Cognitive Solutions in Process Industry: H2020 CAPRI Project

Cristina Vega[a], Daniel Gómez[b] and Aníbal Reñones[c]
Fundación CARTIF, Parque Tecnológico de Boecillo, 205, 47151, Boecillo (Valladolid), Spain

Keywords: Process Industry, Automation, Industry 4.0, IIoT, Cognitive Platform, Innovation, Digital Transformation, Industrial Plants, Smart Modules, Smart Industry, Open Data, Open Source, Open Science, Asphalt.

Abstract: The CAPRI project is a H2020 project that develops Cognitive Solutions (CS) to the Process Industry and a Cognitive Automation Platform (CAP) towards the Digital Transformation of process industries. CAPRI enables cognitive tools to provide to the existing process industries flexibility of operation, improving the performance and quality control of its products and flows. The project is developing and testing different CS's at each automation level, from sensors to planning. The content of this paper is focused on the CAPRI asphalt production applying different CS's for the sensors and control levels. Specifically the paper discusses a cognitive sensor for measuring filler quantity to the filter at drying process (noted as CAS2) and cognitive control concept applied to optimize the operation of the rotary dryer (noted as CAC1). The paper explains also how the CS's are being integrated by means of an open source architecture based on FIWARE. The paper provides also open access to the data and algorithms used as part of the commitment of CAPRI with open science.

1 INTRODUCTION

Big data and artificial intelligence (AI) are giving a huge boost to Industry 4.0. Intelligent software solutions based on AI models can process high volumes of data generated to identify trends and patterns that can be used to make manufacturing processes more efficient and reduce their energy consumption (ElMaraghy & ElMaraghy, 2022).

An extension of this is to incorporate cognitive features that enable sensing complex and unpredicted behaviour and reason about dynamic strategies for process optimization, leading to a system that continuously evolve its own digital structure as well as its behaviour. This way, an industry process will have its own cognitive capabilities over time based on the data it will collect and experience it will gain (Abburu, et al., COGNITWIN - Hybrid and Cognitive Digital Twins for the Process Industry, 2020).

Cognitive computing (Essa, et al., 2020) is an interdisciplinary field, which uses a collection of technologies to build a machine that have reasoning capabilities like a human brain. Cognitive computing integrates machine learning techniques to facilitate computers to recognize the objective world and to make decisions. Cognitive technologies have large influence on different systems and technologies such as cloud, mobile, wearable devices, IOT, big data, and industrial production (Abburu, et al., Cognitive Digital Twins for the Process Industry, 2020).

This paper is organized as follows: Section 2, introduces the novel paradigm of what is known as cognitive manufacturing. Section 3, shows how this concept is present in the H2020 CAPRI project. More specifically, the asphalt use case is shown and presented as an industry sector where CS's could make a big improvement in terms of efficiency. Then, in the following sections, two of the CS's developed for the asphalt use case are explained. Section 4 deals with the Reference Architecture that is being deployed as part of the CAP concept, based in the open source FIWARE framework and how the reference architecture enables an easy integration of the CS explained for the asphalt plant. Section 5 ends with the conclusions and next steps.

[a] https://orcid.org/0000-0002-7670-5088
[b] https://orcid.org/0000-0001-6123-2401
[c] https://orcid.org/0000-0002-4702-4590

Vega, C., Gómez, D. and Reñones, A.
Cognitive Solutions in Process Industry: H2020 CAPRI Project.
DOI: 10.5220/0011562000003329
In *Proceedings of the 3rd International Conference on Innovative Intelligent Industrial Production and Logistics (IN4PL 2022)*, pages 267-278
ISBN: 978-989-758-612-5; ISSN: 2184-9285

2 COGNITIVE MANUFACTURING

One of main challenges for process industry plants is to enable an efficient monitoring and control when the production or environments are complex, e.g. due to harsh conditions the system is operating in. The basic elements of process monitoring and control loops, including the models which can be used for supporting this task cannot be solved easily using nor traditional techniques from process monitoring (like Statistical Process Control) neither solely by using advanced AI techniques (like predictive analytics) (Cinar, Nuhu, Zeeshan, & Korhan, 2020). This problem requires a better understanding of the underlying data and processes, their contexts and their dynamics, similarly how human cognition is building a superior situational understanding and reasoning (Jacoby, Jovicic, Stojanovic, & Stojanović, 2021), even in very ambiguous cases. CAPRI uses the analogy of human cognition, based on cognitive architecture (Kaur & Sood, 2015), for addressing above challenges. It must be emphasized that the human cognition is extremely efficient in getting a big picture of a situation at hand, i.e. not only what is happening (Eirinakis, y otros, 2022), but also what is causing the situation and what can be the consequences before understanding what is going on and how to react on (Sánchez Boza, Guerra, & Gajate, 2011). Complex behaviour arises from sequences of cognitive cycles and this is exactly how CAPRI envisions the process of monitoring/sensing and controlling/reacting in cognitive plants.

3 H2020 CAPRI PROJECT

Digitalisation represents a new challenge for the European process industries, which need to handle an increasingly wide range of actions (Sharma, Kosasih, Zhang, Brintrup, & Calinescu, 2020). Cognition capabilities will permit the sector to improve its flexibility and performance. The EU-funded CAPRI project (Consortium, 2022) will establish, test and demonstrate an advanced CAP for process industry digital transformation. The platform will help process industries increase its flexibility of operations and improve performance through different indicators and cutting-edge quality control of products and intermediate flows. The CAP will be modular and scalable, allowing the development and integration of advanced applications that address manufacturing challenges in significant process sectors such as asphalt, steel making and pharma.

Figure 1: H2020 CAPRI project introduction.

European process industries need to address resources, materials and environmental constrains by improving its flexibility and performance through cognition capabilities, as existing in human intelligence. Digitisation is the main enabler for such capabilities (Auditors, 2021).

CAPRI Cognitive Automation Platform for Process Industry enabled by cognitive tools will provide existing process industries flexibility of operation, improvement of performance across different indicators (KPIs) and state of the art quality control of its products and intermediate flows.

The CAP will encompass methods and tools for governing six Digital Transformation pathways (6P, Product, Process, Platform, Performance, People, Partnership) (Salis, Marguglio, De Luca, Gusmeroli, & Razzetti, 2022), a Reference Architecture with four levels of cognitive human-machine interaction (industrial IoT connections, smart events processing, knowledge data models and AI-based decision support), a set of reference implementations, both commercial and open source, for batch, continuous and hybrid process industry plants, and a toolbox of CS's for planning, operation, control and sensing.

The CAP will be modular and scalable, so that advanced applications could be developed and integrated on top of it and its validation will take place addressing manufacturing challenges in industrial operational environments of three outstanding process sectors: asphalt (minerals), steelmaking, and pharma industry (chemical). CAPRI results could be applied to a wide range of problems and challenges in future cognitive plants. CAP Platform and the cognitive tools included in it can be replicable in areas of production planning, control, automated processes and operations of many process industry sectors.

3.1 Asphalt Use Case

The asphalt use case of the H2020 CAPRI project is located in EIFFAGE Gerena plant (located in southern Spain). A general overview of the asphalt manufacturing process of the corresponding use case is (El-Haggar, 2007) shown in Figure 2.

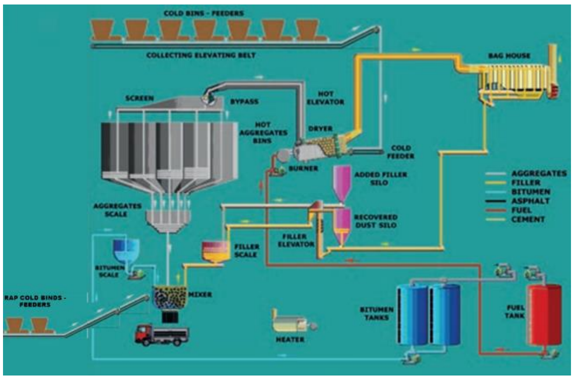

Figure 2: Asphalt manufacturing process diagram.

By weight, 95% of asphalt consists of gravel, sand and filler (aggregates less than 63µm) – aggregates that give asphalt its strength. The remaining 5% comprises an agent that binds all of these materials together. That agent is usually bitumen derived from crude oil. The process begins when the stockpiled aggregates in the cold feed are metered and conveyed to a dryer drum where they are heated to a specific temperature. A first collector removes large dust particles from the gases before entering the bag house, which removes fine particulate matter before they are released into the atmosphere.

Hot aggregates are elevated to a vibrating screen where they are classified by size and stored in different bins. The aggregates, filler and other additives are scaled and mixed with the hot bitumen in the mixer producing the final asphalt mix. In some asphalt mixes, RAP (Reclaimed Asphalt Pavement) is also added. RAP is scaled, taken into account its approximated bitumen content (measured in a laboratory), and added to the mixer. After that, the asphalt mix is ready to be loaded to the truck for shipment (Sivilevičius & Šukevičius, 2009).

3.2 Objectives and Benefits

In the asphalt mix manufacturing process, most of the measured data is not usually exploited although it may provide very interesting information. There could be variables that are not known how to relate with the information obtained or whose relationship is unknown. Even more, some variables are not measured or measured only in the laboratory.

CAPRI project addresses the challenge of integrating relevant information data sources as well as knowledge of the personnel of the plant, at all the levels: planning, operation and control of the plant (Zhang, Huchet, & Hobbs, 2019). The results of the project are translated in terms of costs, effectiveness, and product quality for the asphalt mix manufacturing process. With the development of CAPRI, for the asphalt use case there should be five kinds of improvements in the plant.

At production performance level, the objective is to increase productivity by around 8% with the CS.

CAPRI will act as well in the energy efficiency. Objective is to decrease the consumption of 15% of electricity, 11% recycled fuel and 50% diesel. These will be improved with the cognitive control of dryer drum (known as CAC1). Knowing the humidity and temperature in the input of the drum, adjustments will be made to obtain the best conditions of output, avoiding overheating of aggregates.

The next benefit, in the asphalt use case, is related to the consumption of resources, like, aggregates, bitumen and RAP. In this case, is to reduce 20% of aggregates consumption, 20% of the consumption of bitumen and increase in 500% RAP consumption.

Related with waste generation and the product quality, the point to action is the control of hot aggregates temperature. To obtain this, the cognitive control of asphalt plant dryer drum (CAC1) is required to optimise aggregates heating of temperature, and the cognitive sensor of amount of filler (CAS2) in combination with the other CS's are needed to control the filler present in the aggregates and the filler needed in the final mix.

3.3 Cognitive Solution – Control of the Asphalt Drum (CAC1)

The asphalt drying process aim is to produce a dry solid product of desired quality at minimum cost and maximum throughput. Good quality implies that the product corresponds to a number of technical, chemical and biological parameters, each within specified limits (Yliniemi, Koskinen, & Leiviskä, 1998).

Different control techniques, at different levels, are present in this type of equipment, ranging from conventional industrial controls (like PID) to more advanced control systems like model-based feedforward-feedback until recently applied intelligent control systems based on fuzzy logic or

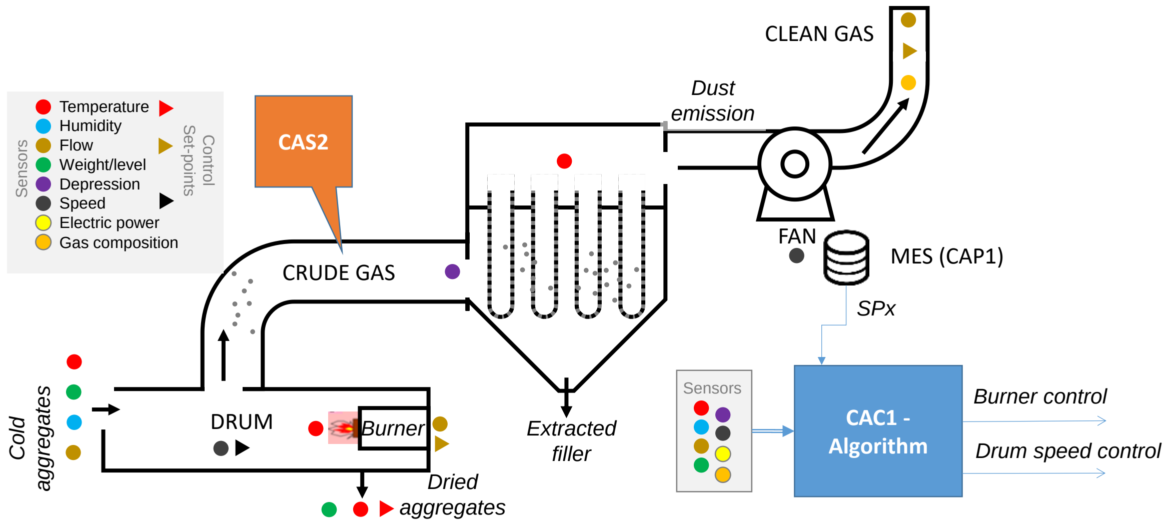

Figure 3: CAC1 and CAS2 Basic Architecture.

neural networks applied to machine learning techniques (Raghavan, Jumah, & Mujumdar, 2006).

Within CAPRI project, CAC1 Cognitive Control Solution objectives are to obtain a dry product at an optimum temperature and fumes (combustion gases) at the possible lowest temperature, on one hand not to damage the baghouse filter and on the other to minimize energy consumption, thus increasing the efficiency of the drying process. The main objective is to decrease the consumption of electricity, recycled fuel and diesel. This way, knowing the humidity and temperature in the input of the drum, adjustments will be made to obtain the best conditions of output, avoiding overheating of aggregates.

This solution has been developed based on a control algorithm where sensors and actuators are used to calculate the optimum values for the different variables that run the drum. Currently, a dynamic modelling of the rotary drum is being created through model-based identification methods (Ljung, 1998) running several experimental tests performed at the asphalt plant taking into account some of the main variables: temperatures, humidity, load to dry, burner, drum speed, combustion gas flow. This identified model will be required like an input for the Model Predictive Control (MPC) (Schwenzer, Ay, Bergs, & Abel, 2021), advanced method of process control that is used to control a process while satisfying a set of constraints. It is in this control solution where the rotary drum optimized control calculations are performed.

The Cognitive Algorithm will be executed in real time by providing the setpoints: drum burner power (%), drum rotation speed (%) and exhaust damper opening (%), to obtain the optimal temperature of the hot aggregates coming out of the drum and to guarantee in this way the desired temperature of the final asphalt mix and also the gas combustion temperature. In addition, this is intended to minimize the combustion gases temperature and to improve energy efficiency and reduce pollution.

CAC1 Data Model and Algorithm

Different attempts have been made to model rotary dryer drums, ranging from physical equations as in (Rubio, Bordons, Holgado, & Rivas, 2001), (Le Guen, Huchet, & Tamagny, 2011), numerical analysis as in (Li, Yao, & Zhao, 2017) and energy and exergy equations (Zhang, Huchet, & Hobbs, 2019).

Regarding control algorithms for rotary dryer drums, several approaches can be found through the literature, from basic algorithms as in (Rubio, Bordons, Holgado, & Rivas, 2001) to an advanced control based on fuzzy logic, (Yliniemi, Koskinen, & Leiviskä, 1998), (Koskinen, 1998), variable structure controller as in (Mahmoud, El-Kasassy, & Areed, 2020). More recently, intelligent control applied to rotary dryer drums has also been approached from different intelligent perspectives: a decisive control module (Pang, Jia, Ding, Yu, & Liu, 2021), rule-based expert and neural networks (Raghavan, Jumah, & Mujumdar, 2006) and a more sophisticated control based on cognition with self-X capabilities as in (Haber, Juanes, Del Toro, & Beruvides, 2015) in a more general way.

CAC1 algorithm applied in CAPRI consists of an identified data-based model and an MPC programmed in MATLAB environment using both MATLAB scripts and SIMULINK function blocks. The identified model has been done using the data with certain predefined conditions and with different tests performed at the asphalt plant. The manipulated variables are the ones used to the tests for identification purposes: First set of experiments were based varying the rotary dryer burner power (and leaving the rest of the variables as constant as possible) and a second set of tests where the varying variable was the dryer drum rotary speed. The CAC1 experimentally data-based identified model, from all sensor measurements and the dynamics (data-based model) in the production chain and related process variables calculates the setpoint SP1 of the drum temperature controller. The setpoint of combustion gases temperature controller leaving the rotary drum dryer SP2, modulating the speed of rotation of the drum will also come from this AC algorithm.

The MPC calculates and changes in real time the setpoints of the plant PLC slave controllers from the setpoints generated by the CAC1 algorithm.

All related CAC1 files can be accessed at Zenodo open CAPRI link (Gómez & Diego, 2022).

3.4 Cognitive Solution – Cognitive Sensor for Amount of Filler (CAS2)

The asphalt plants contain different types of sensors in order to be able to monitor and control the different stages of the production process like temperature sensors, humidity sensors, pressure sensors, load cells and more.

However, not all these sensors per se give a smart understanding and approach to the process. During process assessment in the CAPRI project, some CS have been identified to find an optimal behaviour and reaction to the manufacturing of asphalt mixes to give a high-level cognition reaction to optimize and detect variations and have a cognitive sensing and support of the process that commercial sensors cannot give. One of these identified CS is: Cognitive sensor of amount of filler (known as CAS2).

This cognitive sensor is developed to estimate and measure the fine filler quantity that goes out of the aggregates drying to the baghouse filter (Figure 3 with position of CAS2 solution). The high-level outcome of this cognitive sensor is to obtain the real amount of filler present in the cold aggregates, which allows then wasting less energy in the rotary drying drum and in the filtering (baghouse) process.

Different technologies and approaches can be found to tackle this measurement: Laser technology that uses a time-of-transition technique to measure particle size distribution (Measuring Coal Particles in the Pipe, 2022); machine vision to analyse particulate material on conveyor belts as in (Andersson, 2010); also, techniques applied using intelligent vision with camera images applied to different structures of new neural networks to image processing and estimate the granulometric distribution of small and medium size aggregates, (Fernández, Viennet, Goles, Barrientos, & Telias, 1998); more recent techniques based on 3D particle tracking velocimetry in up and down flows in pipes, (Oliveira, Van Der Geld, & Kuerten, 2017); miniaturized sensors based on nanofibers to determine vibrations and then analyse the possible flow in different structures, (Singh, Lye, & Miao, 2019); also, new capacitive sensors and electrodes using calibration-based and tomographic approaches have also been recently presented to measure particulate flow in pipes, (Suppan, Neumayer, Bretterklieber, Puttinger, & Wegleiter, 2022).

All these techniques are not appropriate to be deployed in asphalt production due to the required harsh conditions of this process: high temperature, pressure, and concentration of abrasive particles.

Eventually CAS2 solution has two kinds of physical sensors, one is a commercial solution, that has never been used under these conditions. The second sensor is a custom sensor based on another commercial sensor, not intended to measure concentrations of particles, but to measure disturbances of the flow, which can then be used to estimate the amount of filler flow through the pipe of baghouse. This second sensor is a research and innovation action of this project. It is based on a vibration measurement that has been validated under laboratory conditions providing an actual measurement of filler flow at a smaller scale process.

Thanks to the knowledge that this sensor will provide (actual mass flow of filler trough baghouse aspiration pipe), the needed filler addition and extracted will be minimized and added only if it is detected that there is less amount of filler than the final hot mix needs.

Therefore, the outcome of this cognitive sensor, the estimation of filler present in the cold aggregates, will help to avoid excessive recirculation and/or unnecessary addition of filler, making the process more energy efficient. In the development of this cognitive sensor, different steps were taken. At early stages, laboratory measures and test were performed with the following results, where all the referred files are openly available at CAPRI Zenodo repository (Vega & Reñones, Cognitive sensor for amount of filler, 2022):

At lab scale, different tests were performed, where different parameters were taken into account. Also, a set of vibration sensors were installed at the actual plant baghouse inlet pipe and compared against a

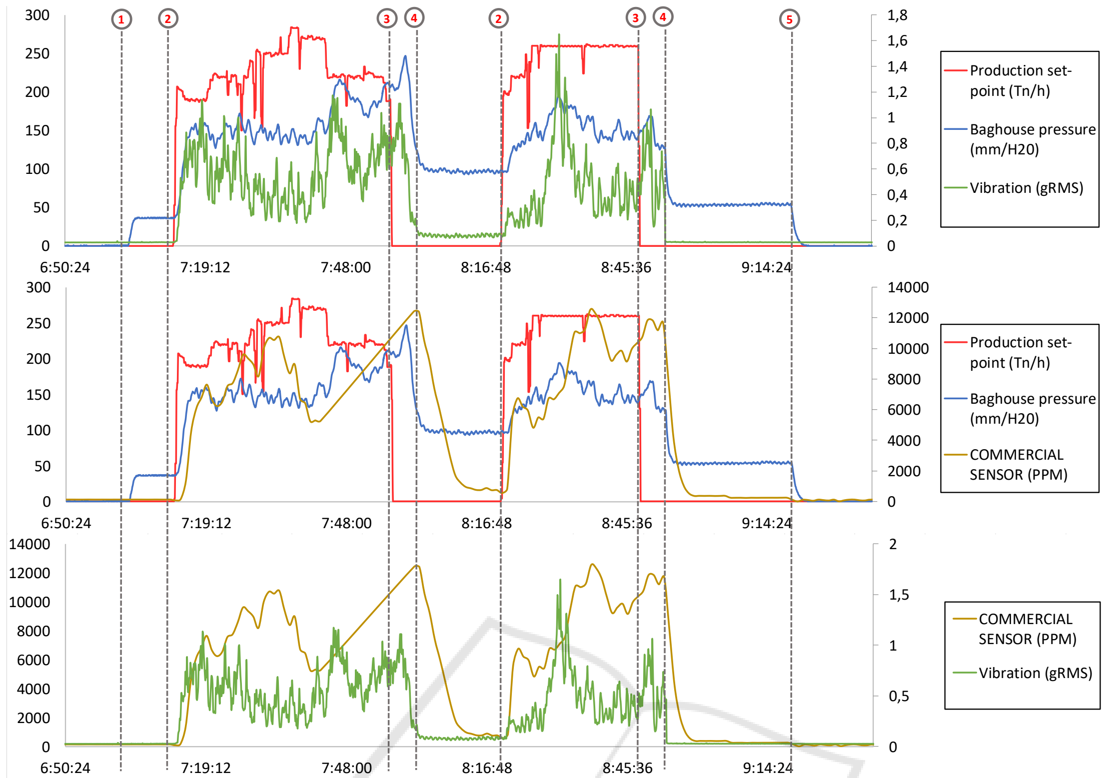

Figure 4: Comparison of sensors measures in Gerena use case plant (Seville, Spain). The process variables of aggregates flow, pressure at the baghouse and temperature at the baghouse are compared with CAS2 cognitive sensor.

commercial solution not usually used at this location due to the harsh conditions present at these points. CAS2 vibration parameter is compared with the results offered by the commercial sensor tested in parallel (measured in ppm) (Figure 4). The data also contains relevant process variables from the control of the plant like the SP of aggregates flow into the drying drum (in T/s) the aspiration pressure at baghouse input pipe (in mm H20) and the temperature at such input. The sequence of operation of the baghouse and drying drum is the following (Table 1 and Figure 4). File named **CAS2_Data_4.csv** is a dataset file that represents the amount of vibration measured in the EIFFAGE asphalt plant during the drying process of aggregates in that sequence of operation.

CAS2 sensor aims to provide an estimation of flow of filler during the drying process of the aggregates. As such, the raw measurements need to be adjusted to compensate the undesired noise when the aspiration takes place but there are no aggregates into the drum to be dried. To compensate this noise a model based on the actual aspiration pressure has been created.

Table 1: Important events of comparison the process variables from Gerena Plant and the CAS2.

TIME	EXPLANATION
1	Aspiration of the baghouse starts
1,2	Baghouse depressure maintains still, sensors starts to measure the flow without filler
2	Flow of aggregates starts
2,3	Production, measure of filler
3	Flow of aggregates stops
3,4	Measure of filler, production off, baghouse on
4	Baghouse depressure decreases, flow of filler stops
4,5	No aggregates, baghouse with constant depressure, low vibration of sensors
5	Asphalt plant stops

CAS2 Data Model and Algorithm

All the performed calculations are explained following the files that can be openly found at (Vega, Reñones, & Sanz, Cognitive sensor for amount of filler [CAS2] - INTEGRATED, 2022). File named **CAS2_dataset_5.RData** is a dataset of raw data used for the creation of the model of CAS2. This model

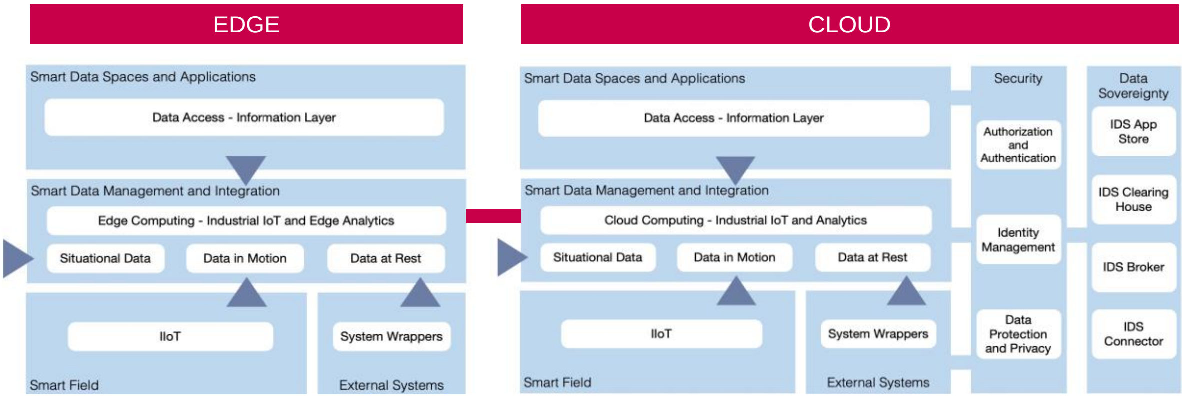

Figure 5: CAP Reference Architecture.

tries to estimate the vibration measured (ACEL1_20-25 [gRMS]) based on the aspiration pressure (variable named as RPA2100 [mmH2O]).

Figure 6 shows a collection of temporary moments in time when the baghouse is running, but there is no material flow, so it is just vacuuming air. Figure 7 shows an operation of the baghouse during one day of production of the asphalt plant and how the different segments used for the creation of the model are selected (marked with red rectangles).

The file **CAS2_sourcecode_1.R** file is an algorithm programmed in an open source, R programming, environment and language. This algorithm creates a model that relates the aspiration (x variable) and vibration variables (f function) in the suction process with the dataset described above. The developed model creates a piecewise linear relationship between the two variables for aspiration values as can be seen in the figure below. It must be also noted that for a certain pressure below a threshold (27 mmH_2O) the output of the model is forced to 0 as the baghouse does not operate and the flow should be 0.

$$\boldsymbol{f}(x) = \begin{cases} 0 & x < 27 \\ 0.00355 * \mathbf{x} - 0.07125 & 27 < x \leq 36 \\ 0.0119 * \mathbf{x} - 0.2872 & x > 36 \end{cases} \quad (1)$$

The model is divided in three intervals as the variation of the variable to model is not continuous but with abrupt changes as shown in the Figure 7.

With this model ready, the next measurements of vibration will be compared with the ones provided by the model and the difference among them corresponds to the vibration due to the aspiration of actual filler through the baghouse pipe.

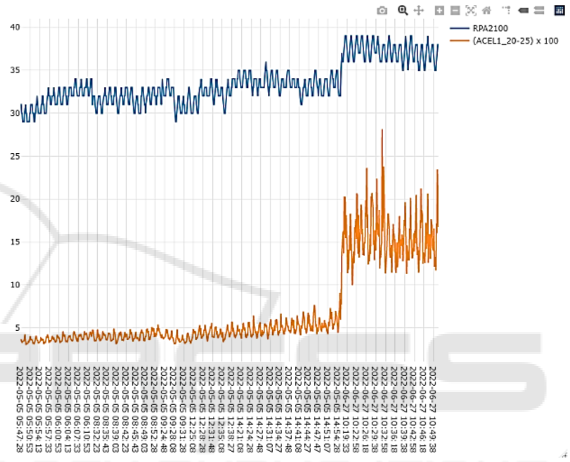

Figure 6: Dataset used for the creation of the model.

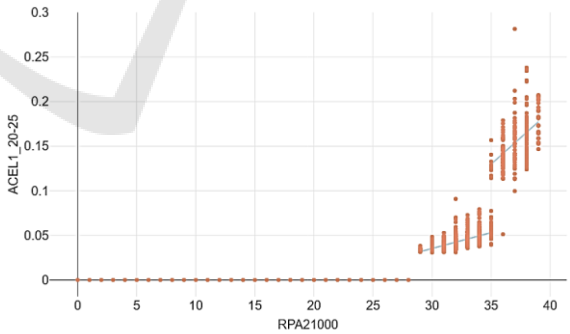

Figure 7: Model aspiration values between 0 to 40 mm H_2O.

4 CAP REFERENCE ARCHITECTURE

In process industries, due to harsh conditions the system is operating in, some sensors might be operating improperly (de-calibrated), or some

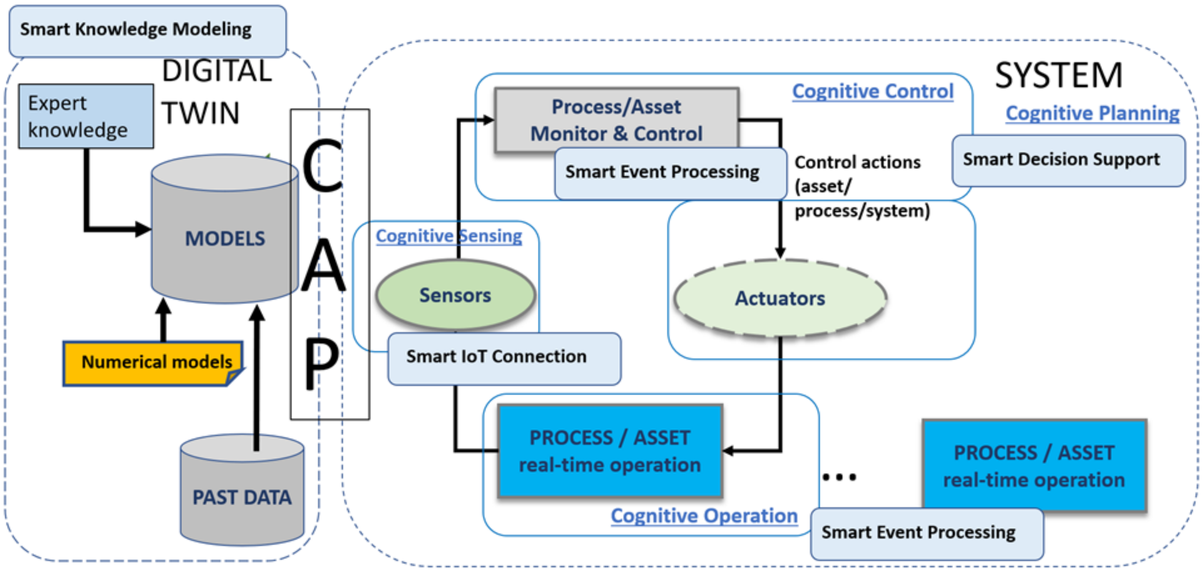

Figure 8: Cognition-driven process monitoring and control loop (cognitive plant) (ToBe).

parameters might be very deviating (instable) in a period of time. On the other hand, the production processes have to be under strict control ensuring stability - otherwise some small issues might be escalating very quickly.

Figure 8 (cf. grey boxes) shows basic elements of a process monitoring and control loop, including the models that can be used for supporting this task.

As explained in section 2, this problem requires a better understanding of the underlying data and processes, similarly how human cognition builds a superior situational understanding and reasoning, even in very ambiguous cases.

Therefore, the analogy of human cognition for resolving above-mentioned challenges is used for an efficient process control in process industry plants. Since one of the most critical issues in understanding/analysing process stability is to observe variations, this artificial (or machine) cognition should be based on a complex, comprehensive but yet very efficient sensing, analysing and understanding variations, including their root causes, as well as their impacts (Wagner, Milde, Barhebwa-Mushamuka, & Reinhart, 2022). This is exactly how CAPRI envisions the monitoring/sensing and controlling/reacting in cognitive process plants (Zaeh, y otros, 2008).

In a cognitive plant, there is a need for monitoring a broader context of the data that is collected and processed in, as well as for a deep multivariate analysis of the variation in data, to be able to detect and react properly to unexpected events. The realization of the cognitive plant is supported by Cognitive components as depicted in Figure 8 (cf. light-blue and blue coloured boxes).

The Cognitive capabilities and corresponding Cognitive components are briefly illustrated:

Cognitive sensing enables getting accurate data from sensors (IoT) or software sensors, even in the cases when the sensing system is malfunctioning (e.g. uncertainty, inconsistency, missing data). It will be realized through Smart IoT Connection component, which is responsible for establishing and maintaining the connection to the production system.

Cognitive control enables reacting on various situations of interest, even if the data is huge, multivariate or changing (i.e. the process is instable). It will be realized through Smart Event Processing component, which is responsible for detecting complex situations of interest in real-time data and reacting correspondingly, e.g. in the context of product/process quality control.

Cognitive operation supports the realization of complex operations in a plant, even in the case of unplanned delays or other types of deviations. It will be supported by Smart Event Processing component, applied on the intra-factory data streams, to guarantee better performance and quality at organization level (and nod only at multi-step or multi-stage levels).

Cognitive planning enables logistics, planning and rescheduling capabilities in the inter-organizational context. It will be supported by Smart Decision Support component, which realizes complex decision-making plans in the form of heterogeneous processing pipelines (Salis, Marguglio, De Luca, Gusmeroli, & Razzetti, 2022).

All Cognitive capabilities will be boosted by Smart Knowledge Modelling component, which is responsible for the overall technical modelling of the plant and the aggregate interdependencies. It will be basis for the Digital Twin (Rožanec, y otros, 2021), as the collection of the digital assets (data, model, services) belonging to the plant.

4.1 CAP Reference Architecture

The CAP Reference Architecture is structured for the development of an advanced cognitive software solution. As a digital enabler, it is an Open-Source solution which is applicable to wide range of use cases, supporting at the same time, a large variety of applications. The design becomes ever harder in the real industrial environment, for this reason, it was done thanks to an iterative process started in the report called D2.1, (Project Deliverables — Capri, 2022), where as a first step, there were a phase of functional and non-functional requirements collection followed by a continuous validations from the pilots. The selected Reference Architecture underlines the concept of edge and cloud cognitive computing with the aim of solving business challenges, creating new value from data and improving the product quality.

The CAP Reference Architecture in CAPRI project is designed with many horizontal layers able to guarantee the interoperability, privacy, protection and data sovereignty. In Figure 5 the core of the architecture is depicted, since it contains the brokering, the storage and the data processing capabilities, including also cognitive process analytics and simulation systems. Data in Motion, Data at Rest and Situational Data are represented using standard information models and made available using standard APIs, (Salis, Marguglio, De Luca, Gusmeroli, & Razzetti, 2022). The sensor layer and the control layer use open-source technologies from Apache (Livy, Spark, StreamPipes, Kafka) and FIWARE (Draco, Cosmos, Orion Context Broker, OPC UA Agent) foundations, (FIWARE - Open APIs for Open Minds, 2022).

4.2 CAP Asphalt Use Case

The platform developed for the Asphalt domain is comprised of the following modules:

Based on previous FIWARE Reference Architecture, following the previous considerations, the asphalt domain platform has been implemented in a Linux Ubuntu distribution based server where the different modules communicate and interact among each other but deployed using the Docker platform (Docker, 2022). The basic structure of this architecture can be seen on Figure 9.

From the Asphalt Plant, real time data (with sample times from 1 or 5 seconds, depending on the data source) is received from a WAGO PLC datalogger using MQTT protocol. This real time data consists of production, event per batch of asphalt mix and IoT data coming from other process sensors not used for production control (e.g. weather station data). In the asphalt domain CAP platform, a mosquitto-based broker (Eclipse Mosquitto, 2022) receives those data and it is redirected through an IoT Agent for JSON (a bridge between HTTP/MQTT messaging (with a JSON payload) and NGSIv2). This IoT Agent has been customized to meet the asphalt domain requirements of data flow. This IoT Agent communicates and send the corresponding data to the Orion Context Broker module (Generic Enabler that provides the FIWARE NGSI v2 API, a Restful API enabling to perform updates, queries, or subscribe to changes on context information). This Broker is the core of the whole FIWARE-based Reference Architecture implemented in the Asphalt domain, (FIWARE - Open APIs for Open Minds, 2022).

From this broker, a Draco (Fiware-Draco, 2022) module has been set up, which is a Generic Enabler that is a data persistence mechanism for managing the history of context. It is based on Apache NiFi and is a dataflow system based on the concepts of flow-based programming. In this case, it manages the data coming through the Orion Context Broker and sends them to a MySQL database which is used for data persistence within the CAP platform.

4.2.1 CAC1 Integration in CAP

CAC1 algorithm reads data coming from the plant directly from the MySQL database, reading the last data set received from the asphalt plant. The calculated outputs are then sent to the Orion Context Broker through a MATLAB S-function used at the Simulink environment.

It is used a library function that, through https, make a POST request to update the corresponding entity via curl.

From this point and through the Broker, using the Draco module, calculated outputs are written to the *CAC_Outputs* table of the database.

From here, the corresponding visualization module is used for the outputs to be shown at the actual asphalt plant which is accessed through a web interface (Figure 9).

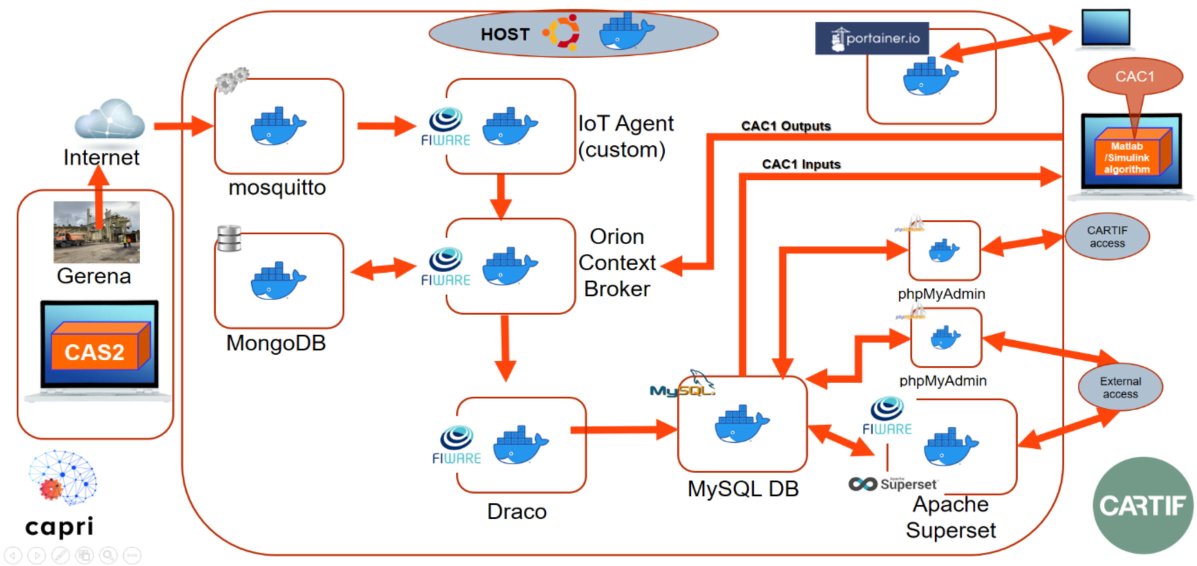

Figure 9: CAC1 & CAS2 Integration in CAP Asphalt Use Case Platform.

The Visualization Module, based on Apache Superset, is connected to the CAC1_Outputs table stored in the used MySQL database, and the corresponding burner power of the dryer drum and the rotary speed are plotted on a time-series chart alongside two numeric fields showing the last current value.

It can be then accessed through a web-based interface for the plant operators to see CAC1 output data.

At this step, it is the plant managers/operators responsibility to apply the displayed value or ignore it based on their experience

4.2.2 CAS2 Integration

In the Asphalt domain, all output dataset coming from CAS2 solution is sent using the MQTT protocol and received at the previous CAP platform. This data is stored in MySQL database with the structure shown on Figure 9. The data is then stored in a table called *CAS2* with fields with self-explanatory names.

To make the measurements of CAS2 sensor available for the process it is needed to store and integrate the outputs of the sensor appropriately. The file available at (Vega, Reñones, & Sanz, Cognitive sensor for amount of filler [CAS2] - INTEGRATED, 2022), **CAS2_sourcecode_2.sql** contains the source code which shows how to integrate the sensor measurement into project's CAP (cognitive automation platform). The calculations directly populate the CAS2 solution data persistence storage at the MySQL database. The code uses a trigger database, which is a procedural code that it is automatically executed in response to certain events on a particular table or view in a database.

In the case of CAS2, each time a new MQTT output is sent to the CAP together with the pressure measured, the trigger function 'processStreamCAS2' is fired and it applies the model estimated (section 3.4) and populates the CAS2 table.

The objective is that once all the asphalt CAPRI solutions are running the results will be available for different purposes like showing them on an interface available to the plant operator or making them available to other CS's for further processing. Providing continuous decision support, the plant operator will not need to actively engage with the CS. The warnings or alerts that have to be displayed on the screen will be to increase or decrease the depressure of the baghouse, to work with the best magnitude of depressure, whose final objective is to extract only the filler extracted not necessary and to lose as less energy as possible. Before the deployment of this CS, plant operator extracts nearly all the filler after the process of drying in the drum, and the necessary filler for the recipe of asphalt in the mixer is added afterwards. This added filler is cold and leads to an unavoidable loss of energy and raw materials.

CAS2 Visualization Module, based on Apache Superset, is connected to the mentioned *CAS2* table stored in the MySQL database and then, through a web-based interface, shown for the plant operators to see CAS2 information.

5 CONCLUSIONS

H2020 CAPRI project develops and promotes digital transformation through a CAP involving a Reference Architecture (mainly based on the FIWARE framework) with four levels of cognitive human-machine interactions and a set of reference implementations both commercial and open source. This CAP coordinates a set of specific CS's at the various levels of functional organization of the automation (from planning to sensors).

The asphalt domain shows as one of the main process industry sectors where the CAP provides flexibility of operation, improvement of performance across different indicators (KPIs) and state of the art quality control of its products and intermediate flows.

The CAP architecture and their different modules have been presented in this domain and two of the CS's, CAS2, Sensors Layer Implementation and CAC1, Control Layer Implementation, which are under refinement, have been explained.

The open source architecture proposed based on FIWARE represents a comprehensive and useful platform to facilitate the integration of different components that needs to interact with data coming in real time from MQTT streams and needs to show their results through an easy to sue webpage.

From here, next steps involve the final integration of the rest of the "layers" of the reference architecture and the final validation to be developed at last project stages, addressing manufacturing challenges in industrial operational environments of the three chosen process sectors, and providing useful feedbacks and lessons learnt.

Different KPI's will be calculated and deployed to see if initial target objectives are met with an evaluation period (6-month minimum) of the performance improvements thanks to the different implemented CS's. This will provide effective stories for replication purposes and dissemination. It is expected that results like the reference architecture will be replicated in other sectors with similar challenges from the point of view of CS's applied to similar unitary processes.

ACKNOWLEDGEMENTS

CAPRI project receives funding in the European Commission's Horizon 2020 Research Programme under Grant Agreement Number 870062.

The authors would like to thank their colleagues from EIFFAGE, ENGINEERING, NISSATECH and CARTIF partners of the project for contributing with some of the examples shown in the paper.

REFERENCES

Abburu, S., Berre, A., Jacoby, M., Roman, D., Stojanovic, L., & Stojanovic, N. (2020, 4). Cognitive Digital Twins for the Process Industry. 68-73.

Abburu, S., Berre, A., Jacoby, M., Roman, D., Stojanovic, L., & Stojanovic, N. (2020, 6). COGNITWIN - Hybrid and Cognitive Digital Twins for the Process Industry. *Proceedings - 2020 IEEE International Conference on Engineering, Technology and Innovation, ICE/ITMC 2020*.

Andersson, T. (2010). *Estimating particle size distributions based on machine vision.* Lulea, Sweden: Universitetstryckeriet.

Auditors, E. (2021). *Digitising European Industry : an ambitious initiative whose success depends on the continued commitment of the EU, governments and businesses. Special report No 19, 2020.* Publications Office.

Cinar, Z., Nuhu, A., Zeeshan, Q., & Korhan, O. (2020). Digital Twins for Industry 4.0: A Review. 193-203.

Consortium, C. (2022, 7 29). *Cognitive Automation Platform for European PRocess Industry digital transformation*. Retrieved from Cognitive Automation Platform for European PRocess Industry digital transformation: https://www.capri-project.com/

Docker. (2022, 07 28). Retrieved from https://www.docker.com/

Eclipse Mosquitto. (2022, 07 28). Retrieved from https://mosquitto.org/

Eirinakis, P., Lounis, S., Plitsos, S., Arampatzis, G., Kalaboukas, K., Kenda, K., Stojanovic, N. (2022, 1). Cognitive Digital Twins for Resilience in Production: A Conceptual Framework. *Information*, *13*(1), 33. Retrieved from https://www.mdpi.com/2078-2489/13/1/33

El-Haggar, S. (2007). Sustainability of Industrial Waste Management. Elsevier.

ElMaraghy, H., & ElMaraghy, W. (2022, 5). Adaptive Cognitive Manufacturing System (ACMS) – a new paradigm. *International Journal of Production Research*, 1-14.

Essa, E., Hossain, M., Tolba, A., Raafat, H., Elmogy, S., & Muahmmad, G. (2020, 5). Toward cognitive support for automated defect detection. *Neural Computing and Applications, 32*(9), 4325-4333.

Fernández, R., Viennet, E., Goles, E., Barrientos, R., & Telias, M. (1998, 1). On-Line Coarse Ore Granulometric Analyzer Using Neural Networks. *Industrial Applications of Neural Networks*, 59-67.

FIWARE - Open APIs for Open Minds. (2022, 07 22). Retrieved from https://www.fiware.org/

Fiware-Draco. (2022, 07 28). Retrieved from https://fiware-draco.readthedocs.io/en/latest/

Gómez, D., & Diego, M. (2022, 7 20). *Cognitive control of Asphalt Drum [CAC1] - integrated.* doi:https://zenodo.org/record/6867477

Haber, R., Juanes, C., Del Toro, R., & Beruvides, G. (2015, 5). Artificial cognitive control with self-x capabilities: A case study of a micro-manufacturing process. *Computers in Industry, 74*, 135-150.

Jacoby, M., Jovicic, B., Stojanovic, L., & Stojanović, N. (2021, 5). An Approach for Realizing Hybrid Digital Twins Using Asset Administration Shells and Apache StreamPipes. *Information, 12*(6), 217. Retrieved from https://www.mdpi.com/2078-2489/12/6/217

Kaur, N., & Sood, S. (2015, 12). Cognitive decision making in smart industry. *Computers in Industry, 74*, 151-161.

Koskinen, J. (1998). Fuzzy modelling of a pilot plant rotary dryer. *UKACC International Conference on Control (CONTROL '98)*, 515-518.

Le Guen, L., Huchet, F., & Tamagny, P. (2011, 6). Drying and Heating Modelling of Granular Flow : Application to the Mix-Asphalt Processes. *Journal of Applied Fluid Mechanics, 4*(2), pp 71-80. Retrieved from https://hal.archives-ouvertes.fr/hal-00612503

Li, M.-L., Yao, Y.-Y., & Zhao, H.-X. (2017). Numerical Analysis of Solid Materials Transport in a Rotary Dryer. *Proceedings of the 3rd Annual International Conference on Mechanics and Mechanical Engineering (MME 2016)*.

Ljung, L. (1998). *System Identification*. Retrieved from http://link.springer.com/10.1007/978-1-4612-1768-8_11

Mahmoud, K., El-Kasassy, M., & Areed, F. (2020, 11). Variable Structure Controller for a Rotary Dryer (Dept.E). *MEJ. Mansoura Engineering Journal, 36*(2), 13-21.

Measuring Coal Particles in the Pipe. (2022, 07 21). Retrieved from https://www.power-eng.com/emissions/measuring-coal-particles-in-the-pipe/

Oliveira, J., Van Der Geld, C., & Kuerten, J. (2017, 7). Concentration and velocity statistics of inertial particles in upward and downward pipe flow. *Journal of Fluid Mechanics, 822*, 640-663.

Pang, S., Jia, J., Ding, X., Yu, S., & Liu, Y. (2021, 9). Intelligent Control in the Application of a Rotary Dryer for Reduction in the Over-Drying of Cut Tobacco. *Applied Sciences, 11*(17), 8205.

Project Deliverables — Capri. (2022, 07 19). Retrieved from https://www.capri-project.com/project-deliverables

Raghavan, V., Jumah, R., & Mujumdar, A. (2006, 11). Control of Industrial Dryers. *Handbook of Industrial Drying, Third Edition*.

Rožanec, J., Lu, J., Rupnik, J., Škrjanc, M., Mladenić, D., Fortuna, B., Kiritsis, D. (2021, 3). Actionable Cognitive Twins for Decision Making in Manufacturing. Retrieved from http://arxiv.org/abs/2103.12854

Rubio, F., Bordons, C., Holgado, J., & Rivas, I. (2001, 4). Modelling and H∞ control of a rotary dryer. *2001 European Control Conference, ECC 2001, 33*(4), 733-738.

Salis, A., Marguglio, A., De Luca, G., Gusmeroli, S., & Razzetti, S. (2022, 2). *An Edge-Cloud based Reference Architecture to support cognitive solutions in the Process Industry*.

Sánchez Boza, A., Guerra, R., & Gajate, A. (2011, 3). Artificial cognitive control system based on the shared circuits model of sociocognitive capacities. A first approach. *Engineering Applications of Artificial Intelligence, 24*(2), 209-219.

Schwenzer, M., Ay, M., Bergs, T., & Abel, D. (2021, 11). *Review on model predictive control: an engineering perspective*.

Sharma, A., Kosasih, E., Zhang, J., Brintrup, A., & Calinescu, A. (2020, 11). Digital Twins: State of the Art Theory and Practice, Challenges, and Open Research Questions. Retrieved from http://arxiv.org/abs/2011.02833

Singh, R., Lye, S., & Miao, J. (2019, 8). PVDF Nanofiber Sensor for Vibration Measurement in a String. *Sensors, 19*(17), 3739. Retrieved from https://www.mdpi.com/1424-8220/19/17/3739

Sivilevičius, H., & Šukevičius, Š. (2009, 6). *Manufacturing technologies and dynamics of hot-mix asphalt mixture production*.

Suppan, T., Neumayer, M., Bretterklieber, T., Puttinger, S., & Wegleiter, H. (2022, 1). A Model-Based Analysis of Capacitive Flow Metering for Pneumatic Conveying Systems: A Comparison between Calibration-Based and Tomographic Approaches. *Sensors, 22*(3), 856. Retrieved from https://www.mdpi.com/1424-8220/22/3/856

Vega, C., & Reñones, A. (2022, 3 18). *Cognitive sensor for amount of filler.* doi:https://doi.org/10.5281/zenodo.6367575

Vega, C., Reñones, A., & Sanz, L. (2022, 7 28). *Cognitive sensor for amount of filler [CAS2] - INTEGRATED*. Retrieved from https://zenodo.org/record/6922993

Wagner, S., Milde, M., Barhebwa-Mushamuka, F., & Reinhart, G. (2022). Digital Twin Design in Production. *Lecture Notes in Mechanical Engineering*, 339-346.

Yliniemi, L., Koskinen, J., & Leiviskä, K. (1998, 9). Advanced Control of a Rotary Dryer. *IFAC Proceedings Volumes, 31*(23), 119-124.

Zaeh, M., Beetz, M., Shea, K., Reinhart, G., Bender, K., Lau, C., . . . Herle, S. (2008, 11). *The Cognitive Factory*.

Zhang, K., Huchet, F., & Hobbs, A. (2019, 5). A review of thermal processes in the production and their influences on performance of asphalt mixtures with reclaimed asphalt pavement (RAP). *Construction and Building Materials, 206*, 609-619.