COGNITWIN

Cognitive plants through proactive self-learning hybrid digital twins

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Deliverable Report

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Executive Summary

The Engineering pilot in COGNITWIN WP3 deals with optimization and operation of energy boilers, designed and delivered by Sumitomo SHI Energia Oy (SFW), aiming at fast adaptation to new and variable energy sources. The Engineering pilot was concentrated on an energy conversion process called Circulating Fluidized Bed (CFB). A specific challenge for today's CFBs, as wells as for energy boilers in general, is the variation in fuel quality, which contributes largely to harmful fouling and corrosion phenomena.

One of the prevailing trends in the energy plant business is that the requirement for fuel flexibility is increasing fast. Therefore, the main challenges in today's energy boilers are ever more difficult fuels and the changing fuel quality, which make optimal operation of boilers extremely challenging. Therefore, there is a demand for adaptive systems that involve cognitive elements to learn the most efficient and cost-optimal ways of operating or controlling the process to maximize power output and minimize fouling and corrosion effects and emissions.

In the research within WP3, a novel approach was developed and used for the indirect characterization of fouling status in heat exchangers (HX), to optimize and improve fouling management in a CFB boiler. The goal, which was achieved, was to have to a system that could adapt to the prevailing process conditions, with respect to the prevailing load level and fuel quality, for example. In addition, the target was that the system would give an indication of when to start the HX cleaning sequence. In addition, a novel condition monitoring scheme based on modal analysis was introduced, which provides a potential direct way of estimating the degree of fouling on heating coil surfaces. Both approaches were tested in real operational environment of a 150 MW CFB boiler with promising results.

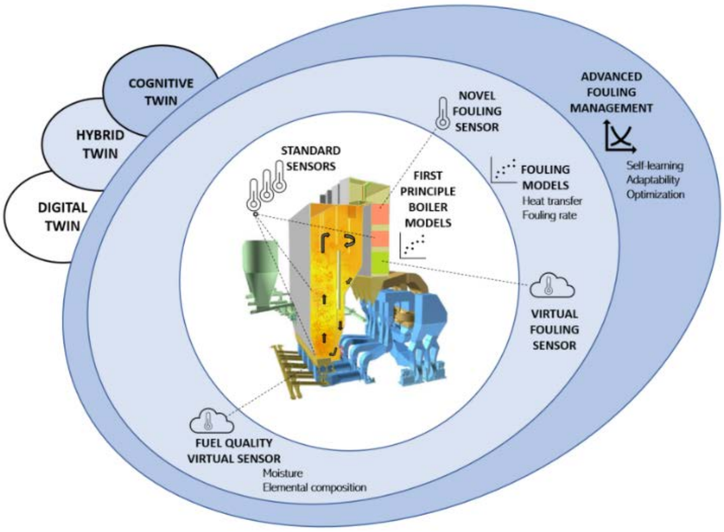

Fig. 1. Overview of Engineering pilot

In COGNITWIN WP3, we have successfully demonstrated the use of twin technology in the Engineering pilot (Fig. 1). The technology helps the operator of the power plant to optimize the boiler controls. The benefits gained by the new COGNITWIN technologies developed for the Engineering pilot (CFB) are improved operating efficiency, lower operating costs, lesser total amount of emissions, and improved reliability and availability. The improvements in the selected KPIs were calculated by comparing the measured performance after the implementation of COGNITWIN to the measured performance prior to the implementation.

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Abbreviations

CFB – Circulating Fluidized Bed
DCS – Distributed Control System
DoE – Design of Experiments
EnKF – Ensemble Kalman Filtering
ECO – Economizer
ETB – Evaporative Tube Bundles
FEM – Finite-Element Modelling
FF – Fouling Factor
FouCon – Fouling Control component
FouMon – Fouling Monitoring component
FUSE – Fuel State Estimation
HRC – Heat ReCovery
HX – Heat Exchanger
IoT – Internet of Things
LIBS – Laser Induced Breakdown Spectroscopy
LTI – Linear Time-Invariant
MIP – Mixed-Integer Programming
OPC – Object Linking and Embedding (OLE) for Process Control
PGNAA – Prompt Gamma-Neutron Activation Analysis
PLSR – Partial Least Squares Regression
PMFIR – Physical Model Finite Impulse Response
SEP – Standard Error of Prediction
SFW – Sumitomo SHI FW Energia Oy
SH – Superheater
SubFUSE – Subspace Fuel State Estimation
TAPH – Tubular Air PreHeater
UI – User Interface
UKF – Unscented Kalman Filtering
UOULU – University of Oulu
XRF – X-Ray Fluorescence

1 Introduction to Engineering pilot

Energy boilers are a critical element in the power industry and will play an important role in the palette of green energy technologies in the future. This pilot case deals with optimization and operation of energy boilers that are designed and delivered by Sumitomo SHI FW Energia Oy (SFW). Inputs to the pilot process are developed technology (design and operation), combustible raw materials with a large variety in chemical composition, energy contents, and air that is fed in to support the combustion. A specific challenge is the variation in fuel quality, which contributes largely to combustion instability, corrosion, and fouling phenomena. Output from the process is energy (electricity and thermal power), combustion products and ash.

The customers of SFW face challenges in plant operation, maintenance, and asset management. The plant operators may struggle with the optimal operation when the fuel is continuously changing, especially when firing challenging renewables such as biomass and bio-residues. The fuel quality may be decreasing, and new challenges are set to maintenance and equipment lifetime as the harmful components in fuel are increasing.

SFW aims at expanding its service pallet in the existing market area for both existing customers with SFW boilers and to new service customers. The company's business model is based on continuous operations and maintenance services for the customers, and on the benefits these services bring to the customer as added value to their operations.

1.1 Circulating Fluidized Bed process

The Engineering pilot concentrates on an energy conversion process called Circulating Fluidized Bed (CFB). A CFB boiler consists of a CFB loop and a convective section. The main parts of the CFB loop are furnace, gas-solid separator, solid recycle system (loop seal) and optional fluidized bed heat exchanger. The convective section, also referred to as back-pass, is composed of superheater, reheater, economizer and air preheater [1]. The pilot CFB boiler is presented in Fig. 2.

In a CFB boiler, preheated combustion air is delivered into the furnace in two stages by air fans. Primary air is delivered through an air distributor grid that is located at the bottom of the furnace. Secondary air enters the furnace through ports located on the walls above the furnace floor. The velocity of the gas in the combustor is typically in the range of 3 to 6 m/s generating good mixing. Fuel is delivered directly into the lower section of the furnace or through the loop seal. The fuel burns in the bed of solids generating heat. The heat from combustion flames and flue gases is transferred to the water-steam circulation of the boiler and preheating of air. [1][2]

1.2 Pilot plant

The twin technology described in this report is demonstrated in real operational environment of a CFB boiler designed for combined heat and power production. The boiler unit is a 150 MW CFB boiler designed by Sumitomo SHI FW for wood-based fuels such as clean wood, recovered wood, and demolition wood collected from both households and industry (See Fig. 2). The plant is in Västerås, Sweden. The boiler has been in operation since November 2019.

Currently, the unit uses primarily wood waste from households and industries as fuel, and it covers total of about 36 % of the heat demand and yearly production of Mälarenergi AB. The new plant makes it possible for Mälarenergi to use only renewable and recycled fuels, which is the beginning of a new era without coal and oil at the cogeneration plant in Västerås [3].

The heat exchange surfaces suffering from fouling and cleaned regularly by steam sootblowing include the screen, three superheaters (SH), evaporative tube bundles (ETB), economizer (ECO), tubular air preheater (TAPH), and heat recovery (HRC). These surfaces can be seen in Fig. 2. Screen and evaporative tubes are evaporative surfaces, which means that they are used to vaporize water, whereas the superheaters are used to produce superheated steam which is the final output of the boiler. Economizer is a water preheater for warming up the boiler water by the hot flue gases. TAPH and HRC are preheaters for the combustion air.

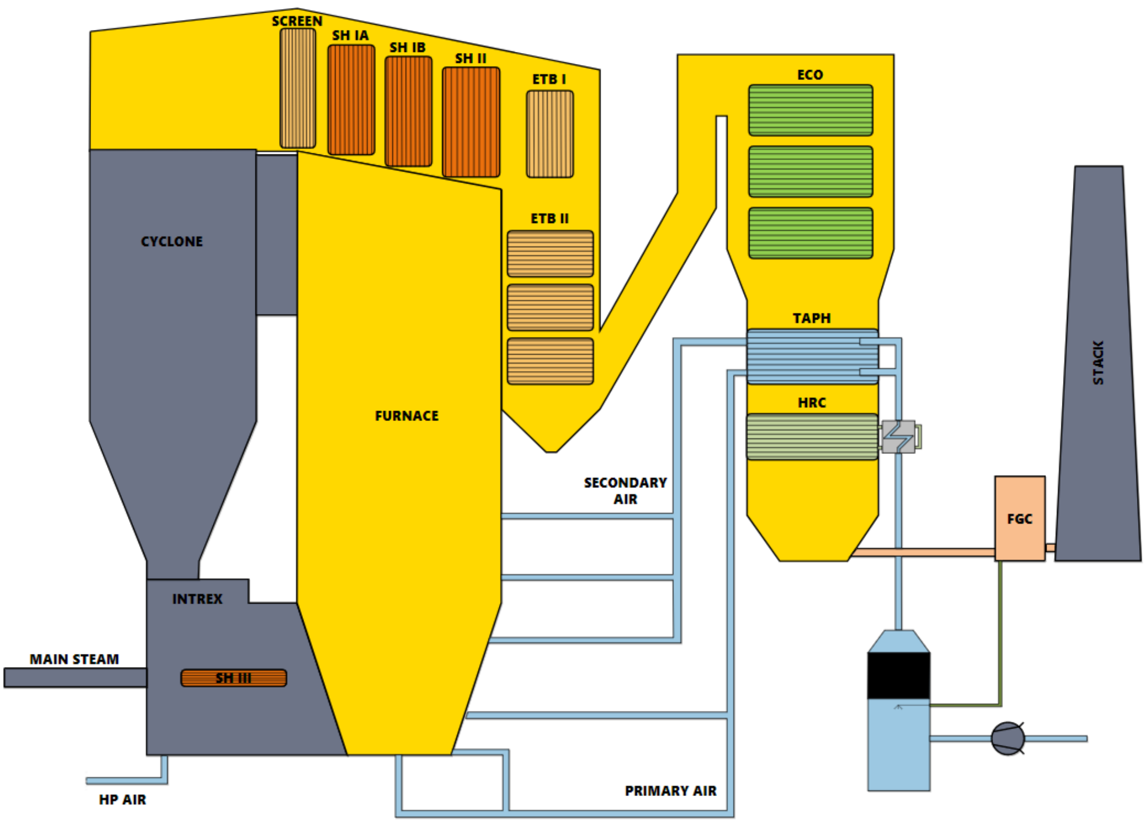

Fig. 2. Simplified presentation of the pilot CFB boiler in WP3.

This unit has been selected based on potential challenges in the operation and optimization of the combustion process that are common for the fired fuel mix. Common operational challenges arising when firing recycled and/or demolition wood are formation of deposits on the convective HXs and consecutive corrosion phenomena, as well as occasional agglomeration and circulation problems in the boiler hot loop area. Further operational challenges are connected with a variation in fuel moisture content. For these reasons, fouling management would be important for this plant; however, it is also very challenging to develop digital tools for fouling management. Advanced digital tools for better control of fouling are beneficial to optimize the process and cut the operating costs.

1.3 Pilot problem and user story

1.3.1 Challenging fuels

The world is accelerating toward carbon neutrality, which has a substantial effect on the whole energy production sector. At the same time, there is an increasing variation in the quality of solid fuels. Certain critical properties of the incoming fuel, such as moisture and chemical composition, are usually unknown in detail but may vary a lot depending on the type and origin of the fuel. For example, biomass and waste fuels induce instability in combustion due to their non-homogeneous nature: fuel moisture, elemental composition and particle size vary significantly, and therefore a stable energy supply is hard to maintain. One of the driving forces for using more challenging fuels is the price: the prices of certain fuels of good quality (e.g., good quality pellets of virgin wood) have increased enormously in recent times, whereas some fuel types like demolition wood are often much cheaper [4].

Nonetheless, use of these challenging fuels may pose problems that have to be tackled. For example, common operational challenges arising when firing recycled and/or demolition wood are formation of deposits on the convective heat exchangers (fouling) and consecutive corrosion phenomena, as well as occasional agglomeration and circulation problems in the boiler hot loop area. Further operational challenges are connected with a variation in fuel moisture content. All these problems lead to unavailability issues, unplanned shutdowns, and extra maintenance which in turn makes it challenging to produce energy efficiently and economically.

As illustrated in Fig. 3, for example in winter times, one challenge is the snow and ice covering fuels, which may increase the moisture content of the incoming fuel (on the left). In addition, some fuel types like chipped demolition wood (on the right) may contain challenging fractions such as pieces of plywood which potentially cause problems like accelerated fouling and agglomeration phenomena, because of certain substances like glues that are used in their production.

Fig. 3. Challenging fuels. 1) Snow covered fuels in winter (left), 2) chipped demolition wood (right)

1.3.2 State-of the-art of fouling management

Utilization of biomass and waste fuels in highly efficient CFB boilers is often connected with elevated risk of fouling and corrosion (See Fig. 4; note that the illustration is not connected to COGNITWIN pilot plant). Fouling occurs as gaseous or liquid compounds that are formed during a combustion process deposit on colder surfaces, e.g., on convective heat exchangers. Ash-forming elements from fuel react with flue gases or with the solids suspended in the flue gas forming fouling components via complex mechanisms that are not yet fully understood. [5]

To ensure proper operation, it is vital that the HX surfaces of boilers fired by waste-derived or biomass fuels are cleaned frequently to maintain adequate heat transfer between the flue gas and fluid. On the other hand, excess cleaning of HX surfaces wastes money and resources, and soot removal based on fixed time intervals – as is usually the case in these boilers – may not be the most efficient way of operation.

Especially in the case of biomass fired boilers, the deposited alkali metals sodium and potassium reduce the rate of heat transfer and affect the boiler. These deposits are being removed regularly by specific sootblowers, which can be operated, for example, by steam. Typical soot removal methods in power plants include:

- Steam sootblowing: the deposits are blown with superheated steam at boiler pressure to remove them
  - Steam nozzles can be moving or stationary, steam is typically taken from the primary superheater
- Acoustic (infrasound)
  - Directing a pressure shock on the deposit; typically pneumatic, for HX surfaces in the lower temperature areas
- Water cannons
  - Directing a water jet to the area to be cleaned; typically, evaporator surfaces (not superheaters)
- Hammering
  - Induces vibration to the system by mechanical strike; used in extremely fouling conditions (waste-to-heat, oil shale fuel etc.)
- Detonation cleaning
  - Based on exploding a bag of gas mixture; typically, a onetime operation in waste-to-heat plants, when the conventional methods are not adequate

Soot removal in the selected pilot plant is performed by steam sootblowing, which means in practice that high-pressure steam is being regularly blowed onto the HX surfaces. In addition, there are two infrasound cleaners located in the economizer section, but they were left out of the scope already in the early phase, because the possible economic benefits gained by optimizing their operation were considered quite small.

Before COGNITWIN, the steam sootblowing was operated periodically every 14 hours in the pilot boiler unit, without any type of evaluation or optimization based on varying circumstances, such as load, fuel quality etc. The focus in COGNITWIN fouling management was on the superheater section of the boiler, which is the part where the fouling is the most significant.

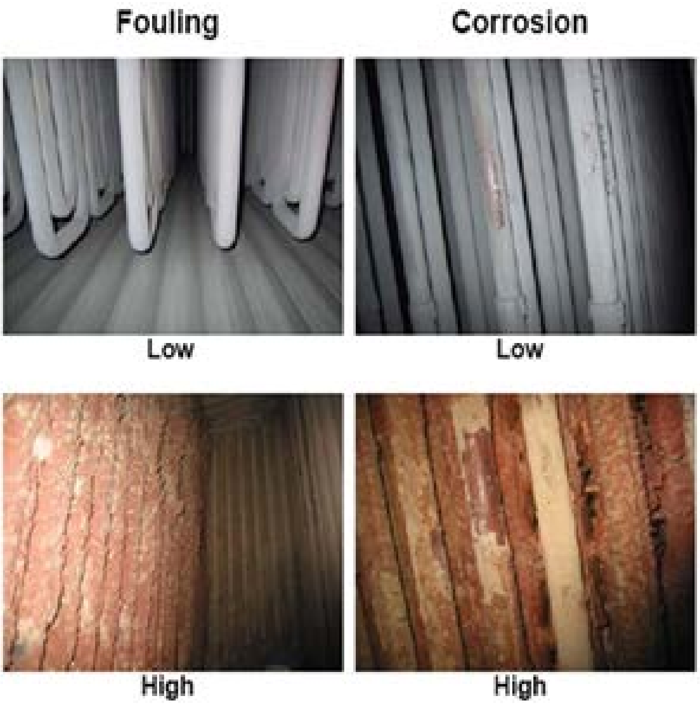

Fig. 4. Fouling and corrosion of heat exchanger tubes

1.3.3 User story description

The goal in COGNITWIN WP3 was to optimize the timing of boiler cleaning operations, e.g., to maximize profits vs. costs in the steam sootblowing. The starting point for the methodology development was that it should be able to adapt to prevailing conditions, for example to changes in fuel and load demand. A more detailed description of the user story in the WP3 pilot can be seen in **Table *1***.

Table 1. User story of the Engineering pilot

Use Case Template	Description
Use Case Name	Boiler fouling management
Use Case ID	SFW-UC-1
User story expression of use case	As 1) 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 2) 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

1.4 Pilot objectives

In the beginning of the project, the objectives of COGNITWIN WP3 were defined as follows:

- Find commercially available sensors and soft-sensor solutions able to characterize and categorize fuels utilized in power plants according to their quality and properties
- Combine the data gathered with these novel sensors to the process data from the power plant with hybrid cognitive models
- Combine these models into a cognitive digital twin of a commercial boiler and utilize the twin to optimize the controls and operation of the boiler so that fuel quality fluctuations are compensated for.

After describing the pilot problem and the corresponding user story, it was possible to formulate the actual research questions and specify the goals and main tasks in the project. Since fuel quality is one of the principal factors affecting fouling on heat exchangers, the pilot problem was elaborated further and divided into following research questions:

- Phase I (*Digital Twin*): What is the plant fuel feed composed of?
- Phase II (*Hybrid Twin*): How to monitor fouling on heat exchange surfaces?
- Phase III (*Cognitive Twin*): How to control fouling, by plant operation or maintenance?

Based on these research questions, the sub-goals and main tasks in WP3 were further formulated as follows:

Main objective: Improve fouling management
- Objective I: Improve fuel quality monitoring
    - Task IA: Develop virtual sensor for fuel quality
- Objective II: Improve fouling monitoring
    - Task IIA: Develop virtual sensor for fouling
    - Task IIB: Develop acoustic sensor for fouling
- Objective III: Improve fouling control
    - Task IIIA: Develop advanced tools based on Twin technology to improve and optimize fouling management

1.5 Alignment of pilot work and Deliverables

1.5.1 Main activities and their schedule

An overview and structure of the pilot can be seen in Fig. 5. The target in Phase I was in utilizing a physical model for the boiler furnace (the so-called hotloop model) and tuning it by available sensor data to achieve a virtual sensor for fuel quality. This provided hybridization of physical knowledge with data and serves as a part of the digital twin platform. The boxes with the dotted lines describe research paths that were verified in the pilot but not included to the final demonstration.

The work made in Phase II has resulted in a virtual fouling sensor, which basically works as the basis for the last step to optimize fouling management in the pilot plant. It is to be emphasized that the digital twin framework is included to the hybrid twin framework, as is depicted in Fig. 5. The final phase of the work in WP3 was to develop tools and methods for improving and optimizing the fouling control in the pilot boiler.

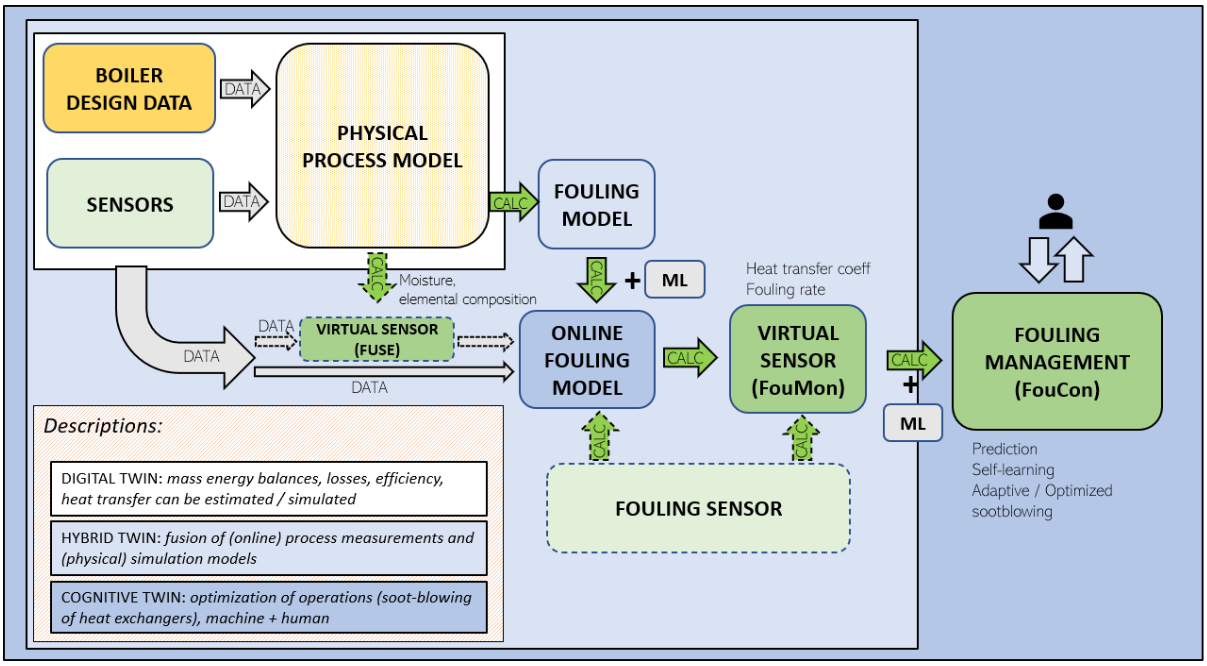

Fig. 5. Final structure of Engineering pilot

COGNITWIN was started in September 2019. The realized schedule of the main milestones in the Engineering pilot can be seen in **Table *2***.

At the beginning, there was some delay in starting the actual pilot actions, because we did not have the pilot plant agreed in the starting phase. Piloting co-operation was finally agreed with Mälarenergi AB in January 2021. However, it was possible to do a lot of the preparative work in advance, and therefore we managed to speed up the pilot development and were able to conclude in time. For example, there was a possibility to use some sensor data from another CFB plant to be able to start the technology development in advance. In addition, history data from the eventual pilot plant was available already at that moment when the pilot was agreed.

1.5.2 Deliverables

In total, three Deliverable reports were produced in WP3 to describe the key milestones and most important phases of the pilot development:

- D3.1: A report on existing level of digitalization, describing challenges for Engineering pilot, incl. identification of novel sensors and collected information for cognitive modelling [6]
- D3.2: A database and digital platform for Engineering pilot [7]

- D3.3: Hybrid models for Engineering pilot [8]
- D3.4: A complete Cognitive Twin for Engineering pilot [9]

Table 2. Realized schedule of key actions in the Engineering pilot

Activity	Status (Schedule)
DATA PLATFORM	
Data collection	Ready (Q1/2020)
Data acquisition (transfer into cloud)	Ready (Q2/2021)
NOVEL SENSORS	
Installation of acoustic fouling detection measurement system	Installed: Q4/2021
Onsite testing of system	Ready: Q2/2022
PILOT MODELS & TOOLS	
Development of process models and on-line diagnostic tools	Ready: Q4/2022
Testing of models and tools	Ready: Q4/2022
COGNITWIN DEMONSTRATION	Ready: Q1/2023

D3.1 [6] focused on describing the existing level of digitalisation in the Engineering pilot and the limitations and opportunities therein, including the identification of sensors and collected information for cognitive modelling. As a continuation to this, D3.2 [7] and the corresponding demonstrator [10] dealt with the digital platform of the Engineering pilot that was developed in COGNITWIN WP3.

In D 3.3 [8] and [10], we concentrated on presenting the Hybrid platform and models for the Engineering pilot. It provided a description of the first approach toward improved fouling management in a commercial-scale Circulating Fluidized Bed boiler by a hybrid methodology that involves both physical first principle and machine learning -based modelling elements. The novel hybrid modelling approach focuses on the characterization of fouling on heat exchangers, in order to finally optimize fouling management in a CFB boiler in the final cognitive phase of the project.

In this final Deliverable D3.4 [9], we concentrate on presenting a summary of the earlier work in WP3, and a description of the final demonstration of the Cognitive Twin running at the Engineering pilot plant. We also evaluate the benefits gained by COGNITWIN based on a separate demonstration period.

In addition, three video demonstrations on developments for solving the Engineering pilot problem are also available. The first video (M18) [10] demonstrates the model-based state estimation solution for the fuel characterization problem, whereas the second one (M30) [11] is focused on the hybrid twin methodology and its application. The third video (M42) [12] demonstrates the practical implementation of the twin technology to the fouling monitoring problem.

2 Sensors and digital platform

2.1 Plant and cloud data infrastructure

In 2022, which was the second year working with COGNITWIN, the complete digital environment was set up and ready at our selected pilot plant. As a result of this, more than 2 000 signals were being processed and collected by the new IoT and cloud platform. Here, only a short summary on the hybrid platform is presented. A more detailed description of the digital platform was presented in D3.2 [7]. The list of signals required for the Twin technology development was formulated in co-operation with project partners, and in this case, it comprises about 230 signals.

The onsite part consists of an IoT edge device that is connected to DCS as an OPC client via an OPC/UA connection. The cloud connection is realized by the Azure IoT Edge runtime, which is a collection of programs that turn a device into an IoT Edge device by enabling it to receive code to run at the edge and communicate the results.

After the edge device has transferred the online data to the cloud, all the tools and components of Microsoft Azure environment are available. For example, Azure Data Lake enables the developers, data scientists, and analysts to store data and do processing and analytics across platforms and languages, by means of batch, streaming, and interactive analytics. Another useful Azure compatible component is the Databricks, which can be used to process large workloads of data by fully managed Spark clusters and can also help in data engineering and data exploring by machine learning. After data analysis, modern visualization tools, such as Azure Time Series Insights and Microsoft Power BI, can be used for formulating new flexible services for process condition monitoring and optimization.

2.2 Standard sensors in CFB

In the delivery projects of SFW, the provider of the automation and DCS systems vary depending on the customer. Therefore, there is not a single standard DCS system that would be in use in every delivered power plant. However, the most important measurements are usually the same in every plant. Typically, there are about 2 000 measurements in each CFB, of which around 200 may be critical process indicators. The critical process parameters that are currently measured downstream of the furnace are:

- Temperature and pressure measurements in critical locations (bed, air, flue gas, steam, input water)
- Flow measurements (air, steam, water)
- Flue gas composition after the boiler (e.g., oxygen, emissions components, H_2O concentration)

A list of sensors and data sources for the Engineering pilot is provided in **Table *3***.

Table 3. Sensors and data sources used in the SFW pilot model

COMPONENT TYPE	PARAMETER	LOCATION
Sensor	Temperature of air supply	Air supply ducts
Sensor	Temperature of furnace bed	Furnace bed
Sensor	Temperature of fluidization	Various locations in furnace chamber
Sensor	Flue gas temperature	Various locations in flue gas duct
Sensor	Water temperature	Heat exchanger supply lines
Sensor	Steam temperature	Heat exchanger input and output lines
Sensor	Air supply flow	Air supply ducts
Sensor	Coolant flow	Water and steam pipes
Sensor	Fuel supply rate	Fuel feeders
Process parameter	Fuel mixing ratios	
Sensor	Flue gas composition	Flue gas duct

When it comes to fuel-related measurements, there are some sensors that monitor the mechanical side of fuel distribution (e.g., fuel conveyor speed or, in the best case, the fuel flow), but unfortunately there are no standard, direct and cost-efficient fuel quality monitoring technologies available so that they could be included in a typical CFB installation.

2.3 Study on fuel sensors

In power industry, there is a demand for adaptive systems that involve cognitive elements to learn the most efficient and cost-optimal ways of operating or controlling the process to maximize power output and minimize fouling and corrosion effects and emissions. On the other hand, there are no online sensors available for monitoring certain fuel components that are causing problems in the process, so it is recognized that there is a need to develop either direct measurements or indirect measurements, such as soft sensors that could be utilized by the cognitive model.

At the outset of the project, a technology review was carried out with the aim of identifying technologies, vendors, and established products and systems that could provide on-line measurement of the key fuel quality parameters:

- Elements connected to fouling and corrosion phenomena
- Moisture content in fuel
- Ash content in fuel

The effort was primarily invested in the first point, because knowing the elemental composition would enable us to develop more accurate fouling and corrosion models and would serve as a solid basis for the cognitive tool development in the future. All technologies evaluated here basically have the capability of monitoring the elemental composition of fuel, although some restrictions for their use may arise from some physical constraints like the particle size, measurement environment etc. Elemental analysis is a highly sophisticated task, which is typically performed with expensive equipment in lab environments. The most common approaches – mass spectrometry, plasma-induced atomic emission spectroscopy, neutron-gamma scattering – are all poorly suited for on-line operation.

Furthermore, a candidate technology must be suitable for the test conditions. The preferred test point is at the infeed to the fuel silo. This is an outdoor environment with varying temperature and humidity, and the fuel is likely to be wet and/or dirty. The second-preferred test point is on the conveyor from the silo to the furnace.

The technology review that was made in WP3 produced three promising methods for online elemental analysis of fuel: Laser-induced Breakdown Spectroscopy (LIBS), X-ray Fluorescence (XRF), and Microwave Absorption Analysis. These are described with more detail in D3.1 [6]. Both technologies have been demonstrated earlier on feedstock for coal-fired power plants, but not for those fired by biomass.

During spring 2020, the available fuel quality measurements were under evaluation by SINTEF-SFW co-operation, and the decisions on the use of the possible technologies were made based on this. The evaluated technologies were XRF (X-ray fluorescence), LIBS (Laser Induced Breakdown Spectroscopy), PGNAA (Prompt Gamma-Neutron Activation Analysis), and Flame emission spectroscopy.

The result of this evaluation was that currently there is no feasible online technology available for direct fuel quality monitoring, mainly due to the lack of accuracy and high price of these technologies. Therefore, the efforts on this side were directed towards the possibility of developing a virtual sensor for monitoring the fuel quality in the pilot.

2.4 Acoustic sensing for boiler fouling

As one of the pilot goals was to monitor the fouling condition (balance between deposition of fly ash and deposit removal by sootblowing) of heat exchange tubes in the boiler assembly, it was decided to direct some of the efforts towards the possibilities for direct monitoring of fouling on the heat exchanger tubes.

The usual state-of-the-art to monitor a deposit buildup on HX surfaces is estimating the heat transfer efficiency based on temperature and pressure measurements. While these numerical methods may provide good estimations of fouling buildup, they are also challenged by having many inputs, such as temperature of input and output steam/water, steam/water flow rate, flue gas flow rate and temperature. This leads to punitive error propagation and requires that all sensors and data streams are of good quality. For this reason, an independent, sensor-based method was taken under investigation. The direct monitoring method was investigated in WP3 is vibration monitoring using accelerometers. To the best of our knowledge, this is the first instance of such techniques being applied to fouling effects.

The investigation was initially performed in SINTEFs lab facilities, using sample piping delivered to tests by SFW. In the second phase, the system was installed in the pilot plant and monitored over a campaign period of about four months in total. It is to be noted that the fouling monitoring technology planned for the pilot by SINTEF is of low-TRL (Technology Readiness Level), which means that there is no commercial product available yet. Due to this, the technology was not included to the final Cognitive twin in the Engineering pilot.

The key actions in the development of the fouling monitoring technology in the Engineering pilot are summarized as follows:

- Laboratory tests were performed by SINTEF, with promising results
  - Sample steel tubes were provided to SINTEF for lab tests by SFW
- The laboratory tests proved to be successful, therefore some further study was made regarding the following issues:
  - Signal processing (spectral analysis)
  - Available plug-and-play IoT sensors for industrial environment, with back-end analytic capability
- Physical installation at the pilot plant was realized in two parts:
  - The signal rods for accelerometers were installed by SFW at the pilot plant during the shutdown maintenance period of the pilot plant 05/2021
  - Physical installation of the acoustic sensing system was performed by SINTEF on NOV-2021
- Onsite test campaign was arranged during NOV-2021 – MAR-2022
  - Analysis method development was made by SINTEF during and after the campaign
- Results of the test campaign were analyzed, and further steps were decided

2.4.1 Basic theory and DoE

The core of the approach that was studied is modal analysis: the study of vibrational resonances in mechanical structures. Modal analysis is used in many industries, including automotive, aviation, and civil engineering [13]. In all cases, the goal is to identify and address the risk of dangerous vibrations occurring due to underdamped resonances.

In this study, this method is used instead as an analytical tool to observe variations in the mechanical properties of the HX. In practice, fouling adds weight. Some types of fouling may change the bending stiffness of the tubes. Corrosion may affect the bulk properties of the tube material. All of these affect the resonant mode frequencies of the HX.

Using finite-element modelling (FEM), one may numerically compute resonance frequencies of the HX and estimate the effect of fouling. Fig. 6 is the result of such a simulation. The plots show the predicted vibration spectrum of a HX structure with and without fouling. Note that some peaks (e.g., 3.5 Hz, 5.4 Hz) shift leftward when fouling is present. Other resonances (for instance at 7.3 Hz) are due to other parts of the flue duct and are unaffected by fouling.

Changes in temperature will affect resonance frequencies. The low-alloy steel used for the HX has a typical Young's modulus gradient of ≈0.13 % / K (e.g., [14]). Empirically, the material temperature of the HX decreases 6-8°C between sootblowings; this would lead to a 0.5 % decrease in resonant frequencies due to thermal effects, much less than the simulated frequency shifts shown in Fig. 6.

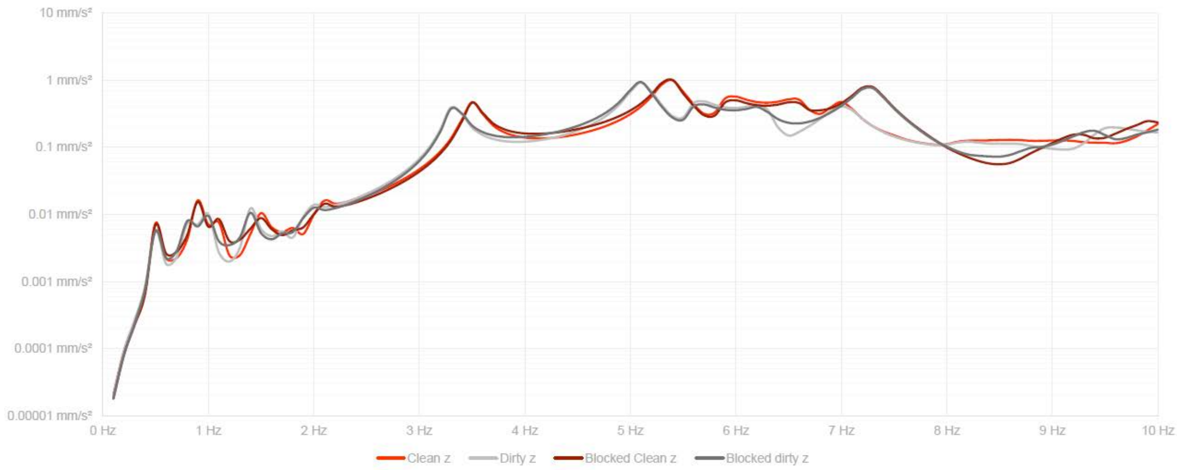

Fig. 6. Simulated vibration spectrum for clean (reds) and dirty (gray) pipes. Data represents steady-state motion under a 100N sinusoidal force

In the practical experiment, HX vibrations were monitored by a suite of accelerometers. A modal shaker was used to induce vibrations at programmable frequencies. Due to the high temperature of the flue duct and for ease of service, the accelerometers were mounted on signal rods that carry vibrations to and from the HX (See Fig. 7). Pictures showing the physical installation of the vibrations monitoring system above the penthouse of the pilot CFB can be seen in Fig. 8. The output of the sensor is a time-series of acceleration measurements.

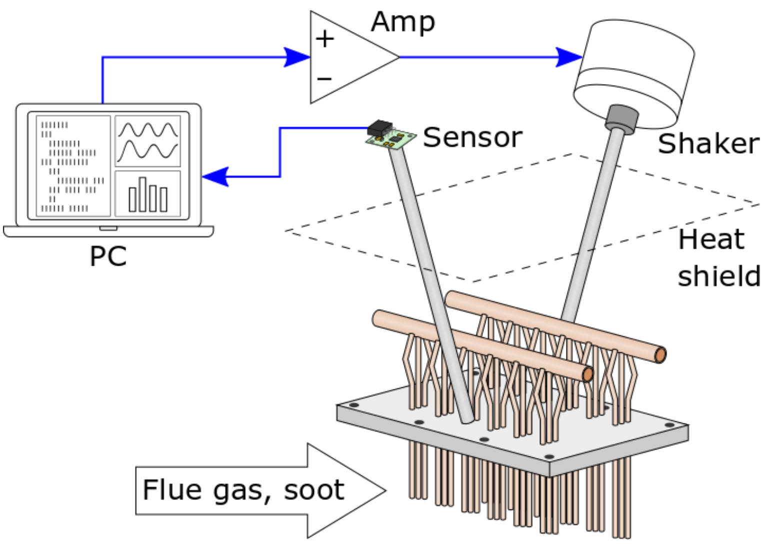

Fig. 7. Schematic of sensor system. Steel signal rods provide a mechanical path from the HX to sensitive electronics outside the hot zone.

The practical methodology of analyzing acoustic sensing data is discussed with more detail in D3.4 [9] and [15]. Two different sensing approaches were tested in COGNITWIN:

- ***Active sensing***. The first method is to demodulate the data to extract the effect of the shaker. As a local oscillator, we use the sine-wave input to the shaker amplifier. This method is highly frequency-selective, removing nearly all features that are not generated by the shaker. Demodulation is performed digitally.

- ***Passive sensing***. The second method is to convert the raw waveform into a spectrogram – a workhorse tool of audio engineering. A spectrogram represents the data in both time-domain and frequency-domain. Unlike the active-sensing method, the spectrogram listens to *all* frequencies up to the Nyquist limit.

Fig. 8. Installation of the vibrations sensing system above the penthouse of the pilot CFB.

2.4.2 Key findings

In the experimental part of the vibration sensing, the collected data were analyzed using the 1) active and 2) passive sensing methods. The time-series obtained using active sensing can be seen in Fig. 9.

The sootblowing instances can be can be clearly seen in the spectrogram, as well as the change in the signal between the sootblowings. A drawback of this method is that the recording of one scan is rather slow, leading to a low-density time series. Several improvements – hardware, control logic, analytics – have been planned for the development pipeline to address this shortcoming.

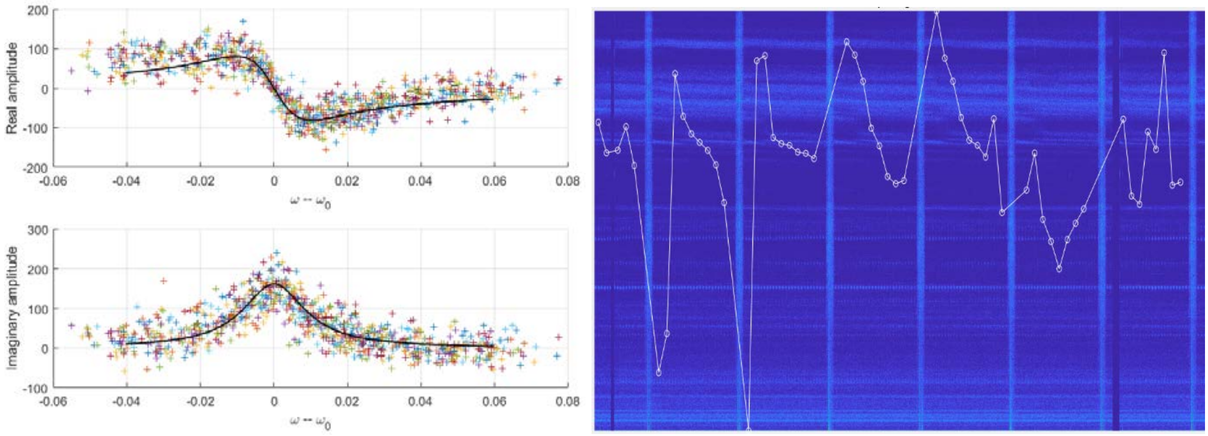

Fig. 9. Active-sensing data for 5.4 Hz resonance. Left: Phasor components, shown in separate graphs with universal resonance curve overlaid. Right: Spectrogram, with resonance frequency overlaid. Sootblowing events are clearly visible as vertical lines representing white noise.

The result of passive sensing is shown in Fig. 10, in which the output is compared to the reference values based on enthalpy-based calculations. The obtained result is a very encouraging starting point for further studies. A standard error of prediction (SEP) of 0.018 was found, corresponding to ≈100 minutes of fouling build-up. With 12 hours of acquisition – a typical sootblowing interval – the prediction error is equivalent to 15 minutes of fouling.

Further predictive improvement is expected in future through refinement of methodology. A shortcoming of acoustic chemometrics is the false assumption by PLSR that features add linearly. Furthermore, PLSR is not intended to measure frequency shifts, i.e., features moving from one observable to another. These shortfalls should be addressed with improved feature engineering and more detailed understanding of the underlying physics. The results of the acoustic sensing study are discussed with more detail in [15].

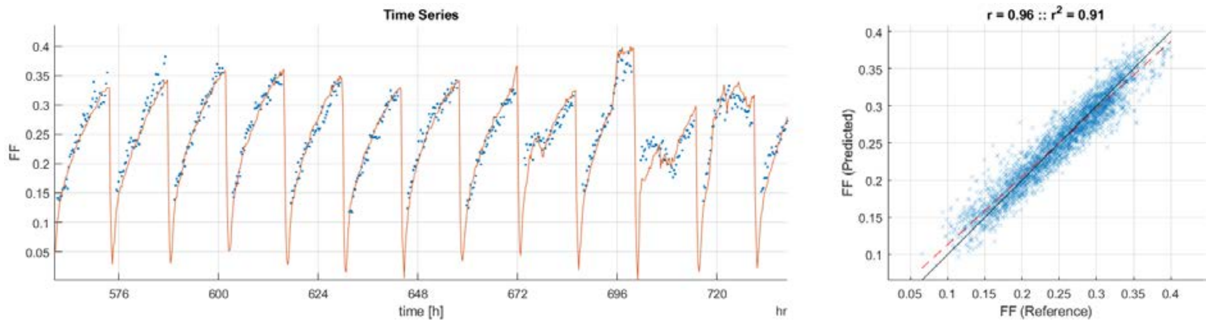

Fig. 10. PLS modelling of FF. Left: Time-series of predicted values (dots) overlaid on reference data (line). Right: Score plot of predicted vs. reference values.

3 Cognitive Twin for Engineering pilot

When formulating the pilot problem and the targets to cope with them in the early phase of COGNITWIN, it was presumed that it would be beneficial to decide the optimal timing of cleaning based on the prevailing condition of the heat transfer process. However, already at the beginning it was also clear that it would require a more advanced monitoring approach to estimate the degree of fouling on each HX surface. The HX surfaces that are being sootblowed by steam in the pilot boiler can be seen in Section 1.2.

As discussed earlier, the accumulation of fouling on heat exchange surfaces cannot be directly measured, but information can be obtained via acoustic sensing (See Section 2.4). An alternative is to use standard process measurements on flows, temperatures, and pressures over the heat exchangers, and estimate the heat transfer from flue gases to the water-steam side [8][16]. In the cases where plant combusts multiple fuel fractions, on-line characterization of the incoming fuel characteristics can provide important information for fouling monitoring. For this reason, a state estimation tool was developed in COGNITWIN to estimate the uncertain fuel fragments [7][17].

The development of twin technology in WP3 was realized as follows, based on the planned phases and the related objectives discussed in Section 0. In phase I, the fuel state estimation (FUSE) component was developed to characterize different fragments in the incoming fuel. FUSE consists of a physical model of 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 the boiler fuel feed. The component was successfully applied to two plant cases, this is because large part of the development was done before the actual pilot plant was eventually agreed in JAN-2021. 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, which can be used for monitoring the fouling on the HX surfaces. A physical model for a heat exchanger was developed and adapted to the superheater conditions specific to the pilot. Improved model-based state estimation was then created by implementing an ensemble Kalman filtering (EnKF) tool. The FouMon approach was successfully tested with the pilot data.

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. An optimization scheme utilizing the model was also developed and applied to solve the sootblowing timing problem. FouCon was successfully tested with the pilot data.

3.1 Fuel state estimation

At the beginning of COGNITWIN, a physical model for the boiler furnace (the so-called hotloop model owned by Sumitomo SHI FW) was made available, by implementation in the Matlab Simulink environment. The model has been developed for the design of the considered pilot plant type. This has been described with more details in D3.2 [7].

The first phase of the Engineering pilot problem considered the unknown factors in the quality of incoming fuel. As a component for solving the problem, a fuel characteristic estimator called FUSE (Fuel State Estimation) was developed by UOULU, including a tool implementing the UKF (Unscented Kalman Filter) state estimation for plant inputs, as well as a tool for tuning physical models (the PMFIR tool; Physical Model Finite Impulse Response).

UKF is an implementation of Bayesian state estimation. 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 techniques based on machine learning and availability of the original physical model results. The FUSE component implements estimation of uncertain plant fuel fractions using UKF, exploiting simulations from a PMFIR-tuned physical model for the boiler. The newest methodological outcomes have been published in a journal paper [18].

The PMFIR principle of tuning physical model outputs was applied for the WP3 pilot problem. In the considered case, the fuel feed consisted of fractions of demolition wood, peat and woodchips. Using the tuned model, the fractions of 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 other plant and the validation of the estimation of fuel characteristics was left incomplete. In conclusion, the FUSE approach was judged as successful, but it was not eventually implemented in the pilot demonstration due to the current operating practices in use at the plant.

3.1.1 Key findings

The approach was verified and validated on real plant data. Fig. 11 illustrates fuel characteristic estimation outcomes on a one-week data set from the real plant. The top left plot illustrates estimated fuel flow components: the signal in orange shows the estimated plant design mixture flow (50 % forest chips/ 35 % demolition wood/ 15 % peat), the signal in blue the same for a feed of pure forest chips. The signal in yellow is an additional moisture component. The total fuel flows are shown in black lines, the estimate and measured signals are indistinguishable. The bottom left plot shows the fuel elementary composition, derived from the flow estimates. The plots on the right show measured and predicted flue gas and temperature signals, used by the UKF.

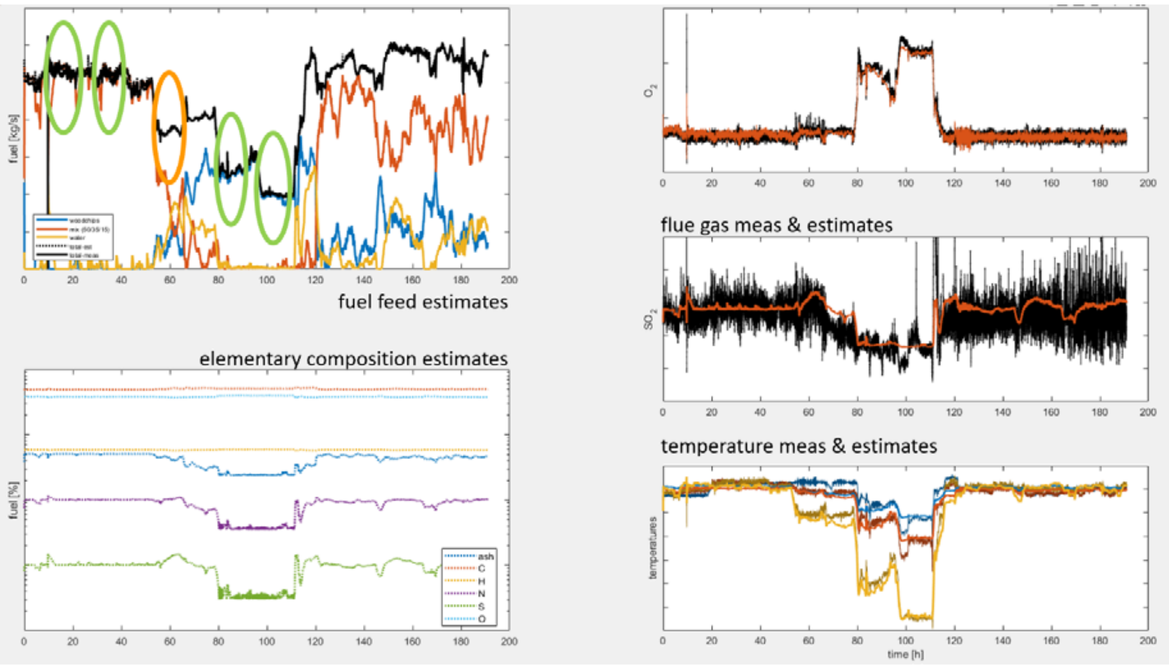

Fig. 11. FUSE tool applied to estimation of fuel characteristics on real data.

A parallel SubFUSE (Subspace Fuel State Estimation) tool was developed in view of the WP3 pilot problem. The tool focuses on data-driven process identification using subspace techniques, where a linear model is estimated from data provided by simulating the nonlinear physical model. The solution for the state estimation problem is then simple and computationally much more efficient. The SubFUSE approach, applied to the other plant case before the eventual pilot, was published in a scientific paper [19].

3.2 Fouling monitoring

In comparison to conventional fuels such as coal, gas, or oil fuelled boilers, fouling in the heat exchangers when using fuels such as bitumen, wood chips, biomass etc is far more intense. The primary reason for this is the presence of higher concentrations of alkali metals and chlorine in bio-based fuels. The fouling mechanism itself is a very complex phenomenon and not fully understood. The deposits on the heat exchanger tubes are usually charred remains of burnt fuels, solid particles and unburnt fuel melts that are carried over by the flue. With time the thickness of the deposit layer increases, and the efficiency of the heat exchanger decreases exponentially [20]. In [8] and [15], we have presented the state of the art for fouling modelling, as well as the methodology developed for this in COGNITWIN.

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 that can be obtained from the boiler design database.

The methodology based on nonlinear Bayesian state estimation tools as well as subspace identification and associated observer design tools, was 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 in COGNITWIN was reported in D5.4 , as it involves also the use of data-driven tools in addition to the physical model-based ones.

The FouMon component was used for solving the fouling monitoring state estimation problem, fusing a physics-based model for a heat exchanger (HX) with process data. The component was developed using the Engineering pilot as the case example (see D3.3), and using a dynamic physical model for a heat exchanger and data from the pilot. Ensemble Kalman filtering was used for state estimation. FouMon 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. Fig. 12 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, and an estimate of the 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.

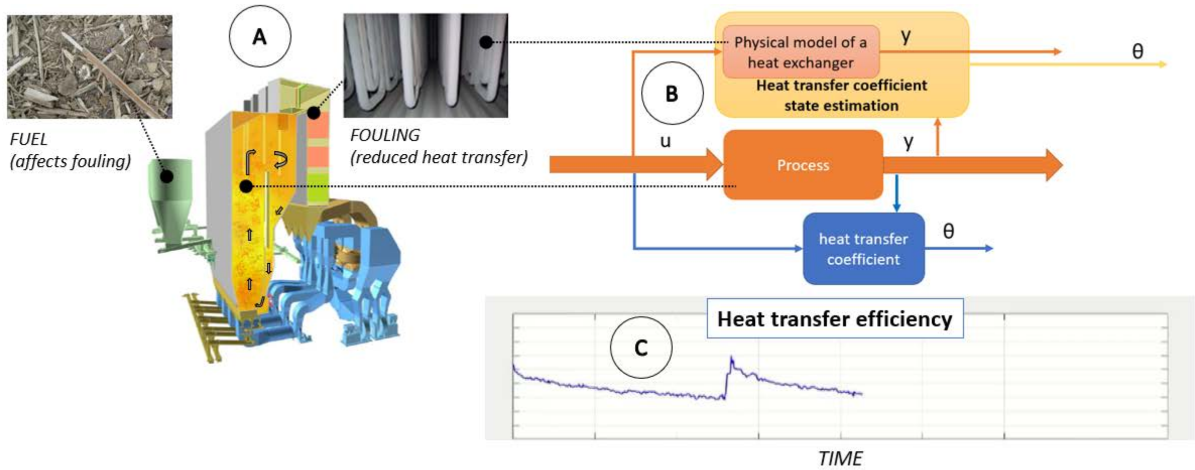

Fig. 12. Twin technology for better fouling management A) The CFB process with HX fouling, B) Model-based estimator for fouling, C) The output of the model-based estimator

3.2.1 Key findings

Heat transfer coefficients obtained using the twin technology are depicted in Fig. 13, for a two-week period in November 2021 in the full-scale pilot during normal operation. Both the on-line heat transfer coefficients α and clean surface heat transfer coefficients α_0 are shown here. Boiler load is shown in Fig. 14, in terms of water-steam and flue gas mass flows.

It can be observed that after the start of each sootblowing sequence (indicated by vertical dashed lines), the heat transfer coefficient estimates increase dramatically, followed by an exponential-type decay until the next sootblowing. There are clear level differences in the signals from flue gas and water-steam side, but the evolution of fouling indicated is very similar. α_0 varies clearly according to the load. It is well visible how the α reach the α_0 value after each sootblowing.

Fig. 15 depicts the adaptive fouling factors (FF). It can be observed, especially with the index based on the flue gas enthalpy estimate, that the estimate is relatively insensitive to the boiler load. The index on the plant data would suggest that boiler fouling rate is smaller at lower loads, which seems to be a reasonable behavior.

Using the state estimation method, an EnKF setup was considered for data points in which the exit flue gas and steam temperatures were available as measured quantities. Fig. 16 illustrates the estimated heat transfer coefficient obtained by using the EnKF method. Note that sootblowing was not modelled but the cleaning and fouling of tubes was based on estimation from observations. The estimated heat transfer coefficient presented in Fig. 16 can be compared to those shown in Fig. 13. Clearly, the estimates resemble each other in detail, and thereby these results support each other.

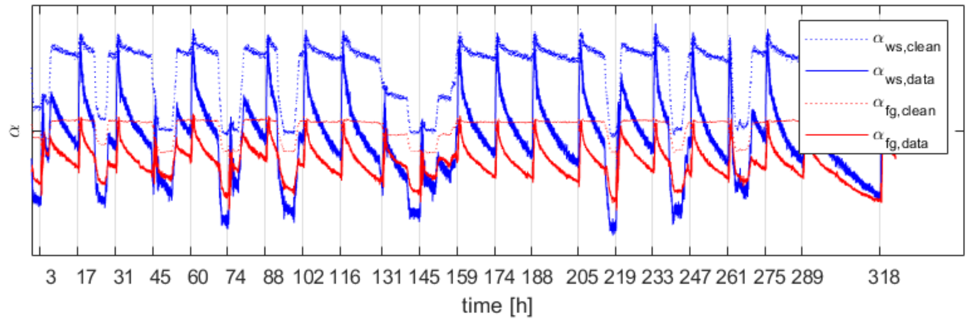

Fig. 13. Heat transfer coefficients. On-line estimates: solid lines, clean state estimates: dashed lines.

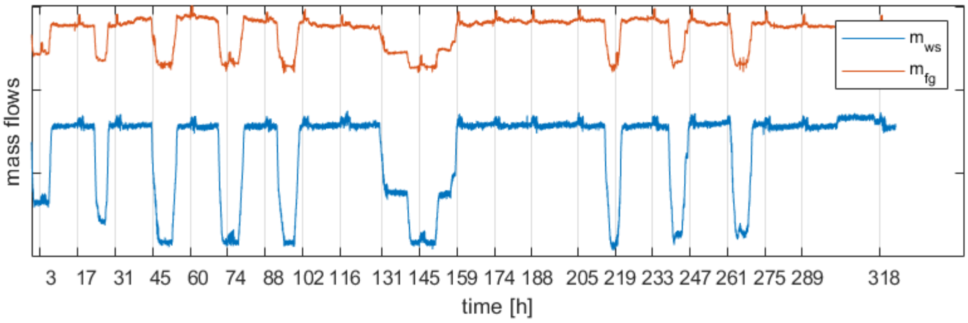

Fig. 14. Boiler water-steam (ws) and flue gas (fg) mass flows.

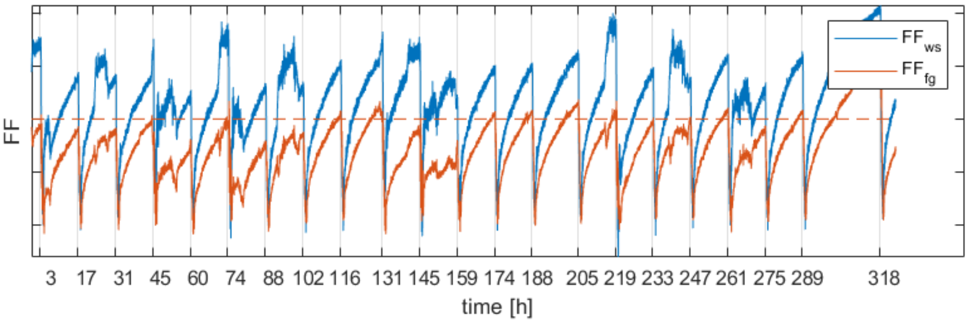

Fig. 15. Adaptive fouling factor (FF) index.

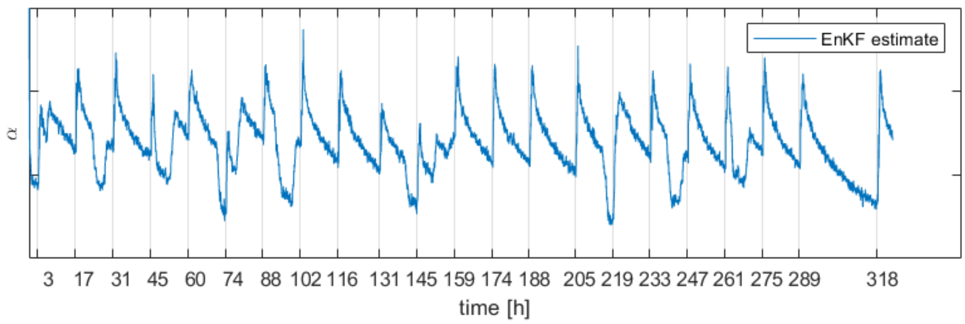

Fig. 16. EnKF estimate of heat transfer coefficient.

With a dynamic model of the heat exchanger, it is also possible to add to the model additional mechanisms describing the complex fouling process. These include the impact of sootblowing and the expected evolution dynamics of the fouling to heat exchange coefficient. The Bayesian filtering approach provides a means to fuse additional measured information to the estimator, the vibration sensing (See Section 2.4) being an interesting potential alternative. A significant benefit of the dynamic model is that the plant can now be simulated in various scenarios, which can be expected to be very beneficial in future studies on optimization. Note that a thresholding of the adaptive fouling factor (See Fig. 15) may already provide an improved means for triggering the sootblowing options. A proper optimization, however, requires more insight on the cost function, constraints and the means on locating the feasible optima.

3.3 Fouling control

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 HX tubes are cleaned by blowing steam at high pressure to detach residues. Typically, this is done by regular intervals. The focus of fouling management in COGNITWIN WP3 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 of COGNITWIN developed by UOULU 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 methodology of COGNITWIN fouling control is explained with more detail in D5.4.

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 specific features of the problem. In the soot blowing case the problem is mixed-integer, constrained, and nonlinear.

FouCon developed for the COGNITWIN toolbox (see D5.4) and adapted to the WP3 fouling control problem, 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 (Linear Time-Invariant) 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.

In Fig. 17, the approach is illustrated by 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.

The MPI/sb optimization cost function was 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.

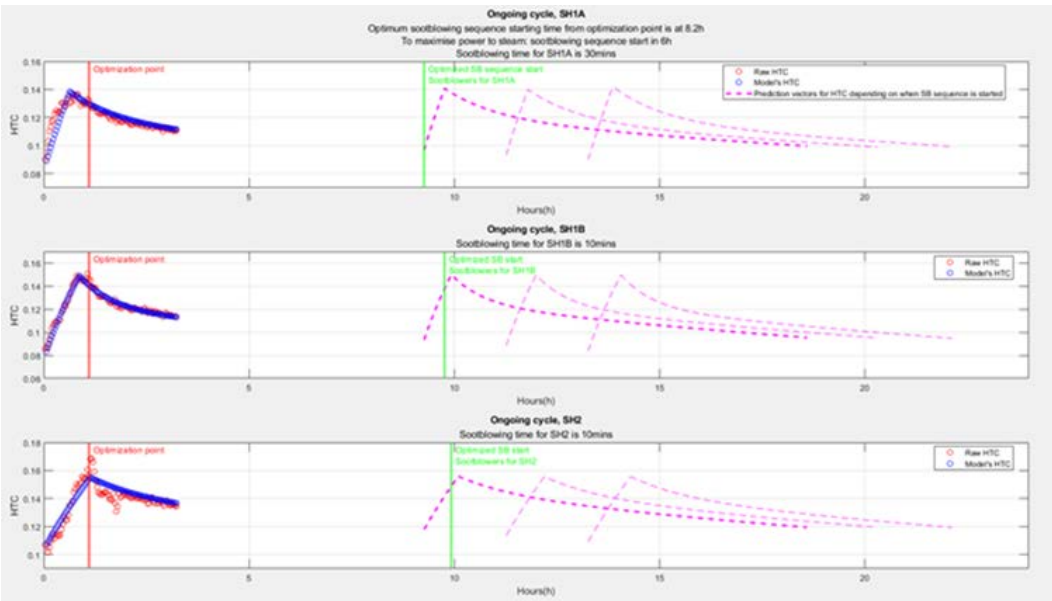

Fig. 17. Soot blowing optimization example for three consecutive superheaters (SH1A, SH1B and SH2)

3.4 Cognitive twin

It is important to note that the 'optimality' of the solution given by FouCon 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.

In Fig. 18, the operation of the whole Cognitive twin for the Engineering pilot can be seen. The system can recommend the preferred actions for fouling management, such as when to start sootblowing to maintain optimal boiler fuel efficiency. The operator can decide whether to follow these instructions or not, depending on his opinion about the prevailing status of the heat exchange. The process is thereby affected by the operator's decision. In the end, COGNITWIN adapts to the prevailing situation by updating the heat exchange models within.

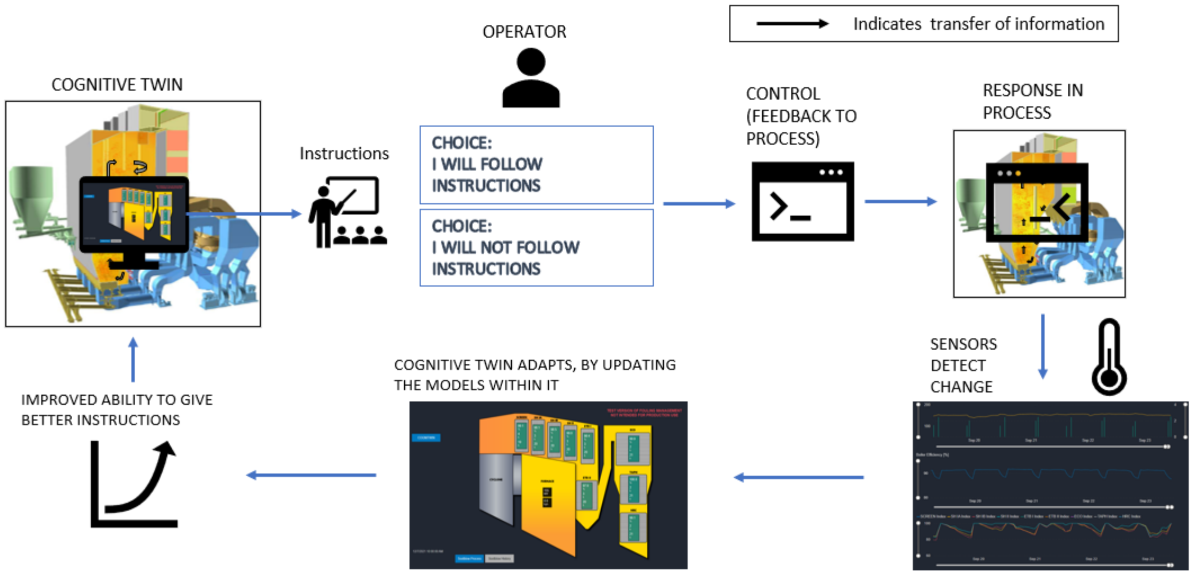

Fig. 18. The operation of the Cognitive Twin in the Engineering pilot

4 Pilot demonstrations

The first version of the tool based on the technology developed in COGNITWIN was installed at the pilot plant in JAN-2022. After this, the algorithms as well as the User Interface have been updated several times during the project.

In addition to this, a separate two month test campaign was arranged in the final months of COGNITWIN. In this demonstration, the plant operators used the tool to optimize the sootblowing in the pilot plant, and after the test, the gained benefits were estimated. Another purpose for the test was to ensure the functionality of the technology developed, and to constitute a proof of concept for commercial operation of the system.

4.1 Demonstrator

WP3 demonstrator was created as a web-based service built upon the Microsoft Power BI service platform (See Figs. 19 and 20). During the project, it was running online as an embedded analytics service and can be viewed by authorized persons of SFW and Mälarenergi (owner of the pilot plant).

The main view (Fig. 19) of COGNITWIN shows all HX surfaces that are being cleaned by regular sootblowing, i.e., the superheaters, evaporative HXs, economizer, air preheater and heat recovery coils. The results of analytics, like the most recent value of the heat transfer index, can also be seen in this view. Currently, the calculations and the view are updated once an hour, which is an adequate update interval considering the nature of the application. The trend view (Fig. 20) shows the history of boiler load, efficiency, sootblowing, and heat transfer indexes in the pilot plant.

4.2 Sootblowing tests

In April 2021, an initial sootblowing test was performed in the pilot plant in which the pause time between the sequential sootblowing processes was altered to get new information on HX fouling. Although useful information was obtained, the weather was warm and the load conditions were relatively low, which was not ideal regarding the objectives of the test. In January/February 2022, another sootblowing test was therefore performed to get new information on HX fouling especially in high load conditions, and to get more useful input data for further development of sootblowing optimization (See Fig. 21). The longest time between two separate sootblowing sequences was about 24 hours, which is about 10 hours more than the current practice at the plant. The results of both tests were analysed, and the findings were used in further improvement of the fouling modelling and process optimization algorithms.

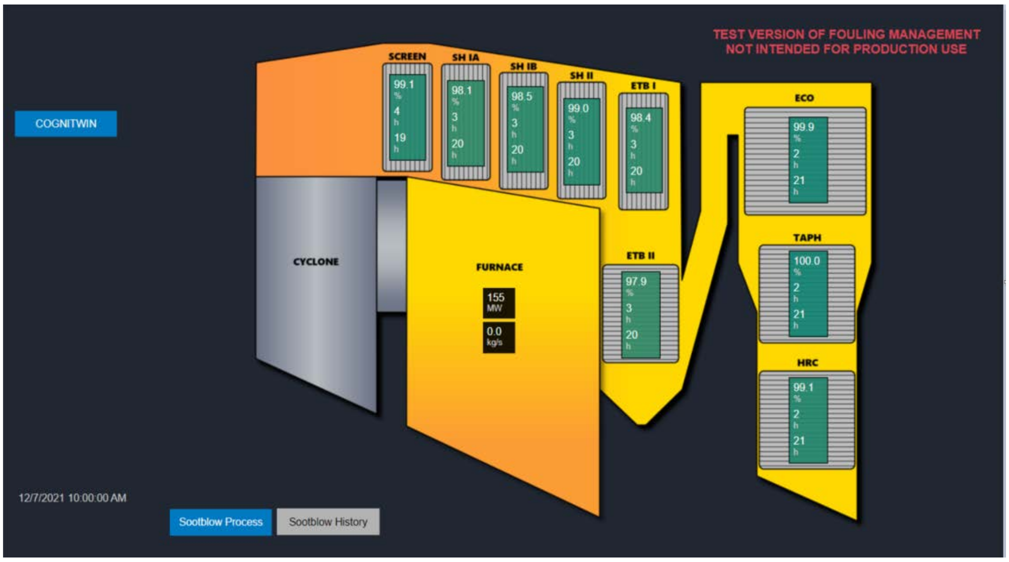

Fig. 19. User Interface of the COGNITWIN WP3 pilot showing the heat transfer indexes of heating surfaces.

Fig. 20. Trend view of the COGNITWIN User Interface showing boiler load and sootblowing, and the heat transfer indexes describing the ability of each HX to transfer heat.

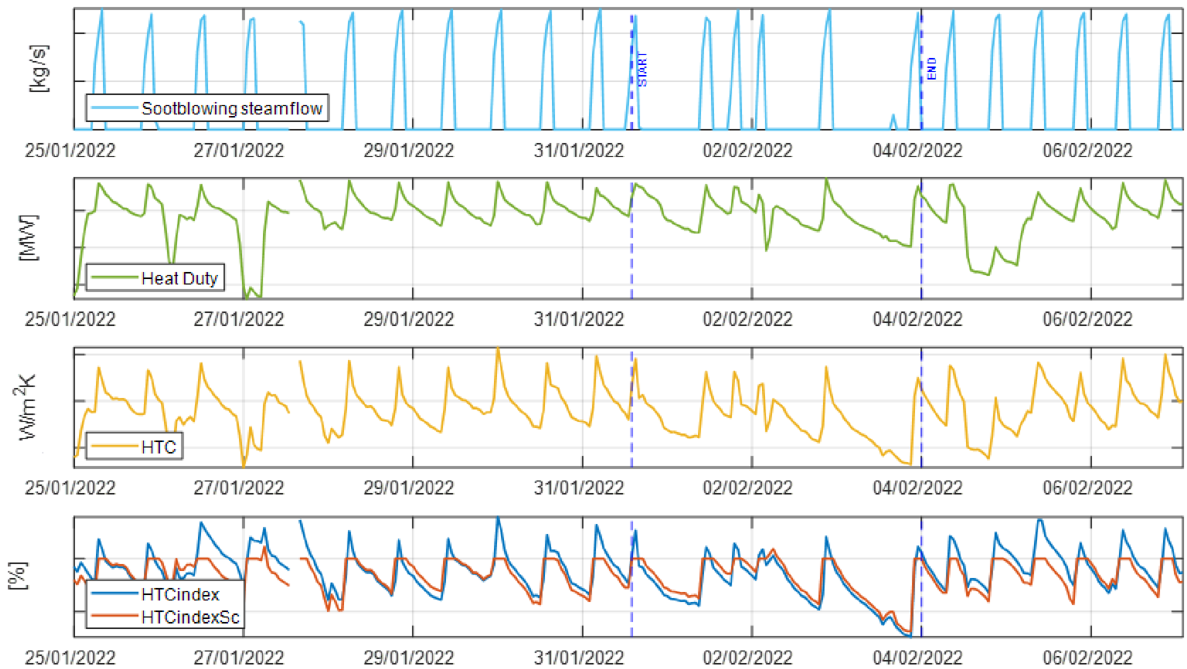

Fig. 21. Performance of superheater 1A in the second sootblowing test. HTC = Heat Transfer Coefficient, HTCindex = Heat transfer Index, HTCindex = scaled Heat transfer Index

4.3 Final demonstration

The final demonstration of COGNITWIN Engineering pilot was set up in DEC-2022 – JAN-2023. In this experiment, the power plant operators used the system's guidance in deciding when to start the sootblowing operation. Based on this demonstration, also the final evaluations for KPIs were performed (See Section 5).

The first part of the test that was performed in December can be seen in Fig. 22. The longest time between two separate sootblowing sequences was about 20h in December and about 32 hours in January. This is a significant extension to the fixed interval (14h) which is the current practice at the plant. The average time between two separate sootblowing sequences during this period was 19 hours, although it must be noted that the operators were not able to follow the recommendation all the time. This was because of a functionality in the plant DCS that restricts the flue gas temperature before the superheater 1A, which didn't come up in the earlier tests. Due to this, on some occasions the operators had to start the sootblowing earlier than was recommended by COGNITWIN. Also, in January there were some problems with the fuel feeding lines, for which the plant was not running all the time.

Despite these difficulties it was possible to calculate some efficiency improvement during the demonstration, which is elaborated with more detail in 5.1. It is presumable that the improvement in the boiler efficiency would have been even more in ideal conditions.

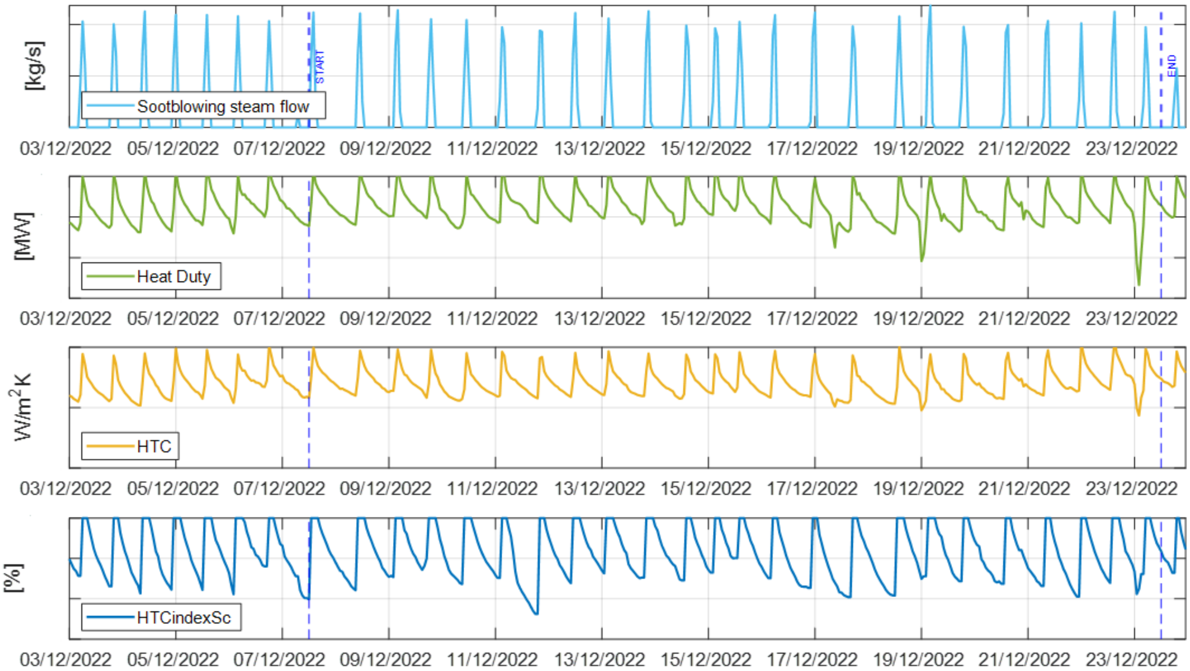

Fig. 22. Performance of superheater 1A in the final demonstration (December 2022). HTC = Heat Transfer Coefficient, HTCindex = Heat transfer Index, HTCindex = scaled Heat transfer Index

5 Measurable KPIs and expected impact

In the first phase of COGNITWIN, the final targets for selected KPI's were defined. The improvements in the selected KPIs have been calculated by comparing the measured performance (KPIs) after the implementation of the COGNITWIN to the measured performance prior to the implementation.

In D3.1 [6], the measurable KPI's and their target improvements were set to:

1. Improved boiler operating efficiency: +0.05-0.10 % in average as cont. performance

2. Lower operating costs, boiler O&M cost: -100 k€/year during the first 5 years
3. Smaller emissions, decrease emissions, avoid limit exceedings: overall levels -20%
4. Improved reliability and availability: +0.3-0.5 % in plant availability

The technical performance of the boiler is measured by boiler operating efficiency which is believed to be improved by cognitive systems by enabling the operators to use optimal operating parameters and set values for each precise fuels, including the process controls, such as O_2 setpoint values, the usage of additives and steam coil air preheaters as well as to optimize the boiler cleaning practices by optimizing the boiler sootblowing frequency directly based on the fuel quality.

The overall boiler reliability and availability are improved by the COGNITWIN technology both directly, by decreasing the bed related process disturbance and erosion/corrosion related pressure part defects, and in-directly, by minimizing factors that may cause or accelerate the boiler ageing or degradation, such as variations in process conditions or forced emergency shutdowns.

Operation economy will improve together with the technical performance and reliability by lowering the operating costs related to consumption of fuels, additives and auxiliary power as well as the maintenance costs for repairing the boiler damages and restoring the boiler back to normal operation.

Environmental issues related to the boiler are mostly related to boiler flue gas emissions. The improved boiler monitoring means and predictive controls decrease the variations in the combustion process and help to optimize the combustion temperature dependent NOx and CO emission, especially emission peaks in load change situations and disturbance events.

The original intention in the early phase of the project was to have a six-month period for both ‘before’ and ‘after’ implementation conditions, to compare the achieved benefits against the pre-set targets. In addition, it was decided that the periods of time should be specially selected in such a way that the fuel and load conditions of the boiler would be as similar as possible. During the project, several delays finally came up, leading to the fact that it was not possible to have so long datasets for comparison.

First, there was a long delay in agreeing with the pilot plant on joining the project, which was due to challenging commissioning of the expected pilot plant during the spring 2020. The agreement was finally done in early 2021, which was over one year from the beginning of the project. The other issue that caused some delay was the fact that a feasible fuel sensor was not found in the early phase of the project, and alternative solutions had to be found for coping with the changing fuel quality. In addition, there were some issues with the COVID in 2021 and 2022, which caused some delay in non-vital on-site installations because of restrictions in access to the pilot plant as well. For all these reasons, the final implementation of COGNITWIN was eventually delayed, and shorter periods of time had to be used in this KPI evaluation.

COGNITWIN was implemented to the pilot plant in two stages as follows:

- “Before” implementation: April 2020 – November 2021

- First implementation: November 2021 – December 2022 (Digital infrastructure + fouling monitoring)
- Full implementation: December 2022 – January 2023 (Final COGNITWIN with full fouling management)

5.1 Technical performance

The technical performance of the boiler is measured by boiler operating efficiency. During the piloting period the plant owner has implemented / applied two methods for optimizing the efficiency:

- usage of steam coil air preheaters i.e., changing the flue gas exit temperature (not included to COGNITWIN)
- implementing fouling management (by COGNITWIN)

The effect of flue gas temperature is not evaluated separately, as this action was not a part of COGNITWIN. The reference values for the efficiency before the implementation are selected from operation after the change in the temperature setting.

Optimizing the boiler cleaning practices is based on the actual status of the heat exchanger surfaces and the predicted change in the status with the precise fuels in use. It optimizes the removal of ash deposits from the boiler heat exchanger surfaces without over-cleaning the surface in vain and increasing the cleaning costs (loss of steam / production). The cleanliness is directly affecting the heat transfer from flue gases to water-steam path, is expected to have biggest impact to boiler efficiency.

The full implementation of COGNITWIN with the sootblowing optimizer occurred already in January 2022, but due needs of further development it was taken into full use in the final COGNITWIN demonstration campaign in December 2022. The evaluations of the technical performance i.e., efficiency was done based on this test campaign during Dec 2022 – Jan 2023, when the COGNITWIN optimizer was in full use at the plant.

The original boiler efficiency (i.e., the reference point) is evaluated by calculating the average plant efficiency in normal commercial operation periods, with the fuel and load conditions of the boiler should be as constant as possible. As the fuel quality and especially the load of the boiler varies almost continuously, the originally planned 6 months period is not realistic. The reference evaluation period(s) are selected from operating periods with full (at least 95%) boiler load. Calculation of the efficiency for all the evaluation periods, is done according to normal EN standards (DIN1942, etc.).

The current, improved boiler efficiency is evaluated the same way as the original, from measured and calculated values on constant, full (at least 95%) boiler load during a test campaign period after the full implementation.

The measured and calculated ranges for boiler operating efficiency values during the full load periods are listed in **Table *4***.

Table 4. Operating efficiency before and after implementation

Description	Load range	Average Efficiency [%]	min Efficiency [%]	max Efficiency [%]	std Efficiency [%]	Improvement [%]
Normal operation, before implementation	>95%	**91.36**	89.81	92.24	0.37	**-**
Test campaign after full implementation	>95%	**91.45**	90.54	92.25	0.39	**0.09**

The targeted average improvement in boiler operating efficiency was +0.05-0.10 %, so the target was well achieved in the pilot.

The improvements in operation economy related to boiler efficiency come from the saving in fuel consumption and costs. The savings are summarized in Section 5.4.

5.2 Environmental performance

Environmental performance of a boiler is measured from the flue gas emissions. High CO (and N_2O) emissions are usually caused by unstable combustion process, typically unbalance with the fuel and air intake (i.e., local or temporary stochiometric unbalance), or by low temperature in bed area caused by changes in fuel quality, typically fuel moisture. The high NO_x emissions, on the other hand, are usually caused by excessive temperatures in the bed area, for example by excessively dry fuel. One of the original objectives in COGNITWIN was to improve the predictability of the fuel quality with additional measurements, such as fuel moisture etc. For the reasons described elsewhere, these new fuel measurements were not eventually installed in the pilot plant, however.

According to original definition, the boiler emissions were to be evaluated by two key factors:

- Overall emission limits over the 6-months periods
- Number of the short emission peaks when exceeding the emission limits for hourly average given in environmental permits (hourly average limits) for CO and NOx separately

As the fuel quality and especially the load of the boiler varies almost continuously, the originally planned 6 months period is not realistic with load variating according to district heating demand. Therefore, the environmental performance of the boiler is evaluated based on many separate operating periods with both full 100% boiler load and as constant load as possible.

The evaluation of emission KPIs is based on several shorter, from two to five weeks, periods of operating with constant, full load. To achieve comparable results and reliable calculation, the data is filtered to include only those 5-min time periods in which the average boiler load has been higher than 95% of the nominal rate. For both cases, before and after COGNITWIN, there are in total four periods selected from periods in autumn right after the summer outage, as well as mid-winter and spring time periods to represent the natural seasonal variation as well as possible.

The evaluation is based on the existing DCS measurements, i.e., sensors installed in the flue gas duct after the flue gas treatment plant. Similar data is collected from the selected operation points prior to and after the implementation. The COGNITWIN demonstration in December 2022 – January 2023 included about 31 days in total with full boiler load. During the test period, the same existing plant instrumentation was used for data acquisition, no additional instruments or measurements were used.

Average emission levels

The first target to improve boiler environmental performance was to decrease the average CO and NOx emission levels by up to -20%.

NO_x emissions were not much affected by the boiler load increase, which is a natural phenomenon. In general, higher boiler loads tend to increase the bed and furnace temperatures, and therefore also the NO_x emissions. In this case the NOx emission, nevertheless, did remain on the constant level despite the 1.1-1.5% higher loads after the partial implementation. The reason for the constant NOx emissions is that they are controlled by the injection of ammonia-water.

Nevertheless, during the implementation it was identified that N_2O emissions were impacted heavily by the improved stability of the combustion process. The increase in N_2O emission may in some cases be an indication of an ununiform furnace temperature profile and can thereby be seen as a sign of incomplete combustion, similarly as CO emission. Therefore, N_2O emissions were used in the evaluation instead of NOx emission, which is controlled by the ammonia injection.

Both CO and N_2O emissions decreased during the evaluation period. The higher boiler loads, enabled by the first implementation phase, already showed some reduction in the average CO and N_2O emissions, also with stable fuel quality. The average CO and N_2O concentrations (mg/Nm^3) and the percentual rate changes from the time periods before and after the partial implementation, as well as the ones during the COGNITWIN demonstration period are listed in **Table *5***.

Table 5. Emission performance before and after implementation

Average emission levels	Before	After	Change	Before	Tests	Change	Total
N_2O emission, 5 min avg	10.9	9.3	**-15%**	9.3	7.0	**-25%**	**-36%**
N_2O emission, 1 hr avg	12.7	9.5	**-25%**	9.5	7.0	**-26%**	**-45%**
CO emission, 5 min avg	5.8	3.2	**-46%**	3.2	2.0	**-38%**	**-66%**
CO emission, 1 hr avg	6.9	3.4	**-50%**	3.4	1.9	**-44%**	**-72%**

Note that the 5-minute averages having lower CO and N_2O concentrations are calculated from the selected time periods using data points with stable, approximately full 100% load, whereas the 1-hour averages (as is the common practice in environmental permits) contain all the operation hours with >95% load level, therefore having more instability variation in the combustion process.

The targeted decrease in the average CO emissions (as well as N_2O emissions) was -20%, which was exceeded clearly. The main contributor to the improvement was more stable combustion and better control of the average bed temperatures in higher loads, especially when the combustion air humidification was in operation. In general, air humidification tends to decrease the bed temperatures, affecting the combustion efficiency and thus increasing the average CO emissions.

Emission peaks

The second target to improve boiler environmental performance was to decrease emission peaks to avoid even momentary exceeding of the limits set in environmental permits. The emissions have both daily and hourly limits set by the environmental permit:

	Daily average	Hourly average
• CO emissions	75 mg/m3n	150 mg/m3n
• NOx emissions	100 mg/m3n	150 mg/m3n
• N_2O emissions	45 mg/m3n	60 mg/m3n

Nevertheless, as the maximum peaks even before the COGNITWIN implementation were below the permitted limits, an additional evaluation limit of 20 mg/m^{3}n was chosen for CO emissions.

Because NOx emission peaks depend on the usage and the control settings of the ammonia-water injection system, which means that it was not possible to control them by the COGNITWIN implementations, the evaluation of the improvement in the reduction of emission peaks is made for CO only (See **Table *6***). The evaluation is based on the hourly average emission during the entire boiler operation before and after the implementation.

The percentage of time when the CO emissions have exceeded the preset limit of 20 mg/m^{3}n and 75 mg/m^{3}n, respectively, are presented in the Table below. Data includes periods of time when operating with full (>95% load) and with relatively constant fuel moisture, before and after the partial implementation. The results are calculated based on annual averages.

Table 6. Emission peaks before and after implementation

Number of peaks [% of time]	Before	After	Demonstration	Improvement
CO emission, limit 20 mg/m3n	1.69%	1.18%	0.45%	-28% / -73%
CO emission, limit 75 mg/m3n	0.23%	0.05%	0.07%	-78% / -69%

The improvement in the number of CO emission peaks clearly exceeds the target value. The decrease in the number of peaks indicates and supports the conclusion of improved and more stable combustion process. More stable process inflicts less sudden changes in the emissions, in other words, less emission peaks that indicate the instability in the air to fuel balance. However, it is to be also noted that there are other contributors to the stability of the combustion process, such as:

- changes in the fuel quality
- stability of fuel flow to boiler
- disturbance events especially in the fuel feeding system
- changes in the operation mode, for example keeping air humidification on / off.

At least some of the other potential contributors have affected to the number of CO peaks during the evaluation periods, especially to the high peaks over the daily limit of 75 mg/m^{3}n. As the details and changes of the fuel quality, as well as the momentary short-term stability of the fuel flows are largely unknown, the actual effect of each contributor to the peaks remains uncertain.

Anyways, the target value of -20% was clearly exceeded and the implementation of Twin technology has played a key role in the improvement, although the actual contribution to the high percentages, up to ~70%, cannot be unambiguously calculated and confirmed.

5.3 Reliability and availability

Boiler availability is usually evaluated by comparing the actual, measured operation of the boiler compared to the maximum annual operation (energy production or time based). Because the pilot plant has very long summer outages due to the very low demand for district heating, and three different boilers are used to optimize the production in fuel cost merit order, the availability is not very practical measure for the improvements in the dependability performance of the pilot.

Boiler reliability is usually evaluated by comparing the actual, measured operation hours and load levels of the boiler compared to the ones required by power and district heating demand. The reliability is measured and calculated as the share of required steam output that the boiler has been able to produce when required. The calculation can be done for example using the methodology defined in [21]:

$$w_v = \frac{W_B}{W_B + W_{nvun}}$$

where W_B is the generated energy during calculation period and W_{nvun} is the unplanned loss of energy generation due to defects.

When making target evaluations for reliability and availability, it is not reasonable to take such unavailability into account that cannot be affected either directly or indirectly by the technology developed. Therefore, for the comparison of the reliability improvement by COGNITWIN, only the unavailability incidents of those boiler parts that are subject to the fuel quality and process controls directly, or are subject to defects directly or in-directly caused or induced by them are considered, such as:

- the fluidized bed process disturbance (direct) and
- erosion/corrosion defects in pressure parts (directly) and
- variations in process conditions or forced emergency shutdown factors that may cause or accelerate the boiler ageing or degradation

<u>Bed agglomeration</u>

During the first operating seasons before the implementation of any parts of COGNITWIN, the plant owner had good quality fuels available, and the boiler did not have any bed related process disturbances that would have had an impact to energy generation. Skilful O&M of the boiler from the beginning of its commercial operation, prior to the implementation of COGNITWIN, set the bar so high that, in practice, there was no room for any improvements.

However, we can make some speculation on this based on the earlier similar cases. Based on previous experiences in SFW's other reference units with recycled wood as fuel, the average value of preventing the problems with proper counteractions in good time is approximately 0,2%. In the pilot boiler this would equal to about 100 kEUR loss per year.

<u>Fouling and corrosion</u>
Some fouling of heat exchangers has been detected in the boiler superheater section. The fouling of the tubes has been only minor or moderate and has not cause any downtime this far. The final version of the COGNITWIN including the optimization of HX cleaning operations has been implemented so recently that the long-term effects to the ash deposits on tube surfaces and to the corrosion tendency of tubes cannot be measured within the COGNITWIN project timeline.

Based on the previous experiences, there is a clear connection between the deposits on the tube surfaces and the corrosion of the tubes, especially in case of recycled/recovered fuels with corrosive components in the fuel (e.g., chlorides) and heavy deposit scales with molten salt components inside. With the average unavailability caused by superheater corrosion (and erosion due to excessive fouling of SH tube bundles) in the reference units with recycled wood as fuel has been about 38 hours per year (i.e., 0,5%). Thereby, preventing or minimizing the corrosion tendency and related problems causing unplanned downtime could decrease the total annual savings by even 300 kEUR/year.

<u>Erosion</u>
The measured reliability during the first 1.5 years, prior to full implementation of COGNITWIN, was approximately 98.7% (See **Table *7***). The only defect incident that caused unavailability (=unreliability) for the power generation was a tube leakage in the separator area of the boiler.

After the full implementation of the COGNITWIN, boiler reliability has been ~100% with no downtime directly or indirectly caused by the fuel quality, process control or erosion, despite higher average boiler load compared to the first 1.5 years. The tools implemented during COGNITWIN enable operating the boiler on overload when fuel quality allows it, without increasing the risk for excessive erosion, but also recommend limiting the boiler load when the lower fuel quality increases the erosion risk.

Table 7. Reliability and availability before and after implementation

	Before	After	Improvement
Unplanned downtime	86.6 h	0.0 h	-86.6 h
Unreliability / Unavailability	1.3%	0.0%	-1.3%
Reliability	98.7%	100.0%	+1.3%

The targeted improvement in boiler reliability and availability is +0.3-0.5%, and thus the target was met during COGNITWIN. Naturally, the long-term effects of the implemented Twin technology cannot be evaluated or reliably estimated during the project.

It is important to bear in mind that the target for improving the plant reliability and availability was originally set based on an average boiler that had been in operation for several years, not for a new boiler. Based on SFW's experiences and references, the expected reliability of an average boiler having a similar size and similar clean and recycled wood as the main fuels is around 98.2%. When counting only the fuel and process control related defects, the average unreliability in these typical reference units is about 1.2% on an average, which is quite on the same level as in the pilot plant prior to COGNITWIN implementation. This estimate can be used in evaluating the potential for long-term savings and operating economics improvements for the piloting plant.

5.4 Operation economy

Operation economy of the piloting plant has improved together with the technical performance, environmental performance, and reliability. The measurable performance indicators for the direct impacts to the operation economy were originally selected as:

- Efficiency improvement and its effect to boiler operation economy (fuel consumption)
- Improvements in utilization of boiler full capacity without increasing risk for degradation
- Economic benefits of decreased emissions vs additive consumption (if any)
- Effect of the avoided downtime and repair costs

The improvement of operation economy due improved **technical performance** is based on the efficiency improvement calculation before and after the implementation. In the end, actual economical saving brought by efficiency improvement depends on the fuel price paid by the plant. Because the fuel price is confidential business information for the end user (i.e., the company that owns the plant) and not public information, the fuel price used here is only estimated by the best knowledge of SFW. The average bio-fuel price in Sweden is between 10 EUR/MWh for recycled/recovered wood, and 20 EUR/MWh for virgin wood fuels, such as wood chips. The economy impact is thus calculated using an average of 15 EUR/MWh as the fuel price.

Improvements in other operation economy are often referring to savings by additive consumptions, lower in-house / auxiliary power consumption etc. compared to operation on similar loads and using similar fuels and with the same output. On the other hand: if the annual production of the boiler is increased without increasing the costs proportionally, the operation economy is improved.

During COGNITWIN, the plant has been able to increase the full load production by up to 3% for continuous extended periods with only minor effect to consumption values and without increased risk for degradation, and without uncontrollably accelerating the direct erosion/corrosion related risks or the in-direct risks such as the boiler ageing or degradation.

The effect of **environmental performance** to the operation economy could not be evaluated due to lack of direct monetary valuation or penalties for N_2O and CO emissions defined in Sweden's Climate Policy Act. In Sweden, only the high NOx emissions are penalized, and counter-wise, low NOx emissions are rewarded. The changes in NOx emissions during COGNITWIN and the consecutive penalties/rewards were evaluated against the changes in the consumption of ammonia. Nevertheless, the annual savings of about 30 kEUR from optimising the NOx emissions and ammonia consumption cannot be accounted for COGNITWIN, and these saving are therefore not added to the final cost evaluation.

From the environmental point of view in a larger perspective, the measured reduction in CO and N_2O emissions during COGNITWIN, and especially the impact of reduced N_2O emissions, is positive. The activities to optimise the cost of NOx penalty charges have probably a relatively small total effect compared to the effect of reducing the N_2O emissions. For example, in 2017 the share of N_2O was around 9% of all the GHGs in Sweden, and it has been projected to increase because of NOx reduction activities. In Sweden, the decrease in N_2O emissions would contribute to reaching targeted 63% cut of greenhouse gas emissions from 1990 baseline by 2030 and net-zero GHG emissions by 2045.

The **reliability and availability** affect the operation economy by two ways: decreasing the amount of unplanned downtime and lowering the O&M costs, especially the maintenance cost. The overall effect to O&M costs, especially the maintenance cost and any indirect cost savings, will be measurable only after several years of use, which is longer than the COGNITWIN timeline. Therefore, some of the overall factors affecting the operating economy, such as all the downtime costs and overall maintenance costs, are only preliminary estimates.

During the evaluation periods, the **unplanned downtime** of the boiler has decreased by 86.6 hours, averaged to one operating season. This avoided downtime does not directly decrease costs but decreases the income and thus profit losses which can be accounted as costs in the evaluation. The cost of downtime is basically the difference between the expected production income from the power and heat sales and the estimated operating costs during the same period, which in this case was 86.6 h per operating season. Each unplanned downtime hour of the piloting plant costs approximately 6 270 € for the plant owner as lost production profit. The decrease in the unplanned downtime achieved during the COGNITWIN equals to approximately 543 k€ annual savings, from avoiding downtime and production losses alone.

The overall **operation and maintenance costs** are confidential business figures of the end user (i.e., the plant owner) and can only be roughly estimated by SFW. Basically, the improvement of the annual operation economics is already calculated in the technical performance section above.

The impact to maintenance costs can be estimated based on the avoided restoration cost of boiler defects, namely the observed tube leakage in the pilot plant. The restoration costs of the occurred downtime are calculated and evaluated based on various data sources and estimates:

- the actual costs from the subcontractor bills OR
- known duration of the inspection and restoration works (in calendar hours),
- estimated number of personnel working at the same time in certain work phases and
- hourly rates of the subcontractors.

The total restoration costs of one tube leakage in separator are estimated to be about 60 k€ when the repair is done as an emergency repair works.

The timeframe after the implementation of COGNITWIN is too short to evaluate the overall maintenance costs reliably. The annual costs of a boiler of this size are around 650 k€/year on an average during the first 5 years. When the long-term benefits of COGNITWIN will fully be realized during the years as minimized erosion and corrosion, and thus as avoided emergency repairs as well as unnecessary maintenance works in the planned annual outages, the target savings can be exceeded with maintenance costs alone.

The impact of COGNITWIN to operation economy of the pilot plant through improvements in the technical performance, environmental performance, and reliability, are summarized in **Table *8***.

Table 8. Operation economy before and after implementation

Operation economy	Before	After	Change	Unit cost	Savings [€/year]
Add. power sales (1700 h/a*)	50.3 MW	50.6 MW	+0.3 MW	42 €/MWh	21 000 €
Add. heat sales (1700 h/a*)	100.6 MW	101.3 MW	+0.7 MW	66 €/MWh	79 000 €
Fuel efficiency (6400 h/a**)	165.2 MW	165.0 MW	-0.2 MW	15 €/MWh	19 000 €
SAVINGS, PERFORMANCE					**119 000 €**
Downtime, production losses	86.6 h	0.0 h	-86.6 h	6 240 €/h	540 000 €
Downtime, repair costs	360 h	-	360 h	111 €/h***	40 000 €
SAVINGS, RELIABILITY					**580 000 €**
* Operating hours when there is a possibility to have overload (average of two years) ** Operating hours in the whole operating season (average of two years) *** When conducted as an emergency repair					

When it comes to the savings achieved by improved reliability, it is to be noted that there may be also factors other than the erosion that may have been affecting to the occurred separator leakage, so the total improvement coming merely from COGNITWIN remains unclear. Nonetheless, the targeted 100k€ savings in operation economy is well exceeded, even merely by performance savings.

6 Conclusion

The Engineering pilot in COGNITWIN WP3 dealt with optimization and operation fouling management in a CFB boiler. In this deliverable and the related demonstrator, we have presented the background problem and illustrated the use of the twin technology developed in the project, as well as demonstrated the benefits obtained by implementing the technology.

SFW customers' business requires high flexibility in the operation. For example, it is important to be able to respond quickly to the market demand, even when using more challenging fuels that may be cheaper to acquire. Power plant operators often struggle with optimal operation when the fuel is continuously changing, especially when firing challenging renewables such as biomass and bio-residues.

Through the pilot we have learned new ways of improving the monitoring of fouling on HX surfaces and got new ideas on how to better support the control of fouling using twin technology with some cognitive capabilities. Especially, we have concentrated on better monitoring of fouling on the heat exchange surfaces through a combination of more efficient direct and indirect monitoring methods, physical models, and the latest approaches in data science which together constitute a novel approach of hybrid modelling.

In the research within WP3, a novel approach was developed and used for the indirect characterization of fouling status in heat exchangers, to optimize and improve fouling management in a CFB boiler. The goal, which was achieved, was to have to a system that could adapt to the prevailing process conditions, with respect to the prevailing load level and fuel quality, for example. In addition, the target was that the system would give an indication of when to start the HX cleaning sequence. In addition, a novel condition monitoring scheme based on modal analysis was introduced, which provides a potential direct way of estimating the degree of fouling on heating coil surfaces. Both approaches were tested in real operational environment of a 150 MW CFB boiler with promising results.

In COGNITWIN WP3, we have successfully demonstrated the use of twin technology in the Engineering pilot. The technology helps the operator of the power plant to optimize the boiler controls. For example, optimized cleaning of HX surfaces leads to a more efficient process which requires less resources per produced unit of power. The benefits gained by the new COGNITWIN technologies developed for the Engineering pilot (CFB) are improved operating efficiency, lower operating costs, lesser total amount of emissions, and improved reliability and availability. The improvements in the selected KPIs were calculated by comparing the measured performance after the implementation of COGNITWIN to the measured performance prior to the implementation.

In any system relying on sensor information, reliable and adequate measurement instrumentation is a fundamental requirement. In power industry, appropriate monitoring of fuel quality is still an open issue, and we are still lacking cost-efficient and reliable methods for direct and real-time monitoring of certain fuel properties, such as elemental composition of fuel. More exact real-time data on fuel properties would enable better decisions, better cognition, and eventually better control of the process.

In the tool development, it was learned that the estimation of highly data-driven dynamics based on plant operating data is complex in the industrial environment, and therefore ensuring the robustness of methods and tools is highly valuable. Introduction of approach exploiting physical model in state estimation was found successful. The approach to fuse several models, including physical, grey-box and data-driven, was found very useful from the fouling monitoring point of view. Already at this point it seems clear that the system will play an important role in fouling management.

The results achieved in COGNITWIN point out the still relatively unused potential of combining the physical models with machine learning in process monitoring. In addition, we have managed to improve and optimize the control of HX cleaning operations using novel twin technology, including a combination of more efficient direct and indirect monitoring methods, physical models, and the latest approaches in data science. From the COGNITWIN piloting activities we have learned new ways to improve the monitoring of fouling using these kinds of hybrid methods.

It is presumable that better data from the fuel used and the fouling itself would make the system even more flexible in finding optimal solutions for fouling management and in coping better with real-world problems such as variating fuel quality. This is an important consideration to focus on when developing future projects. The twin technology developed in COGNITWIN provides an excellent platform upon which to build novel, next-generation technology.

References

[1] Basu, P. 2006. Combustion and Gasification in Fluidized Beds. CRC Press. 496 pages

[2] Zhang, D. and Teir, S. 2003. Circulating Fluidized Bed Boilers. In: Steam Boiler Technology. Helsinki University of Technology, Energy Engineering and Environmental Protection publications. Department of Mechanical Engineering.

[3] Web pages of Mälarenergi AB: https://www.malarenergi.se/om-malarenergi/framtidens-samhalle/vara-anlaggningar/kraftvarmeverket-vasteras/block-7/, accessed FEB-10, 2023.

[4] Web pages of EUWID Europäischer Wirtschaftsdienst GmbH: https://www.euwid-recycling.com/, accessed FEB-10, 2023.

[5] Barišić V, Coda Zabetta E, Krztoń B, State-of-the-art CFB technology for utility-scale biomass power plants, in: Proc. of Power Plants, 2010.

[6] D3.1 A report on existing level of digitalization, describing challenges for Engineering pilot, incl. identification of novel sensors and collected information for cognitive modelling. Deliverable Report of Cognitwin (Cognitive plants through proactive self-learning hybrid digital twins). 2020.

[7] D3.2 A database and digital platform for Engineering pilot. Deliverable Report of Cognitwin (Cognitive plants through proactive self-learning hybrid digital twins). 2021.

[8] D3.3 Hybrid models for Engineering pilot. Deliverable Report of Cognitwin (Cognitive plants through proactive self-learning hybrid digital twins). 2022.

[9] D3.4 A complete Cognitive Twin for Engineering pilot. Deliverable Report of Cognitwin (Cognitive plants through proactive self-learning hybrid digital twins). 2023.

[10] COGNITWIN presents a digital twin service tool for a power plant. Cognitwin Engineering pilot M18 video demonstrator, can be accessed via: https://sintef.sharepoint.com/teams/work-8364/Shared%20Documents/COGNITWIN_Demonstrator_Videos/UOULU-SFW-M18-HD.mp4. 2021.

[11] COGNITWIN Monitoring Tools – with Application to Fouling Monitoring. Cognitwin Engineering pilot M30 video demonstrator, can be accessed via: https://sintef.sharepoint.com/teams/work-8364/Shared%20Documents/COGNITWIN_Demonstrator_Videos/COGNITWIN_M30demo_UOULU_SFW_HD_nosound.mp4. 2022.

[12] Fouling management tool. Cognitwin Engineering pilot M42 video demonstrator, can be accessed via: https://sintef.sharepoint.com/teams/work-8364/Shared%20Documents/COGNITWIN_Demonstrator_Videos/COGNITWIN-M42-UOULU_SFW_WP345.mp4. 2023.

[13] Hui NB, Banik AK, Advances in dynamics, vibration and control. New Delhi: Narosa Publishing House; 2016.

[14] Engineering ToolBox, 2001. Available at: https://www.engineeringtoolbox.com, accessed 14-Jan-2022.

[15] Liukkonen M, Kettunen A, Miettinen M, Ikonen E, Selek I, Neuvonen M, Hansen AH, Edelborg M, Hybrid Modelling Approach to Optimize Fouling Management in a Circulating Fluidized Bed Boiler, in Proc. of FBC24 – The 24th Fluidized Bed Conversion Conference, 2022.

[16] D5.3 Updated Hybrid AI and Cognitive Twin Toolbox. Deliverable Report of Cognitwin (Cognitive plants through proactive self-learning hybrid digital twins). 2022.

[17] D5.2 Hybrid AI and Cognitive Twin Toolbox. Deliverable Report of Cognitwin (Cognitive plants through proactive self-learning hybrid digital twins). 2021.

[18] Ikonen E, Selek I, Fusing physical process models with measurement data using FIR calibration, Control Engineering and Applied Informatics 23(2) (2021) p. 67-76.

[19] Neuvonen M, Selek I, Ikonen E, Estimating Fuel Characteristics from Simulated Circulating Fluidized Bed Furnace Data. In: Proc. of the International Conference on Systems and Control (ICSC'21), 2021.

[20] Sandberg J, Fdhila R, Dahlquist E, Avelin A, Dynamic simulation of fouling in a circulating fluidized biomass-fired boiler. Applied Energy 88(5) (2011) p. 1813-1824.

[21] VGB guideline VGB-S-002-03, Terms of utility industry, Part B: Power and District Heat, Booklet 3: Fundamentals and Systematics of Availability Determination for Thermal Power Plants, 7th edition, 2008.