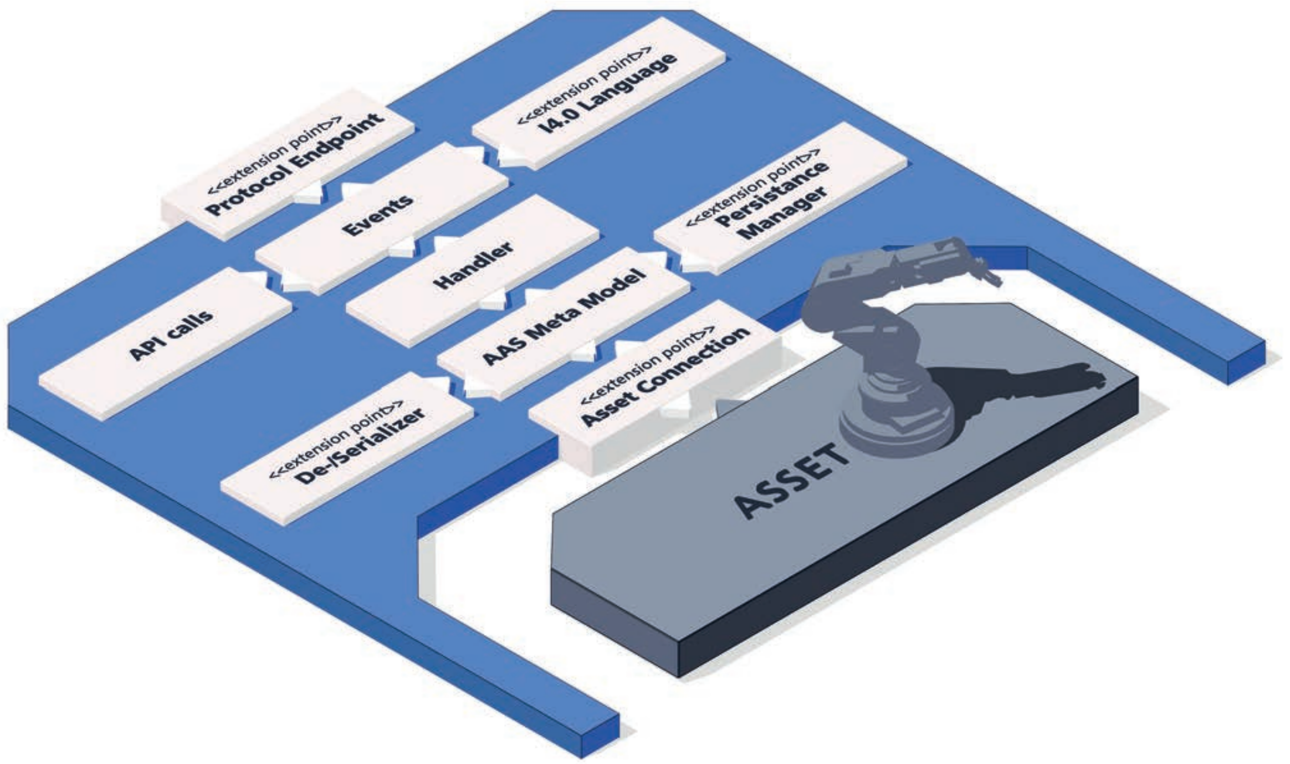
Enjoy the reading & contact us if you have questions or suggestions!

Best regards
The COGNITWIN project

FAST – FRAUNHOFER AAS TOOLS FOR DIGITAL TWINS

DESCRIPTION

Fraunhofer AAS Tools for Digital Twin, short FAST, is an ecosystem of Java-based software components that allows easy and fast creation and management of digital twins (DTs) according to the Asset Administration Shell (AAS) standard[1]. FAST enables creation of DTs with just a few lines of code and provides flexibility and extensibility through extension points, e.g. connecting to different kind of assets via OPC UA or MQTT protocol or an HTTP-based as well as an OPC UA-based endpoint. In addition, FAST includes the FAST Registry, which provides a standards-compliant way to register, manage and discover deployed DTs.



High-level architecture of FAST.

Our vision is that this set of DT tools could be extended into an open source software ecosystem for easy creation, import/export, deployment, and management of DTs (according to the I4.0 standards). Therefore, the FAST software was designed with future extensibility in mind. This is done by introducing technology-agnostic interfaces wherever possible, e.g. for de-/serialization (to support de-/serialization using different data formats), data storage and access (to support different kind of databases), and network protocols (to support integration with any kind of existing or proprietary physical devices).

RELEVANCE TO THE COGNITWIN VISION

FAST is a core technology for the COGNITWIN vision as it enables the creation of DTs which provide the foundation to build hybrid and cognitive DTs on top of "regular" DT created with FAST. Technically speaking, extension to support hybrid and cognitive on top of "regular" DTs can and partially already are integrated with FAST. For example, FAST already provides a way to integrate a DT with Apache StreamPipes[2]. This enables enriching DTs created using FAST with models and processing logic thus making then hybrid or even cognitive DTs.

KEY CHALLENGES

The first major challenge in creating FAST was the fact, that the AAS standard is currently still work in progress. The standard itself is split into three parts of which not all are published yet and those published are still being update regularly.

The second major challenge was to design the architecture of FAST to be as flexible and extensible as possible and at the same time still provide an easy-to-use API for developers. This has been solved by introducing extension points (via Java interfaces) where possible.

TYPICAL USE CASES

FAST can be applied in any use case where an I4.0-compliant DT is needed.

NEXT STEPS

We are currently planning to add more functionality to FAST, e.g. support for additional serialization formats such as RDF, XML, and AutomationML, as well as publish/subscribe-based endpoints, useful caching algorithms and cross-endpoint synchronization. FAST will be published as open-source in the near future.

1. https://www.plattform-i40.de/PI40/Redaktion/EN/Downloads/Publikation/vws-in-detail-presentation.pdf
2. https://streampipes.apache.org/

TMat-SynDat:
A SYNTHETIC DATA GENERATOR

DESCRIPTION

TMat-SynDat 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. TMat-SynDat works with MATLAB Simulink. Random realistic error sources are generated such as degradation of the components and measurement errors. The output of TMat-SynDat is a supervised and annotated dataset in .mat format.

RELEVANCE TO THE COGNITWIN VISION

When real data is missing, models are generated using synthetic data. TMat-SynDat aims to generate such data to fulfil the data requirements of the AI/ML algorithms. The generated data is labelled because of the boundaries that determine the error condition for an error source variable. This enables the usage of supervised machine learning, specifically predictive maintenance.

KEY CHALLENGES

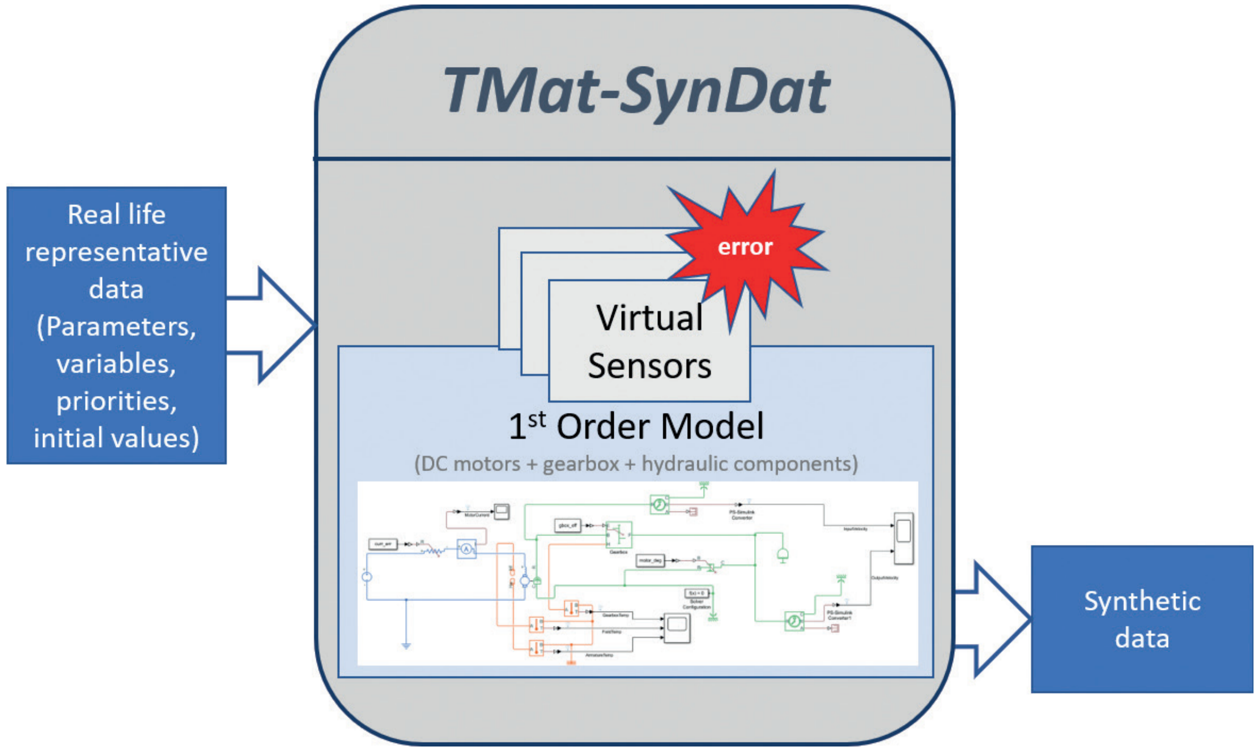
Obtaining a reliable and accurate vibration output signal, that is compatible with the digital twin model was a challenge. To gather a satisfactory vibration output, the digital model was renovated with the removal of several obsolete fault models and sensors, and implementation of new fault subsytems, as well as a subsystem to generate a vibration signal.

To find a suitable consistency tolerance for the solver configuration of the model was another challenge. Default value for the consistency tolerance (10^(-8)) provided by Simulink caused some of the simulations to raise error flags, which led to whole simulation process being halted, due to calculational insensitivities of the motor current signals. This consistency tolerance was alleviated to 10^(-6) in order to get rid of false error flags and obtain a smoother simulation process.

Determining the threshold levels for the error source variables, which indicates whether a simulation condition is healthy or faulty, was another challenge. As the values for the error variables are randomly given from a specified interval, choosing very small healthy condition boundaries resulted in domination of the sampling of faulty conditions, which lowered the accuracy of determining the healthy conditions in the classifier model training step, as healthy condition class was undersampled. To overcome sampling inequality, the threshold values specifying the healthy conditions was broadened, leading to a better accuracy of the classifier.

TYPICAL USE CASES

This component can be applied to use cases in which failure data need to be generated for machines that may be composed of electromechanical components



TMat-SynDat Component.

such as DC motors, hydraulic press, gearbox, and different sensors. TMat-SynDat has been tested and used for the NOKSEL case, where both healthy and faulty data was generated to be used in predictive maintenance purposes. The generated synthetic data can be used for estimation of remaining useful time of a machine.

NEXT STEPS

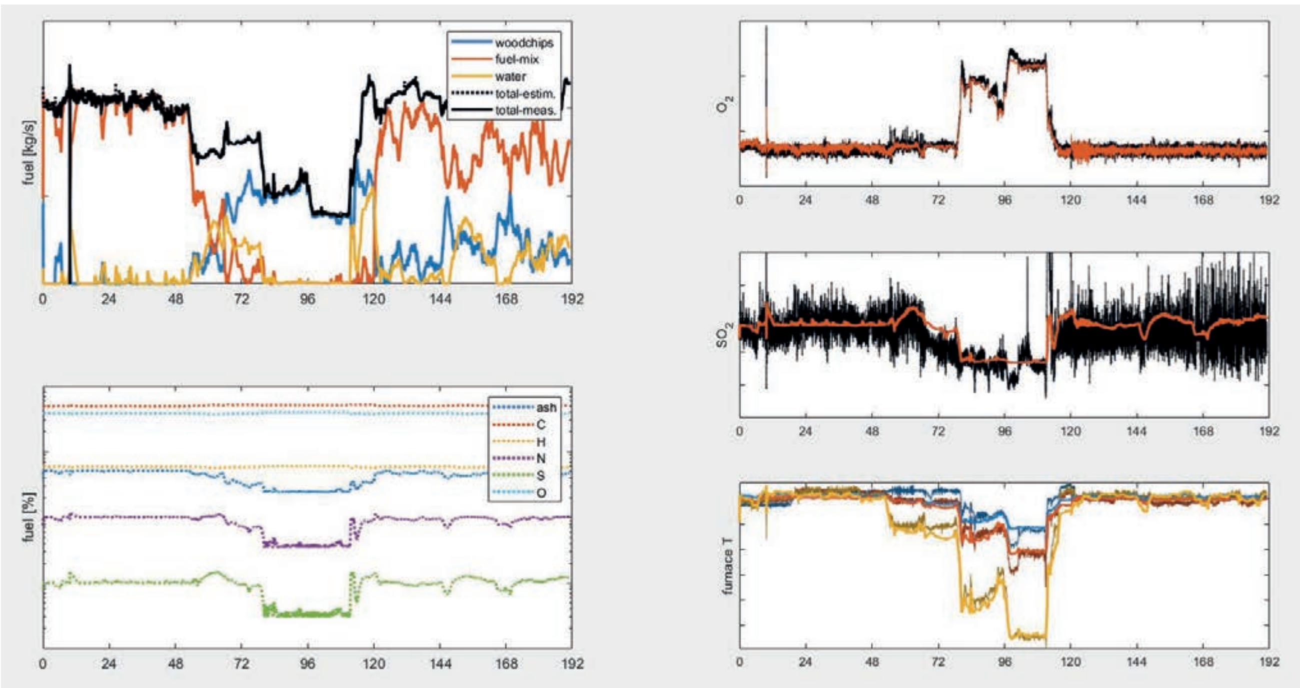
The model calibration will be finalized by using real data, and the 1st order model developed for the NOKSEL's machinery component.

FUSE-TOOL

DESCRIPTION

A state-estimation tool has been developed based on the needs of the COGNITWIN power plant pilot case problem, in cooperation with University of Oulu and Sumitomo SHI FW Energia Oy. The pilot case considers monitoring and control/maintenance of heat exchange surface fouling in combustion of wood-based fuels such as clean wood, recovered wood, demolition wood etc. As a component towards solving the problem, a fuel characteristic estimator has been developed.

The FUSE tool fuses process physical model with on-line measurement data from the plant. The state estimation approach uses a non-linear plant model to predict the plant behaviour. The states with uncertainties are estimated by providing initial, state and measurement noise characteristics in the UKF framework. An optimal correction to the state estimate is provided by the algorithm, using the difference between prediction and measurement. In addition, a physical model tuning method was proposed, including an application for state estimation.



RELEVANCE TO THE COGNITWIN VISION

The tool supports the COGNITWIN hybrid digital twins by providing means for fusion of physical models with process measurements. With the FUSE tool, the uncertain states of the system can be estimated on-line, based on process measurements and corresponding predictions by the physical model. The estimator was applied to the COGNITWIN Engineering pilot (Circulating Fluidized Bed boiler delivered by Sumitomo SHI FW Energia Oy). The physical model tuning method provides another approach to fusion of physical models with data.

KEY CHALLENGES

The tuning of physical dynamic models to local site conditions is a laborious and demanding task, requiring interaction with the experts of the case plant, a good quality measurement infrastructure and sufficiently rich historical data sets. The learning and state estimation algorithm developments are challenging, e.g. due to requirements of robustness in the industrial environment and feasible computational loads during on-line operation.

TYPICAL USE CASES

The FUSE tool was developed using a pilot-driven approach, as a solution to the COGNITWIN use case problem. The case considers characterization of input fuel feed mixture to a circulating fluidized bed, in a model-based approach using measurements from the furnace and flue-gases. Among the bayesian state estimation techniques, the unscented Kalman filter (UKF) was found to be most appropriate for the boiler pilot case as

1. it can handle nonlinear plant models,

2. it does not require the Jacobians to be explicitly evaluated, and

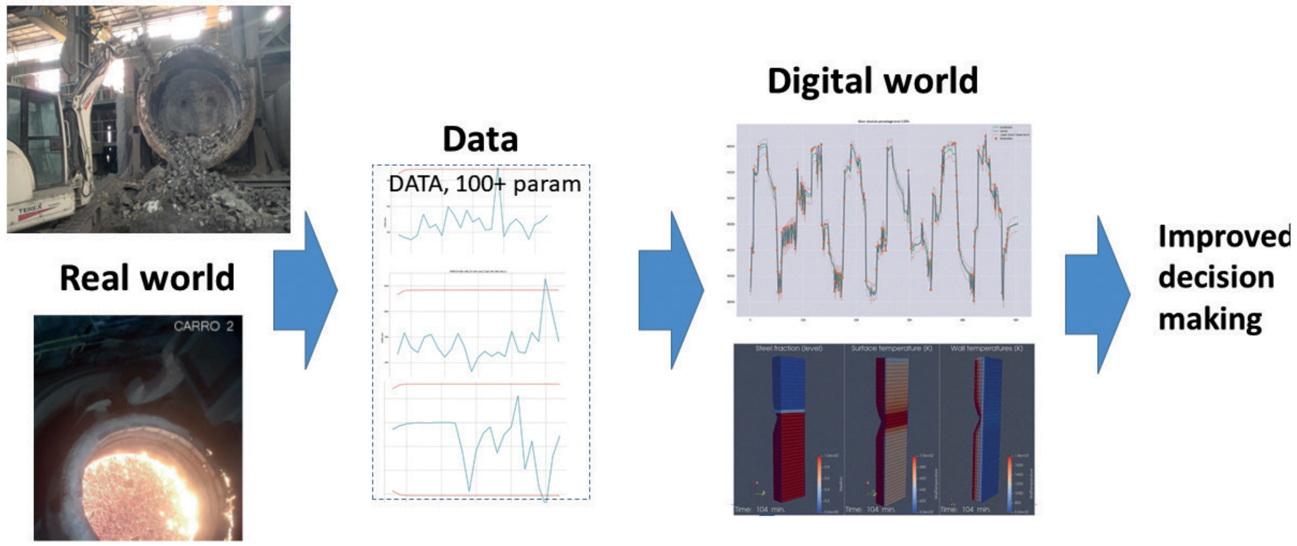
3. the amount of required model predictions / computational load can be kept feasible.

It can be expected that similar conditions are found in other heavy process industry applications, and that the tool and the associated methods/procedures are applicable for other input/parameter/state estimation problems as well.

NEXT STEPS

A generalized FUSE tool is provided for the COGNITWIN toolbox, providing a flexible implementation for the UKF state estimation using a physical plant model. Next, the tuning process will be included and provided in the COGNITWIN toolbox. The work will then proceed in looking at solving the fouling monitoring and control problem.

ToolWearMonitor: SERVICE FOR MONITORING TOOL WEAR / EQUIPMENT WEAR PROBLEMS IN THE PROCESS INDUSTRY



An example of the use of ToolWearMonitor.

DESCRIPTION

This service enables efficient monitoring and analysis of the degradation of equipment used in harsh conditions in the process industry. Degradation is usually a slow process, but it is unpredictable due to the dynamic environment in which the equipment operates. To develop accurate prediction models for remaining useful life, the service uses all available data (i.e. real-time process data / time series, product characteristics data, etc.) and numerical models. The prediction can be in the form of the remaining useful cycles or the prediction of the degree of degradation. The service should be used by a technical operator as additional information for deciding on equipment replacement/repair.

RELEVANCE TO THE COGNITWIN VISION

The service supports decision making in difficult situations by using and combining all available data, models and (human) knowledge as defined in the COGNITWIN vision. It bridges the gap between the real world (i.e. the physical asset such as plant, tool, equipment) and the digital world (i.e. digital twin of the asset) by providing the current and future status of the real asset (e.g. regarding the wear process) based on synergy between data and models.

KEY CHALLENGES

Two main challenges are:

1. the processes are too complex, so numerical models are not accurate enough or developing such models can be time-consuming and expensive;

2. the environment is harsh, so data is missing because equipment is inaccessible and / or data is incomplete because equipment is replaced before it breaks.

The core issue is the integration of the multiple different models (e.g. numerical and data-driven models) to exploit the full potential of digital twin models while increasing their transparency and accuracy. The approach is based on the hybrid digital twin paradigm, where the process of hybridization goes beyond solely connecting models and data, which usually requires accurate models and complete data. We propose orchestration of data and models as a new method for connecting (imprecise) models and (incomplete) data.

TYPICAL USE CASES

A typical use case is tool wear / equipment deterioration, especially in processes that take place in dynamically changing environments. In such cases, the technical operator makes a low-risk decision and suggests changing / replacing the equipment before it becomes inoperable. The right time to change the tool brings significant cost savings.

NEXT STEPS

Further work is to improve the performance of the system through further testing in the Sidenor pilot. The focus is on validating the improvement in accuracy through the introduction of the hybrid models.

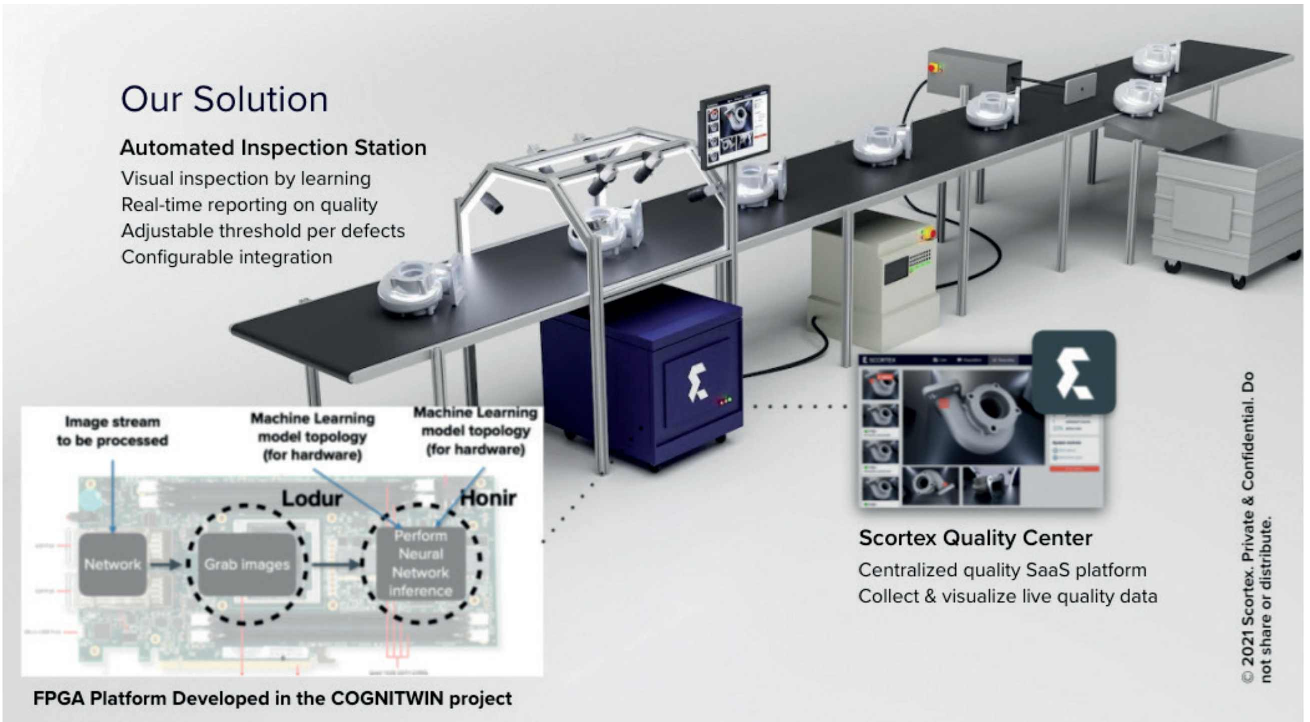
SCORTEX FPGA PLATFORM

DESCRIPTION

One of the limits of deploying deep neural networks in the real world is speed. 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. In order to solve this issue, Scortex is building an edge inference engine based on FPGA technology platform that allows fast inference on production lines.

FPGA can basically be seen as an alternative to GPU / TPU / CPU.

To the best of our knowledge, Scortex is one of the first company to have succeeded in having a deep learning model running on FPGA with the following performances: we are able to run inference of one of Scortex's (custom architecture) model up to 100 frame per seconds of 1920x1200 pixels coloured images.



Scortex FPGA Platform.

RELEVANCE TO THE COGNITWIN VISION

At the heart of COGNITWIN are sensors and real time decision taking, with retroactive feedback loops. When it comes to perception, deep learning is one of the most promising technology out there. Our FPGA platform focus on one kind of sensors; cameras; and allows the processing of multiple frames at a very high rate. This allows real time perception and decision taking in the 3D world.

KEY CHALLENGES

FPGA implementation can require a deep understanding of VHDL code. There are very few people with this skill available on the job market. Luckily for Scortex, we were able to build a great team!

TYPICAL USE CASES

Scortex technology can be used in any setup where perception from cameras is required. More specifically, the technology bears interest when a very high frame rate and real time processing is needed on high resolution images. This is often the case in factories.

As of now, Scortex's goal is to use it internally in its quality inspection solution since it will increase its accuracy / speed ratio.

NEXT STEPS

Scortex plans to make the technology more versatile so that it can support more applications. Benchmarking of the solution on data from the COGNITWIN partners will be key to show the viability of the solution.

NEUROSCOPE

DESCRIPTION

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. Developing a neural network for a specific task is a difficult and often iterative process, where a model is trained, checked, adjusted and checked again. Since a neural network is essentially a black box, where only input and output are known, but not the process by which the input leads to the output - the need for tools helping to explain the neural networks behaviour is both pressing and obvious. Neuroscope offers a solution by providing an easy-to-use graphical user interface for the visualization on all layers of a neural network for image classification and semantic segmentation. It this way, the user can see how the model internally processes the input and thus speed up the development of deep neural networks significantly.

RELEVANCE TO THE COGNITWIN VISION

A digital twin allows to generate synthetic data of production processes, which can be used in artificial intelligence applications to improve product quality or predict maintenance intervals. These Deep Learning methods are based on neural networks, which are difficult to understand. Neuroscope helps the user to comprehend a network’s behaviour thus enabling a quicker and more efficient design.

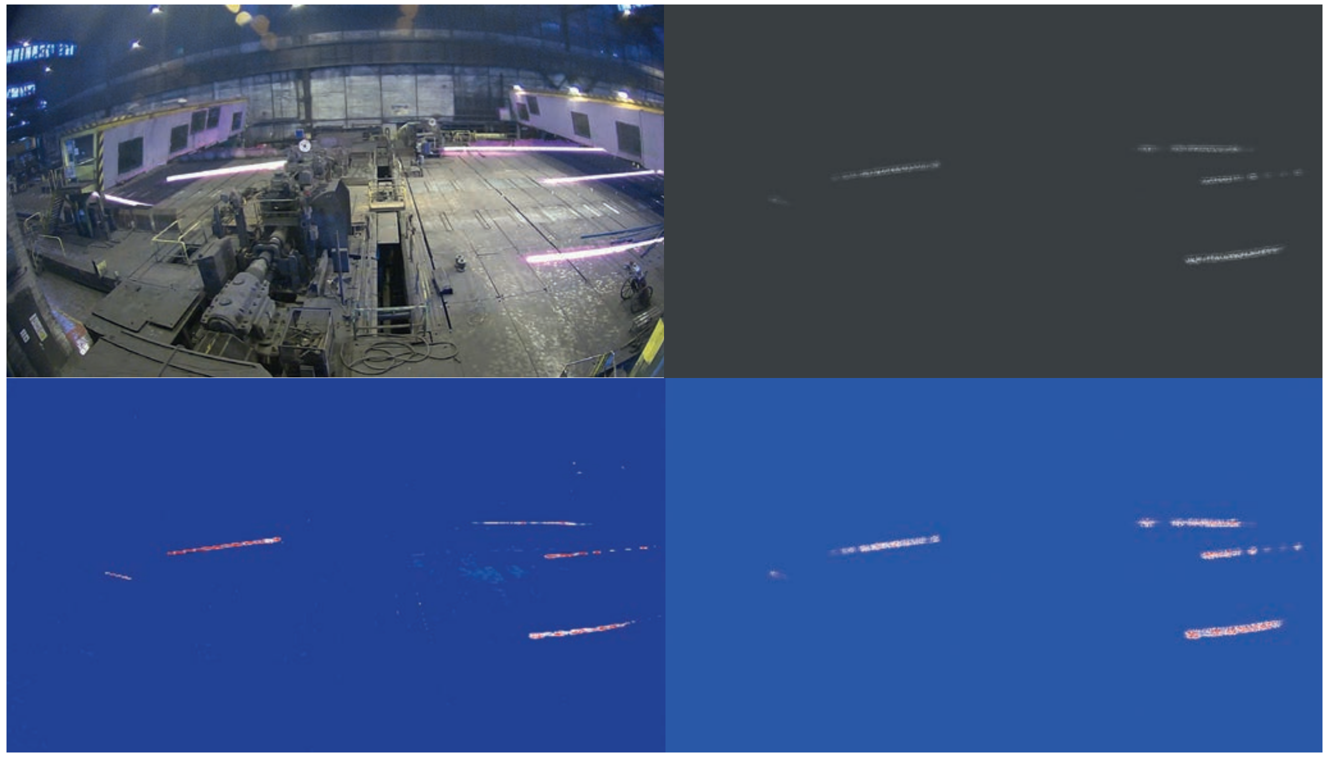
KEY CHALLENGES

The main research challenge was posed by the adaption of the visualization methods originally developed for image classification to work for image segmentation also. By studying and then adjusting the corresponding algorithms based on the specific differences between classification and segmentation neural networks we were able to achieve this goal.

A technical challenge during the development of Neuroscope was the accommodation of CNNs generated from different frameworks like Keras and Pytorch. This was solved by transforming the model descriptions to an intermediate standardized format which served as a basis for the implementation of all visualization methods.

TYPICAL USE CASES

In the COGNITWIN context, a typical use case for Neuroscope is to improve the model generation for image-based Machine Learning applications like the detection of billets in the Saarstahl steelworks. The neural network’s task is to segment the pixels of a camera image from the shop floor of the rolling mill of Saarstahl as a component of an automated optical detection and tracking process (top left). 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 the locations of the billets, as well as some localized areas of low activation (bottom left). The activation map computed by the Guided Backpropagation method (bottom right) highlights pixels of high activation exactly at the billet locations. The analysis of these three types of visualization maps raises the question why the activation maps don’t show high activated pixels monotonously within the bounds of the billets. This observation could be the indicator of a poorly trained deep learning model or scarce training data. Using Neuroscope thus leads to a better understanding of a neural networks behaviour and allows for easier optimizations.



Visualization of the class „billet“ using Neuroscope: top left: original image, top right: saliency map, bottom left: guided Grad-CAM, bottom right: guided backpropagation.

NEXT STEPS

The next steps include expanding the support of additional frameworks as well as including models using advanced Keras and Pytorch libraries like Lightning. We also plan to add further visualization methods specially designed for trinary image segmentation of correct billets, erroneous billets and factory floor background.

CYBERNETICA'S COGNITWIN TOOLBOX COMPONENTS

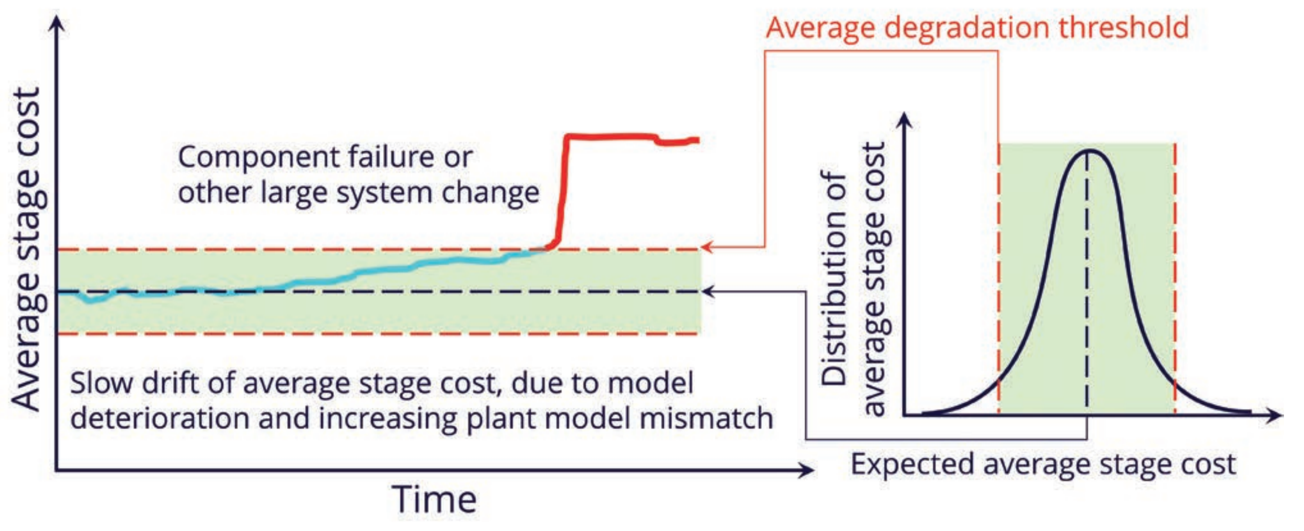
DESCRIPTION

Cybernetica's CogniTwin toolbox components target different aspects of digital twin development and deployment.

Cybernetica ModelFit and Cybernetica RealSim are primarily geared towards off-line modelling and simulation. Off-line tuning of physical and data-driven models and estimators allows for the evaluation of digital twin response to many process situations and anomalies that would normally be sampled with low frequency. Similarly, off-line simulation of closed-loop control allows for more effective assessment of a digital twin's self-correcting capabilities.

Cybernetica ProXim and Cybernetica Viewer are aimed at providing operators and engineers with the opportunity to study digital twin behaviour and results from a user-friendly interface. These tools establish a necessary link between the digital twin and user understanding. Cybernetica CENIT is the backbone of the digital twin where online calculations are performed. CENIT digital twins can be used both to develop both soft sensing (monitoring mode) and control (optimisation mode) applications. When used for optimisation, the digital twin is used to predict process behaviour and optimise future process inputs to achieve targets for selected process variables (KPIs). A Kalman Filter for adaption of the digital twin is available. Cybernetica OPC UA server can be employed to simplify communication between the digital twin and plant databases.

The cognitive extension of CENIT adds self-diagnosing capabilities to Cybernetica CENIT.



Example of KPI error detected by cognitive self-assessment of controller performance.

RELEVANCE TO THE COGNITWIN VISION

A framework for self-monitoring of the digital twin for optimisation applications in Cybernetica CENIT is under development. For given KPIs, the digital twin's simulated stage cost is compared to actual plant stage cost in order to enhance CENIT's capacity for self-learning. By overseeing and checking whether the stage cost is within acceptable and unacceptable deviation, CENIT is able to assess its own performance and determine when and if digital twin maintenance is warranted.

KEY CHALLENGES

The main challenge for the cognitive extension of CENIT is the additional computational expense incurred by the stage cost oversight analysis. The computational load may, depending on resources available, limit the frequency of online self-assessments.

TYPICAL USE CASES

When ready for deployment, the cognitive extension of CENIT will be applied for all instances of Cybernetica CENIT digital twins for optimisation of both batch and continuous processes. The stage cost oversight method can also be applied to other digital twin applications where either first principles, data-driven or hybrid models are employed.

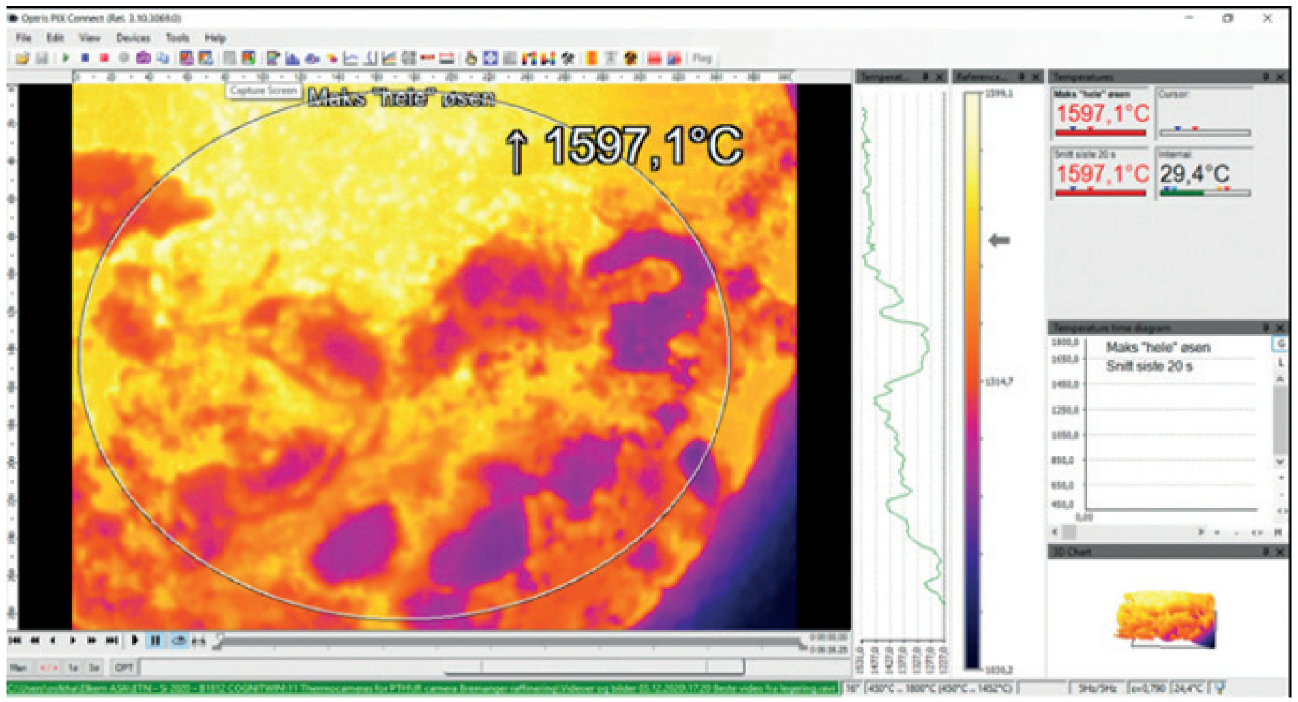
NEXT STEPS

Further work for the cognitive extension of CENIT will focus on developing methods for automated identification of sources for digital twin error.

DEVELOPING A DIGITAL TWIN FOR REFINING/ ALLOYING OF FERROALLLOYS: TEMPERATURE MEASUREMENTS USING AN INFRARED CAMERA

DESCRIPTION

During batch processing of liquid ferroalloys it is necessary to control the chemistry as well as the temperature of the molten alloy. Process control is based on theoretical mass/energy balance models, as well as empirical data and experience. However, due to the complexity of the system (high temperature, fluid flow, heat transfer, fluctuating input parameters) it is extremely important to measure various parameters during the process. In particular, the temperature of the system rely key information regarding status of chemical processes. The actual measurement(s) can be done in several manners, but in general a contact free measurement does not disturb the process and is the preferred method. In the COGNITWIN project, Elkem Bremanger is developing a solution for continuous temperature surveillance of the ferrosilicon (FeSi) refining process utilizing infrared cameras mounted above the ladle with liquid metal.



Infrared image of metal surface in the ladle; darker areas are slag and brighter areas liquid ferrosilicon. Temperatures can be recorded from single pixles or average from a group of pixles.

RELEVANCE TO THE COGNITWIN VISION

The use of IR camera temperature measurements will enhance the available process information and support mathematical models that calculate the current and future process status. This part of the project if focusing on the use of smart sensors, communication with the plant data processing system and development of online process models, aka hybrid/cognitive twins.

KEY CHALLENGES

Refining of ferrosilicon involves high temperatures and significant amounts of dust and smoke. Thus, it is necessary to use IR cameras that are able to “see through” smoke and dust. This is achieved by choosing a suitable operating wavelength for the camera. A benchmark study was done where various cameras were tested at the plant, which resulted in the installation of a 1µm infrared camera. Currently, efforts are ongoing to obtain a live video stream from the camera that can be accessed remotely. Due to the harsh environment, sufficient cooling and protection of the camera is critical otherwise lifetime will be much too short to justify this type of investments.

TYPICAL USE CASES

IR cameras are well suited for contact free measurements for a large range of temperatures for many industrial applications.

NEXT STEPS

Use temperature measurements from the camera directly into the process model (hybrid twin).

DIGITAL TWIN FOR CONTROLLING GAS TREATMENT CENTRE (GTC) IN ALUMINIUM PRODUCTION: MAIN FAN CONTROL BASED ON NEEDS AND CONDITIONS

DESCRIPTION

When producing aluminium by Hall Heroult Electrolysis process, the off gas from the process is has hydro fluoric acid gas (HF). The GTC then ventilate the electrolysis cells and recover as much of the fluoride in the gas (up to 99.95 %), by drey scrubbing the gas with alumina. The flow rate of gas should be enough to seal the electrolysis cells preventing the off gas being emitted to the atmosphere. The engine of the GTC is their main fans, often done by 2-4 large fans of 500-1300 kW size. Meaning that it is quite a source for power consumption. Moreover, the extraction of gas also influences the process itself by drawing energy from the process. A constant energy extraction is desired; hence the extracted mass of off gas should be kept as constant as possible. When process and ambient temperature varies and the process demands varies, the mass of off gas extraction will vary, this since the fans only process actual cubic meters, i.e. volumes, whilst the expression of mass would be expressed by normal cubic meters (DIN 1343; P= 1013 mbar, 273,15°C).

RELEVANCE TO THE COGNITWIN VISION

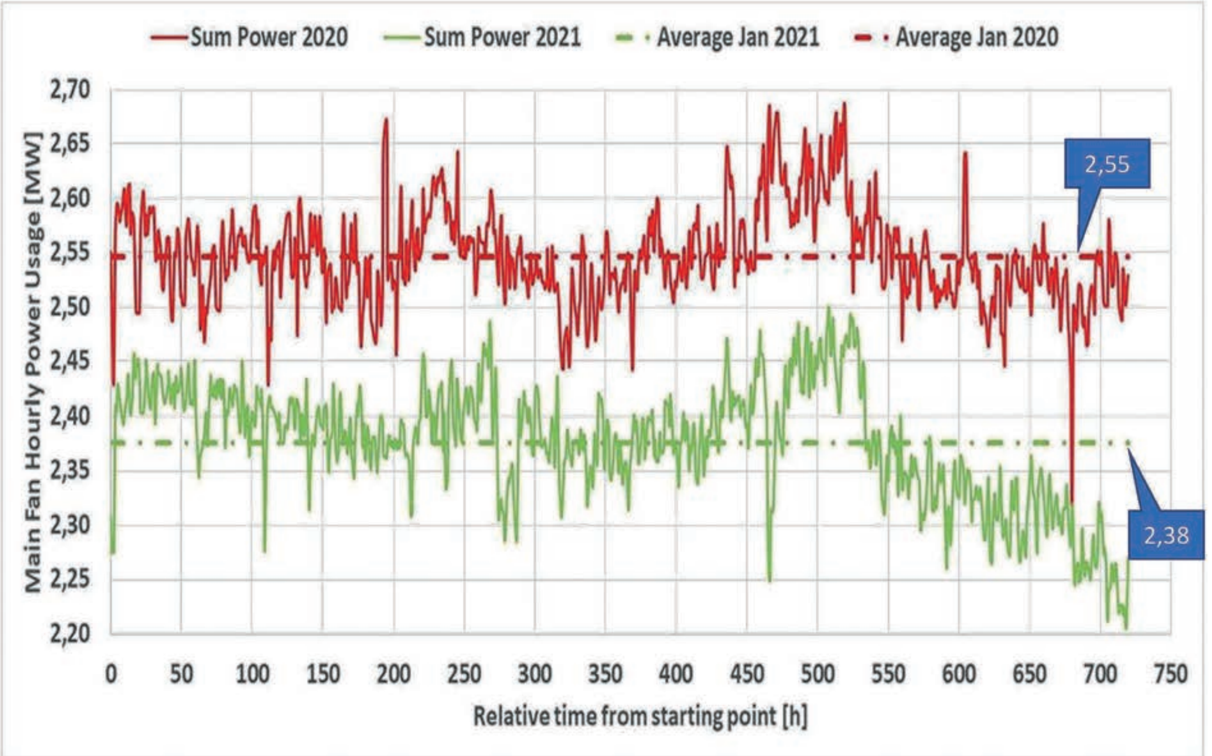
Accurate gas flow combined with continues extracted process and ambient conditions data is needed to control the main fans. Since the main fans are of such size, they cannot be too sensitive to changes, but be able to intelligently follow the needs and demands from process. Meaning that correct measuring of current conditions combined with scheduled process events and weather forecast should be treated in a digital twin with later cognitive abilities to optimise the power consumption.

KEY CHALLENGES

The main ducts in a GTC system is often in the size range equivalent to a diameter of ø4-8 m, meaning the to measure the gas flow is a challenge. Also, the gathering the right metrological data in combination with process data is a challenge. One need a correct but fast-moving logic to respond to this. The gas flow being very turbulent also constitutes a challenge to how to best control this.

TYPICAL USE CASES

By simply saying that the normalised gas flow should be constant, i.e. constant energy extraction, the main fans in a test set up has shown promising potential for saving power. The test shown in Figure, is 4 main fans of 710 kW set to constant normalised gas flow. When comparing the before and after constant set point, one saves 122 MWh or ~7% during 720 hours of operation, at the same time supplying enough suction to the process. When considering private households' consumption in the same period it becomes equivalent to 72 households. When considering the fact, that in Hydro Norway alone one has ~50+ of fans of this or larger size, the saving of power potential becomes considerable, not to mention the aluminium production in general.



A test example.

NEXT STEPS

So far this has been done only by setting the fans constant. Next step will be to link the process plans and weather forecast to the system, and firstly control the fans through a data driven model, then later ad cognitive capability trough pattern recognition, to potentially save even more in parallel with providing sufficiently to the process.

CONSORTIUM

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