Cognitive plants through proactive self-learning hybrid digital twins

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Deliverable Report

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Executive Summary

This document is a deliverable "D2.1: A report on existing level of digitalization and describing challenges for Steel pilots, incl. identification of novel sensors" of the project COGNITWIN. This report is the result of the first stage (M1-M6) of the project development. This document describes the following characteristics of each pilot site:

- Description of the pilot cases and their specific challenges
- Planned innovations to be implemented
- Definition of the existing level of digitalization and platforms in use
- Current data available and current data analytics tools in use
- Measurable KPIs and targets

Saarstahl AG Pilot: The initial situation in the Nauweiler rolling mill was assessed and two main points for action were identified: **improving the billet identification upon entrance into the mill train and enable seamless tracking of billets in the blooming train**. The first point is tackled by installing an improved billet identification system and the latter is to be solved by setting up a computer vision tracking system for which the cameras have been installed. The overall goals of SAG's COGNITWIN approach are to improve rolling line efficiency by 15%, reduce energy consumption and process emissions by 15 % and to set up an automatic error detection.

SIDENOR Pilot: The Cognitive Digital Twin will help to reduce refractory wear and increase operational ladle lifetime. The goal is to increase ladle refractory lifetime to 80 heats for full relining and 40 heats to partial relining. As part of this the ambition is to reduce the critical refractory depth for renewing the refractory lining.

During the first 6M of the project, initial industrial starting point for ladles information has been assessed in SIDENOR. The relevant process data and type of available measurement of the ladle profiles were also established considering the requirements of the rest of the partners for the tasks to be developed. The definition of the data requirements has been started and first data set has been provided to the technological partners.

NOKSEL Pilot: NOKSEL's current (as-is) Spiral Welding Pipe (SWP) production system was analyzed, the purpose of the planned cognitive digital twin regarding **predictive maintenance for the SWP** was described, and the targeted KPIs related to the COGNITWIN project were identified. With the COGNITWIN SWP System, the main targets are to achieve:

- 10% reduction in energy consumption, and
- 10% reduction in shifted average duration of downtimes.

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Acronyms

SAG – Saarstahl AG

SIDENOR – SIDENOR Aceros Especiales S.L.

NOKSEL-Noksel Celik Boru Sanayi A.S.

1 Introduction

In the COGNITWIN project, three different pilots in steel production will be implemented. Each pilot covers a particular segment of a multi-billion euros industry and has its own specific challenges that need to be fully understood in order to develop techniques and methods to overcome them. The main objective of the first phase of the project (M1-M6) is to establish the basis of the co-innovation procedure in which industrial partners, technology providers and research organisation of the COGNITWIN consortium will cooperate. The partners need to develop full understanding of the cases, align expectation and map the resources available within the consortium. This document summarises this work.

By this work, realistic objectives and performance goals for each of the pilots' digital twins have been clearly identified. The detailed current status on sensors already in operation have been mapped out. In addition, the state of the models used, input and output data, their accuracy, speed and level of detailing, are clarified up to the limit of the confidentiality of prior backgrounds (IPR) is not compromised. When it comes to exchange of data and interoperability this will be worked on in collaboration with WP4 and provided in D4.1. In addition, a list of sensors, that have not been in use in the pilots but which the project team assessed the benefit, is made.

A work in assessing the different types of information that is available by each pilot is made (data, including assessment of data quality, numerical models, and existing data-based models). Based on these assessments, a detailed work plan will be developed for a successful implementation of the next phases of the project.

This document is composed of three main chapters. Each chapter presents one of the pilot cases. In each chapter, the following template has been followed:

- Process description
- Current challenges
- Pilot specific aim
- Innovation
- IoT platform and architecture in use
- Current data analytical models in use
- Description of Data available
- Measurable KPIs and Final impact

In the steel production process, from pig iron to rolled bars or wire rod, a multitude of sensorial and relational data from various sources arises. In order to generate additional value from this, a linkage between data from different sources is needed, but due to the typically harsh conditions in a steel production plant, technologies such as RFID sensors are often unsuitable for this task.
A computer vision based system can provide a robust alternative as cameras can often be placed at a certain distance from the target to be observed, shielding them from the gravest impact of the harsh environment.

The steel industry is a key driver of new developments in the refractory industry due to the high market share of steel refractories in the range of 60 to 70% and the harsh conditions for refractories in the steel making processes. In fact, the annual refractory consumption in a steel plant that produces more than 750.000 ton of steel per year, can reach around 10.000 ton.

Ladle refractory is a key factor in secondary metallurgy management for all steelworks despite particular differences due to process, installations or product conditions. It has clear economic implications but also affects quality, productivity and safety of the steelmaking installations and people involved. At the same time, the spent ladle bricks are generally sent to the landfill generating an additional cost and a waste of historically considered critical materials like Magnesite. From the refractory utilised in the steel industry, a 49% is dissolved in the process and 36% ends in a landfill.

Spiral Pipe Manufacturing industries has promising features for market uptake of digital technologies and provide a convenient infrastructure for ground-breaking innovations as it is immature yet. Condition monitoring market is expected to witness high growth value like 2.21 billion USD in 2017 and expected to reach 3.50 billion USD by 2024. Digital twin is gaining attraction and digital twin related sales are foreseen to reach about 18.29 billion USD in 2024.
It is estimated that machine downtime costs UK manufacturers £180bn every year. The research by Oneserve, found that ”... Each time the machine breaks down, it takes on average, 9 hours to fix. But some report having to wait 72 hours for a resolution, taking an enormous hit on the production schedule and decreasing productivity.... “. In another words; broken machinery and faulty parts are hampering productivity, equivalent to almost 3% of all working days. Therefore; by reducing maintenance costs in manufacturing environment will result to both efficiency increases in steel pipe production, decrease in maintenance cost and save energy more.

2 Saarstahl AG – Pilot

2.1 Introduction to Saarstahl & Process description

The Saarstahl AG - with its locations in Völklingen, Burbach and Neunkirchen along with Roheisengesellschaft Saar in Dillingen (Saarstahl and Dillinger Hütte each with 50%) - is a German steel manufacturing company with a global presence on the steel production market. Saarstahl AG specializes in the production of wire rod, hot rolled bars and semi-finished products of various sophisticated grades. These products are important preliminary products for the automotive industry and its suppliers, general mechanical engineering, oil and gas industry, the mining industry and other steel processing branches. The primary goal of the SAG use-case is to track individual billets in the Nauweiler rolling mill train, thus providing a linkage between various sensor data as well as other relational data on individual billets collected before and after the non-continuous part of the mill train.
Schematic overview of the Nauweiler rolling mill:

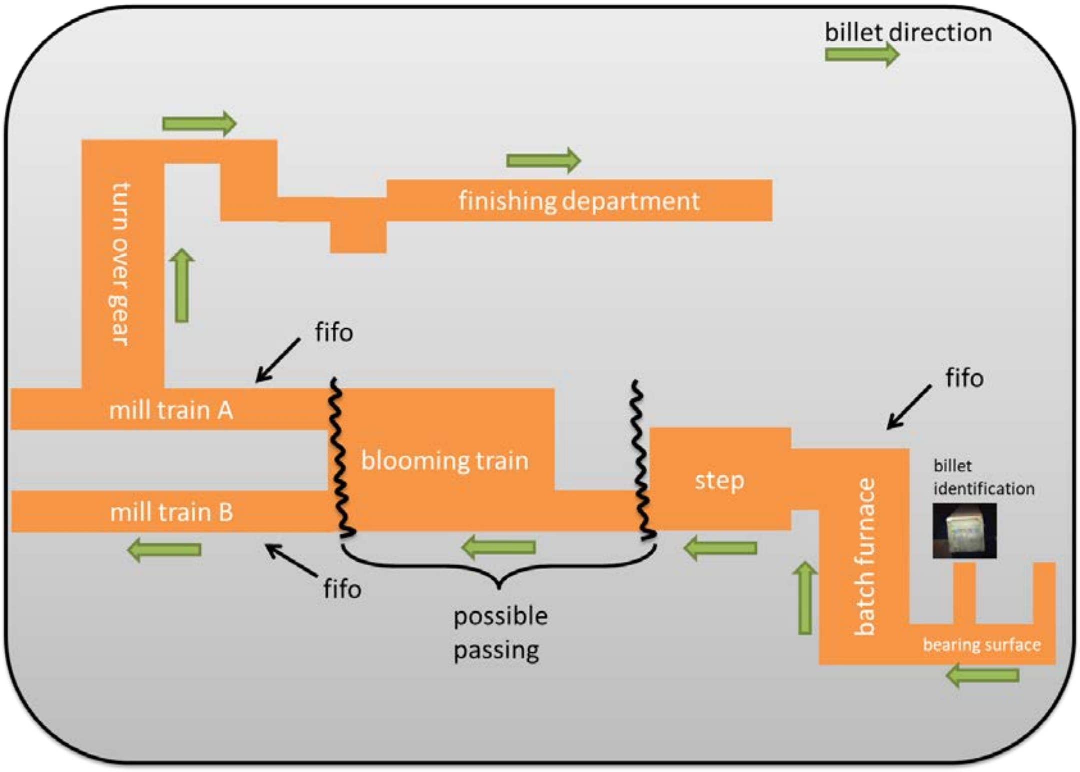


Figure 1: Schematic overview of the Nauweiler rolling mill

The cold steel billets coming from the steel mill have an ID stamped on to them. When a steel billet enters the Nauweiler rolling mill train, this ID is automatically read before the billet enters the oven to be heated for rolling. Upon leaving the oven, the heated billet enters the first sequential rolling stands in the step. After that, the roll strand enters the blooming train, a non-continuous part of the mill train, where it moves back and forth, repeatedly passing through several rolling stands. Here rolled bars can overtake one another, or a bar can receive a too severe bend to be rolled further and needs to be put aside and removed from the mill train area after cooling down. Operators will occasionally enter the area while the mill train is active, introducing the need for an automatic anonymization of employees/people in the video stream. This non-continuous part of the mill train is where a computer vision tracking system is to be installed. The pace with which the roll strand moves back and forth through this section is moderate; not more than 20 km/h. After this non-continuous part, the roll strand enters another continuous part of the mill train where rolling is completed.

2.2 Current challenges

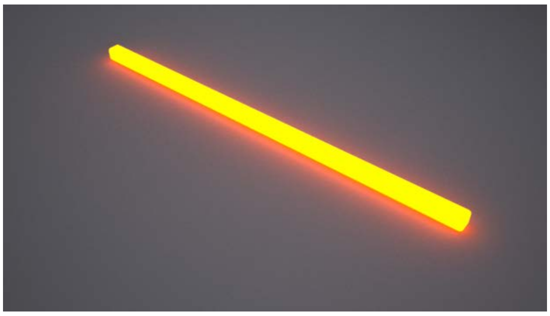
The mill train is not continuous, such that rolled bars might overtake one another at certain points.

- Rolled bars are not distinguishable by their appearance and can only be uniquely identified by tracking them seamlessly throughout the process. The tracking system cannot be implemented through conventional means such as RFID, other sensors or thermal cameras due to the harshness of the environment and manual operation of some appliances, rolled bars possibly lying in very close proximity to one another and erroneous bars occasionally being left to cool down in the area. Marking the bars themselves could damage the corresponding part of the bar.

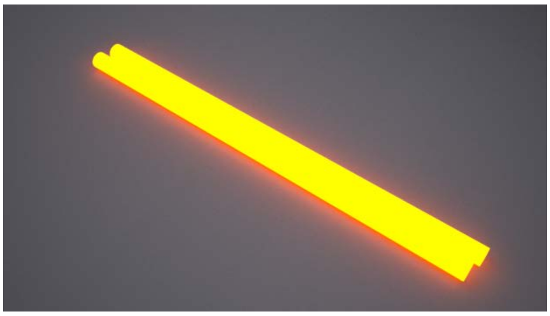
- To deal with legal issues as well as issues with the work council arising from the installation of cameras also capturing employees, a system for automatic anonymization of people appearing in the video stream is required.
- Training data for the tracking system will need to be generated synthetically as certain constellations, in particular erroneous bars, occur to seldom to obtain sufficient real life training data.

Examples for synthetic billet representations (courtesy of Maria Luschkova, DFKI):

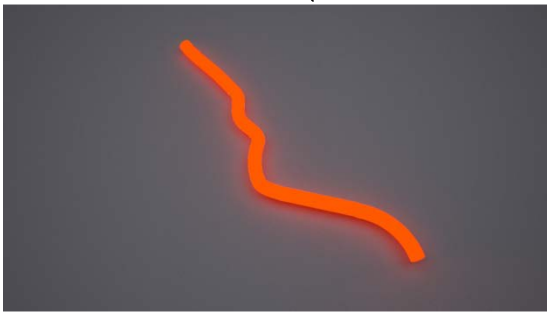
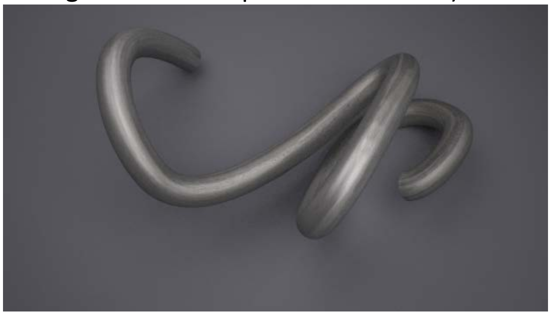
- Different temperatures




- Billets in close proximity



- Erroneous billets (bent or too cold for further rolling due to some process deviation)


2.3 Pilot specific aim

The objective of the SAG use case is to track individual billets in the Nauweiler rolling mill train and thus to be able to associate sensor and other data collected throughout the rolling process to the corresponding billet. Combining the data from the rolling mill associated to the billet with data collected beforehand at the steel mill will allow SAG to extend the digital twin of the billet to span the entire production process and enable the twin to acquire cognitive elements. The digital resp. cognitive twin in return can then be used e.g. to optimize production processes, recognize causes for deviations and, depending on the specific situation, react in real time to prevent deviations from occurring. Another benefit of the envisaged computer vision tracking system will be to detect deviations and erroneous billets.

When the computer vision tracking system is trained, an intuitive interface for the operator will need to be provided. The interface should identify the individual billets in the blooming train, thereby providing an intuitive means for supervising model performance and warn the operator when a high risk of a potential defect in the rolling process is detected. Ideally, the interface should also provide any additional information the operator might require. The possible content of such additional information will have to be determined in close collaboration with the responsible engineers and operators. Moreover, a possible automatization of the entire blooming train will need to be evaluated once the computer vision tracking system has been integrated into the process and proven its performance. However, this will most likely extend the scope of the COGNITWIN project.
As a first step to attain this goal, the status quo concerning trackability of billets in Nauweiler was determined and necessary improvements/required additional sensors were identified.

Two main points for action were identified

- old billet identification system -> closed proprietary system, performance good but not perfect, and improvement only possible by manufacturer, hardware in use was reaching end of estimated lifetime. When automatic identification fails at present, the ID has to be entered into the system manually.
- blooming train -> billets presently cannot be tracked in blooming train. Due to harshness of environment, rolled bars possibly lying in very close proximity, erroneous bars cooling down in the area and manual operation of some appliances, conventional means such as RFID or other sensors or thermal cameras are not suitable for tracking.

2.4 Innovation

Added sensors:

- improved billet identification upon entrance into mill train: in-house development -> can be adapted and improved in-house if needed, without relying on third parties, hardware can easily be replaced if necessary, full integration into IT infrastructure facilitated by system being in-house development. A prototype is running in parallel to the old system since December 2019.

Figure 2: The billet identification system

- 3 Full HD cameras in blooming train: the situation in the blooming train was analyzed together with local engineers to determine optimal placement of cameras and specify camera requirements, also taking network installation requirements into account. The camera data is to be used as input for a Computer Vision tracking system based on deep learning. The tracking system cannot be implemented through conventional means such as RFID or other sensors or thermal cameras due to harshness of environment and manual operation of some appliances, rolled bars possibly lying in very close proximity to one another and erroneous bars occasionally being left to cool down in the area.

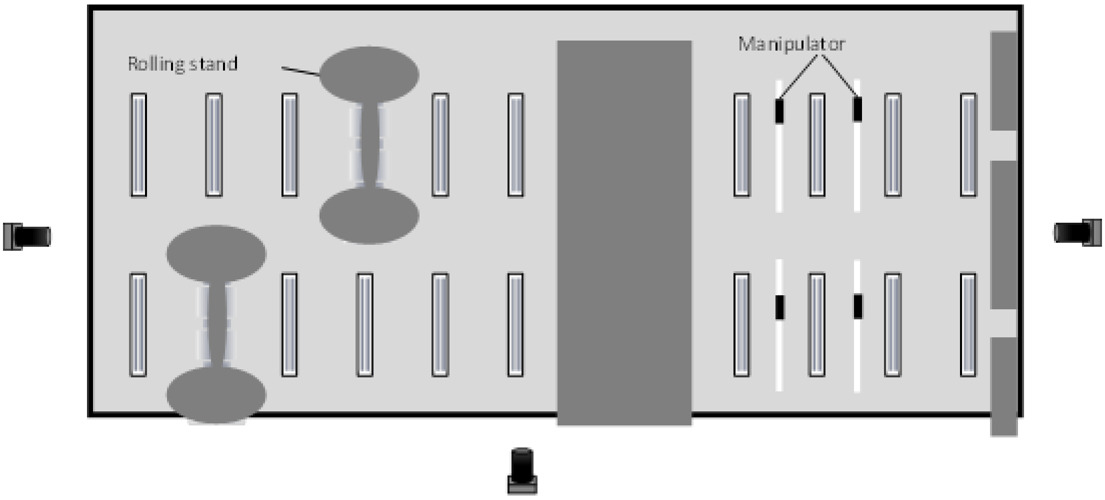


Figure 3: Schematic overview of the blooming train with newly installed cameras

When running in production, the computer vision tracking system will need to process input from 3 Full HD cameras in real time; the number of frames per second required will need to be determined in the process of model evolution. Camera input should be via a to be defined protocol.

The model should be based on Keras/Tensorflow and code in Python to allow for convenient further in-house development or retraining if necessary and seamless integration into existing infrastructure. Moreover, the model should be containerized. It should be possible to run the model in an independent and isolated environment [Docker or Podman].
The output of the tracking system should be location and state of billet with timestamp upon entering and leaving blooming train/in blooming train in fixed time intervals [erroneous billet leaving blooming train to the side rather than entering further rolling process] and be provided by a defined interface. The model/container must be reached by an asynchronous queue or a synchronal REST interface. Operator interface/visualization should be web based [graphic/schematic overview of blooming train with depiction of billets], communicating with model via defined interface.

The toolbox should offer an automatic anonymization of people. Operators will occasionally enter the area while the mill train is active, introducing the need for an automatic anonymization of people in the live and recorded video stream. The anonymizer should obscure employees with workwear and helmets.

Code needs to be accessible and documented to allow for further in-house development.

Ideally, the code and necessary process steps for generating training data and training the model should be adaptable for other situations where object tracking might be desirable.

2.5 IoT platform and architecture in use

The rolling mill in Nauweiler is controlled by SAG's Manufacturing Execution System and SAG's Material flow tracking system. These applications flexibly exchange data (sensor and controlling data) to due interoperable data models between the assets and the high level software systems.
Standards in use: OPC Unified Architecture, Enterprise Service Bus (Kafka or RabbitMQ), REST-Service
Components/services within the platform: MES (Manufacturing Execution System; in-house development), MFT (Material Flow Tracking; in-house development), Interfaces (REST or Message queue).

2.6 Current data analytical models in use

At present, there is no tracking system in the blooming train.

2.7 Description of Data available

The data provided for the tracking system will be a video stream stemming from 3 Full HD Cameras and possibly some additional video or image data.
For training purposes, recorded video files will be provided in addition to the synthetic training data.

2.8 Measurable KPIs and Final impact

- Improve rolling line efficiency by 15%

  By identifying and reacting to situations likely to cause erroneous bars, the rolling line efficiency is improved already. Additionally providing a linkage in data associated to individual billets throughout the production process will allow SAG to use advanced analytics to identify other causes for deviations in the production process and react to these by e.g. adapting rolling parameters for individual billets. Moreover, the final version of the tracking system should allow for further automatization of the rolling process in the blooming train altogether [although this will most likely exceed the scope of COGNITWIN project].

- Reduce energy consumption (15%) and process emissions (15%)

  Each occurrence of an erroneous bar means a new billet needs to be cast and rolled, leading to additional energy consumption and process emissions. Moreover, the return transport to the steel mill for remelting has further impact on process emissions. Thus by identifying and reacting to situations likely to cause erroneous bars, this additional impact can be reduced. Moreover, providing a linkage between data associated to individual billets over the entire process will allow SAG to use advanced analytics to identify other causes for deviations in the production process and react to these to reduce the level of scrap from the production goods even further [i.e. the level of billets/rolled bars with too severe deviations to be sold to the costumer that are remelted].
- Automatic error detection

  At present, there is no automatic detection of situations in process that will likely lead to e.g. bent bars or of erroneous bars in assigned section. Erroneous bars are identified manually. The target is to identify over 95% of erroneous bars automatically and to identify over 90% of situations likely leading to erroneous bars automatically. As to the tracking: At present, around 95% percent of all billets enter and leave the mill train sequentially, however, since there is no tracking system installed so far, it is not possible to safely link the sensor data obtained in and after the mill train to data associated to a particular billet ID obtained earlier in the production process. The goal is to track at least 98% of all billets successfully throughout the mill train and recognize when tracking failed such that at most for the two billets in the non-continuous mill train section at that time data from later in the process cannot safely be linked to one of the two respective billet IDs, only to the two IDs together/two-ID-tuple.

3 SIDENOR – Pilot

3.1 Introduction to SIDENOR & Process description

SIDENOR is one of Europe's leading steel manufacturers and has operations in several countries and having their steel production unit in Bilbao, Spain. The primary business area of SIDENOR is to recycle scrap steel and develop them into one of several hundred steel grades they can manufacture in their production facility, depending upon their customer specifications and requirements. Their production process is a three-step process that starts at the Electric furnace followed by secondary metallurgical processes and finally casting. Each of these steps are described briefly below and, in the schematic, shown in Figure 4.

1. Electric furnace: Scrap steel is melted in electric arc furnaces, then the molten steel is tapped into one of the 10 ladles they have.

2. Secondary metallurgy: The tapped steel is then transferred to stations where melt refining and alloying is done to produce different grades of steel based on their customer requirements/specifications. It involves processes such as de-oxidising, de-gassing, de-sulphurisation, alloying in tight specification ranges, improvement of steel cleanliness by separation or modification of non-metallic inclusions, and homogenisation of composition and temperature.
3. Continuous casting: After customer specifications of the steel is met with, the melt is then poured into a continuous casting steel tundish and after cast in billet or bloom formats.

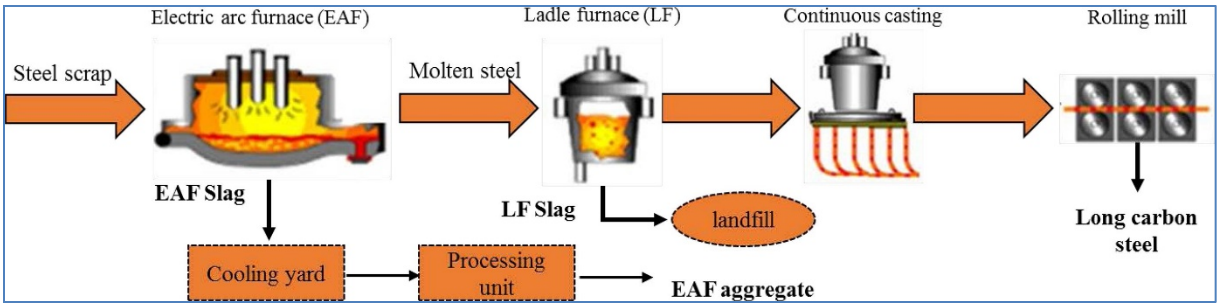


Figure 4: Steelmaking process in SIDENOR's steel production plant at Bilbao, Spain.

Along all the secondary metallurgy process the liquid steel is handled in the ladle that is also the vessel from which the steel is fed to the continuous casting machine. Thereby the ladle is highly important, and key from different points of view:

- Safety
- Quality
- Energy efficiency

Ladle refractory wear problem is the combined effect of thermo-physical-chemical processes activated by working conditions. The understanding of the whole process requires splitting the different stages:

Tapping → Liquid Steel → Casting → Cooling and Burner Heating

These steps are repeated for each heat although the numeric aspects may vary greatly as the times of the processes for the ladles are not necessarily regular; ladle operations are usually affected by any operational incidence or even decision in the steelmaking shop. The extent of refractory degradation during ladle operations depend on physical-chemical conditions imposed by the process, and by mineralogical, micro chemical and technological characteristics of the refractory.

3.2 Current challenges

In the COGNITWIN project, the main focus for SIDENOR is on the refractory linings of the ladle. The ladle is composed of different refractory layers and different working refractories suffering those wears in a different way. Secondary metallurgy can only be performed with high performance refractory linings in the steel ladle. Engineered refractories in steel ladle lining provide technical and economical solutions for challenging conditions.
Mentioned aspects depend on the ladle lining configuration. At SIDENOR, ladles are composed of different refractory layers which get wear in a different way.

Figure 5: Ladle with freshly layed bricklining.

Refractories for steel ladle side walls must withstand slag attack by aggressive, metallurgical reactive slag. In addition, the refractory lining must be thermodynamically stable in contact with steel in order to avoid re-oxidation of the steel and problems with cleanliness. The ladle refractory lining profile consists of MgO-C bricks at the hot face (wear lining) and high Alumina or burned Magnesia bricks behind (permanent or safety lining). Whilst the wear lining is replaced after each cycle, the permanent lining remains one year. There is an insulation layer between the steel shell and the permanent lining. Also, between the permanent and the wear lining, a back-filler material is allocated to compensate the thermal expansion of the wear lining bricks. The expansion joint between the wall lining and the upper lip ring is filled with gunning mix to lock the lining into the steel shell.

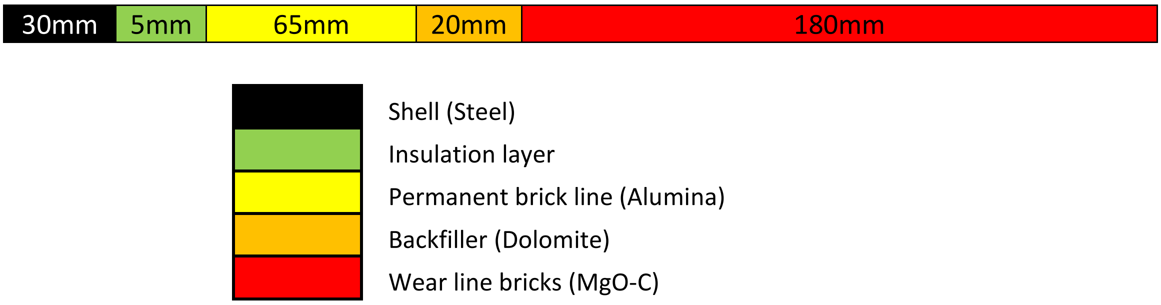


Figure 6: Ladle lining profile: The structure of the ladle wall.

The ladle can be divided in different zones depending on the refractory configuration or process requirements. At first, several zones can also be distinguished at different heights of the ladle: barrel, transition and slag line. Different kind of MgO-C bricks are used depending on their position in the ladle.

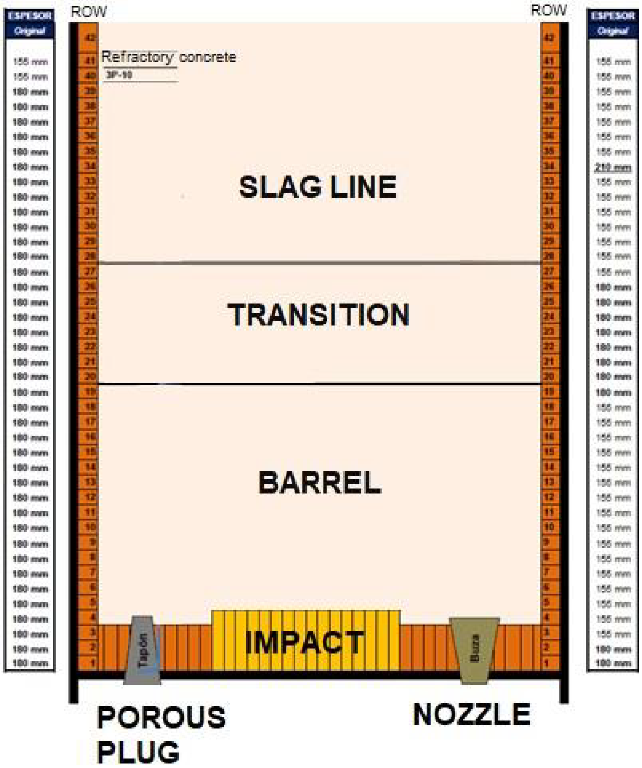


Figure 7: The three zones in the ladle - slag line, transition and barrel. Porous plug is inlet for inert gas and the nozzle is to tap the molten steel.

From quality point of view, the focus is on the working or wear refractory. The refractory grade (MgO content, kind of binder used, binding procedure etc.) is highly important but also this material maintenance. One of the indexes that link both concepts is the wearing of the refractory, caused by chemical (corrosion because the continuous contact with slag and in a lower extent corrosion because the contact with molten steel) and mechanical (the steel is stirred in the ladle by gas injection through the porous plug in the bottom; the steel in movement also contributes to refractory wearing) phenomena.

With regard safety, refractory plays important role since it is avoiding the liquid steel to get in direct contact with the metallic shell of the ladle. In principle working refractory layer should be enough to hinder this contact, but as mentioned, the working refractory gets worn, which means that there could be a steel leakage. Therefore, the second refractory layer (safety or permanent layer) has to be installed. Ladle refractory wear has been an important concern for steelmakers, not only for the economic aspects, but also for the influence that ladle lining condition has on productivity and quality of the steel (inclusions, adequate casting temperature…). Also, ladle breakouts due to premature wear of the working lining can happen if lining is not properly operated (for example during preheating), representing a severe risk

<u>Ladle refractory wear</u>

The ladle life, expressed as the number of heats processed in a given ladle, must be very predictable and reproducible for safety reasons and to avoid process delays. The usual approach to this issue is to inspect the ladle lining condition after some number of uses determined by the experience of the personnel involved and the operating rules established at the plant, usually based in tradition. When a ladle is removed for repair or disposal it is commonly realized that part of the remaining thickness of the bricks is still useful for operation, implying an impact both in productivity and costs. It should be noted that the ladle refractory consumption, in any given shop is strongly affected by the specific operating practice.

The working life of a steelmaking ladle is cyclic by nature, rotating along different stages: tapping, secondary metallurgy operations on molten steel, draining of ladle during casting and preheating of lining as preparation for next tapping. Different mechanisms of attack and degradations are active during each stage. During the empty ladle and tapping stages, thermo-mechanical stresses are the main cause of alteration, due to the very intensive temperature variations and to the mechanical impact of molten steel against the ladle wall. On the contrary, during in-ladle metallurgical operations when molten steel and slag are in contact with the lining, thermo-chemical stresses are the main causes of alteration.

Another aspect that makes difficult the development of better wear phenomena understanding is the difficulty to get reliable data. In this sense, existing laser systems have evolved to offer faster readouts and more robustness but: 1) they are still very expensive and cumbersome for daily use, 2) their orientation is mostly for void detection or severe damage (mostly in torpedoes and converters) and 3) they do not provide heat by heat basis ladle wear data.

Nowadays SIDENOR's measurement procedures for brick remaining thicknesses are manual and visual. Manual since they make measurements of a number of rows of the refractory brick's remaining thickness during the demolition phase after each campaign; and visual as they estimate the thickness by means of an experimented member of the team observing the ladle wear pattern.

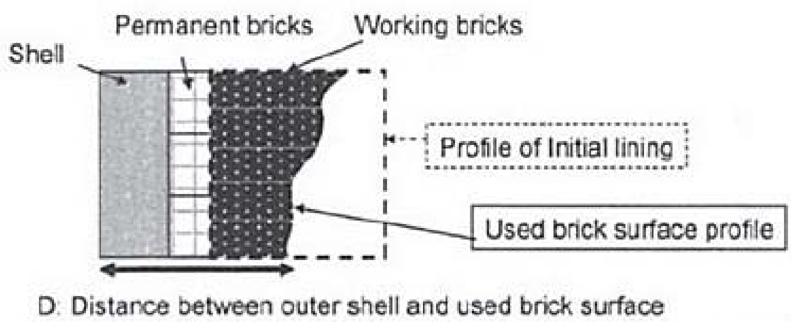


Figure 8: Section of the ladle displaying the remaining and etched brick lining.

On the other hand, due to the argon flow during stirring, the porous plug side (left) will show greater wear than the nozzle side (right). This is because argon impacts directly and more strongly on the wear lining of the porous plug side. To compensate this fact, the thickness of the wear lining is slightly higher in this side (but for the slag line which is the same on both sides).
And finally, the impact zone is where liquid steel hits the ladle during casting. The dimensions and refractory grade are quite different due to the mechanical requirements. In this case, spinel bricks are used.

<u>Refractory life control</u>
In SIDENOR, there are 10 ladles in operation with an average life of 85 heats. The refractory lining in the ladle is made up of MgO-C bricks (see figure 5), which gets worn out/etched out little by little

with each heat/cycle due to the molten steel melt ladle holds during the process. After a certain number of heats, if refractory lining in the ladle is not sufficiently thick, they run the risk of having a leakage/spillage of the molten steel in the production unit that can cause severe health hazards and production shutdown.

However, to ensure the safe operation of the ladles, and to avoid such a scenario, a technician looks for damages or health of the refractory lining in the ladle after **each heat**. The technician decides whether to repair the lining or to completely demolish the existing lining and have a completely new brick lining in the ladle. This decision is made by visual inspection of the lining and also by checking if selected process parameters are within "normal" operating range, no analytics done. The most important process parameters will be discussed later. Usually the technician makes decision for full re-lining of the ladle keeping safety as a priority and works on the "*Better safe than sorry*" philosophy. This however has a drawback, the Technician might/could decide for a full refractory brick replacement even when this is not actually needed. They are sent to reparation after 45 heats.

In this reparation, the wear lining of the slag line and part of the transition zone is removed, replacing it with new MgO-C bricks. Before removing, the MgO-C bricks are measured row by row, just to know the real wear of the lining. The measurement results (remaining thickness) are included in a template of the ladle, where the most affected areas are highlighted, as well as the zones where the refractory has been optimised (in green).

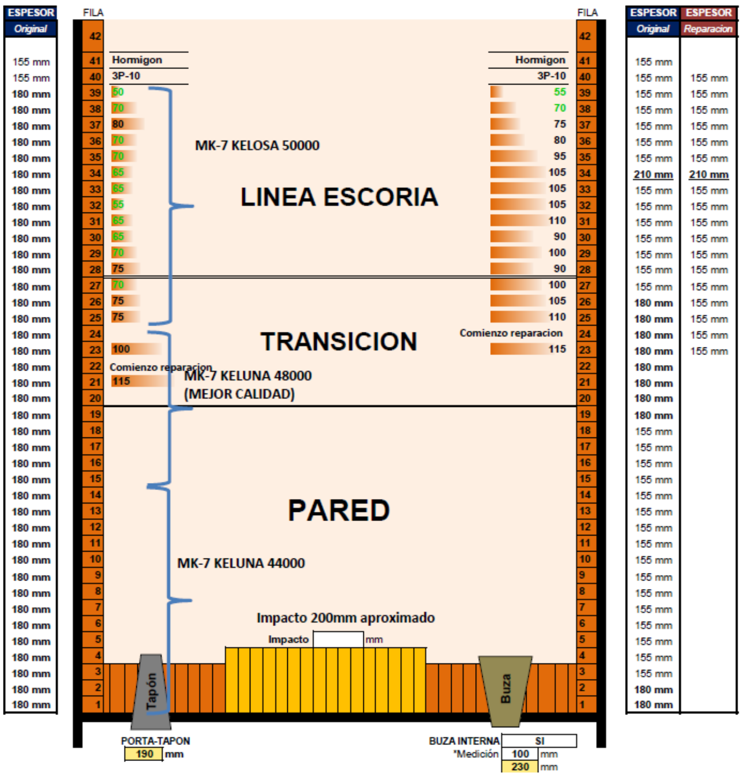


Figure 9: Ladle reparation: data sheet with remaining thickness.

The same practice is repeated at the end of life of the ladles. In this case, each row is measured and the remaining thickness included in the data base. The experience shows an average wear rate of 3 mm/heat

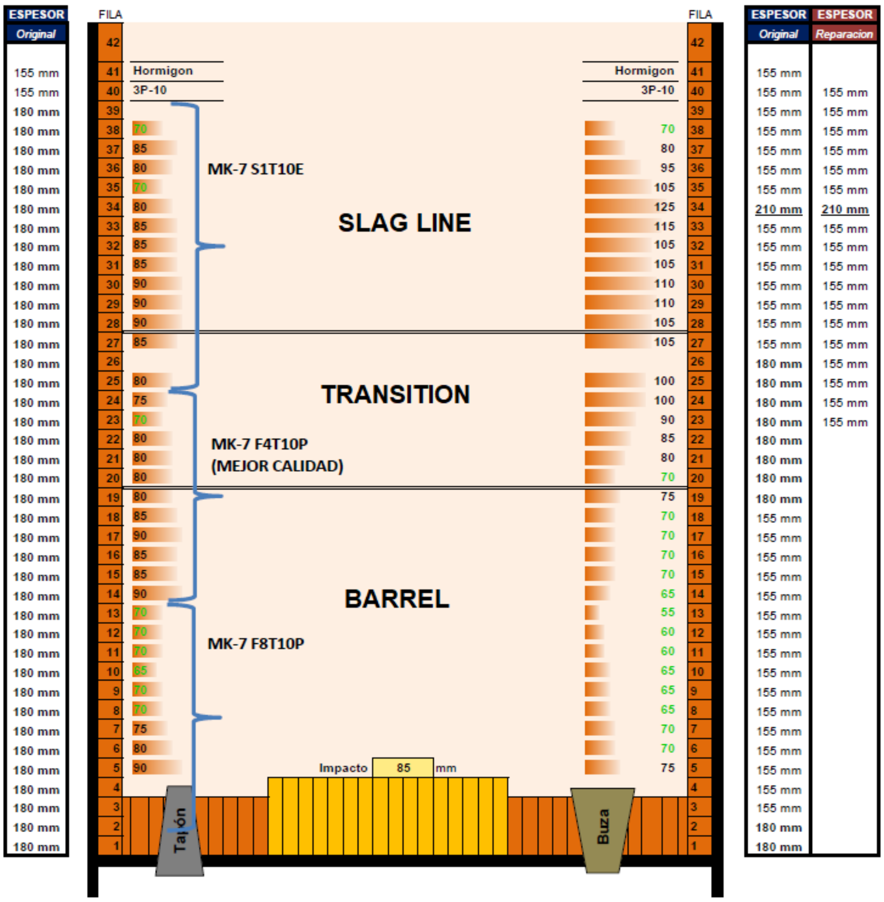


Figure 10: Ladle demolition: data sheet with remaining thickness.

From experience and from historical data, the average number of heats per cycle before

- the lining needs a **repair**[1] ranges from 33 to 46 and
- the lining needs a full **replacement**[2] ranges from 69 to 82.

The ladle refractory lining bricks are placed in layers along the inner wall of the ladle and typically the ladle has about 41 rows (42nd being protection for the rim) and in each row there are approx. 64 bricks. The line deterioration is not even around the inner walls. The side of the ladle with pressurised inlet for argon/N2 inert gas (porous plug side) wears out faster than the other side. This is because of the stirring and swirl caused due to injection of the pressurised inert gas. The visual inspector (VI) looks for damages in the lining and sometimes they only repair the lining instead of replacing the whole brick lining. The bricks in the slag line (to most layers) get worn out faster than the ones in the layers below. This is because of the chemical interaction between the slag and refractory lining in the top layer. This is seen in the Figure, check the brick thickness in the left-hand side highlighted in ***green oval*** and the brick thickness in the corresponding row at the right-hand side.

[1] Repairing the lining means, replacing damaged refractory bricks with new ones from the slag line.
[2] Demolishing existing all refractory bricks and replacing them new ones.

The brick replacement during reparation happens only in the slag line and transition line. In figure 1, the columns in ***blue*** on either sides denote the thickness of the brick in originally (when laid in fresh) and the numbers just inside the ladle after the bricks shows the thickness of the remaining brick thickness after 33rd heating cycle (it was taken out for repair). The lining is also affected by the steel grade they produce. This is because for instance the type of alloys added to the molten steel will depend on the steel grade they are producing. The quantity can range from 7000kg alloys/heat to 1500kg alloys/heat, being average 4000kg/heat

Today they have

1) 10 ladle in operation
2) Average wear rate of the brick lining 3mm/heat cycle
3) Average brick lining life: 85 heats, repair needed at 45 heats.
4) Barrel or the bottom ladle layers is replaced at the end of each cycle (85 heats)

The VI takes the decision when the repair/replacement of the brick line is needed to be done. As a rule, SIDENOR has decided, should the brick line thickness fall to 50 mm, they will have to replace all of those bricks.

3.3 Pilot specific aim

The aim of this WP is to develop ML/AI models with cognitive capabilities that predict when the refractory lining in the ladle need to be replaced (or repaired). We will aim to develop physics and data-based models to model the disintegration of the brick lining.

Physics based model for disintegration of the brick lining

In the following section the essentials of a physics-based model that can predict the erosion of the refractory is described. The description below does not cover the specifics of the sub-models since they are yet to be assembled after a thorough study of the process. However, it does cover the overall concept is discussed, together with the critical elements of the model. Figure 8 illustrates a schematic of a ladle that represents the most critical phenomena.

The gas injected from the bottom may result in formation of a "mushroom" above the gas nozzle. The mushroom is a result of reactions between oxygen in the gas and components in the steel. This may form a semi porous medium that will impact the contact time between purging gas and steel as well as reduce the stirring of the steel. When gas penetrates the free surface high agitation, convection and surface waves appear. This will increase the heat transfer and mass transfer between steel/slag and the refractory.

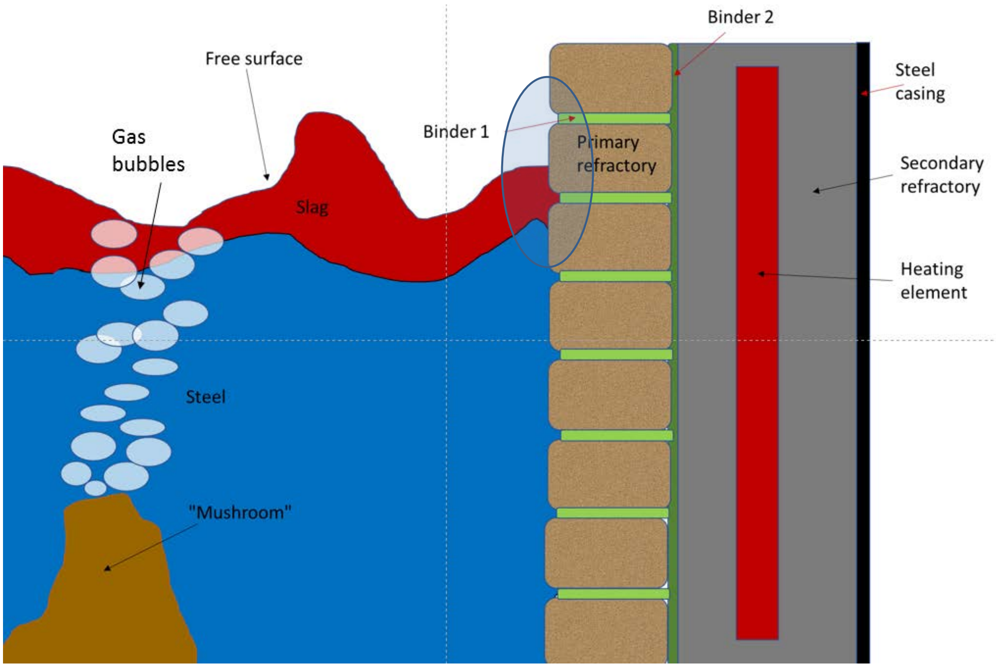


Figure 11: A scheme of a ladle, representing steel, slag, gas bubbles, surface waves, refractory materials and binders, together with elements inside the outer refractory.

The erosion of the refractory is known to be a result of i) Thermal stresses, ii) Dissolution of the refractory bricks into slag/metal, and iii) dissolution of the binder materials into slag/metal. In addition, mechanical stresses imposed on the refractory during cleaning operations will impact erosion and lifetime. The impact of thermal stresses will be most severe at the bottom of the ladle when hot steel meets colder refractory. As the metal speed at impact is high here is where we expect maximum thermal stresses. If observations tell that refractory erosion is small here this mechanism may be ruled out as secondary. Refractory bricks are cemented together with a binder which could be dissolved into the steel of slag. If this mechanism is important the refractory bricks may fall out of the refractory rather than the bricks themselves being eroded. The importance of this mechanism can be assessed from observations of the refractory erosion patterns.

At the side wall of the ladle the refractory bricks may dissolve into the slag/metal. In simple terms the dissolution of the refractory will depend on the solubility of the refractory bricks into the slag and metal. The loss rate of refractory is represented by the product of solubility of the refractory brick in slag/metal as well as the mass transfer coefficient. The equation that represents this is the mass flux $\overrightarrow{J_i}$, representing loss of refractory material from refractory to metal and slag:

$$\overrightarrow{J_i} = \alpha_{steel}\overline{k_{steel}}\rho_{steel}(X_i^{eq,steel}(T, X_j^{steel}) - X_i^{steel}) + \alpha_{slag}\overline{k_{slag}}\rho_{slag}(X_i^{eq,slag}(T, X_j^{slag}) - X_i^{slag}) \qquad (0.1)$$

Here i lables the species that makes up the refractory (Al_2O_3, CaO, SiO_2, ..). In this simplified presentation we assume that the refractory components may dissolve into the metal and slag in their basic forms. Here α_{steel} is the fraction of time then the steel contacts the refractory ($\alpha_{steel} + \alpha_{slag} = 1.0$), $\overline{k_{steel}}$ and $\overline{k_{slag}}$ are the time averaged mass transfer coefficient during the periods when the actual phase contacts the refractory, $X_i^{eq,steel}(T, X_j^{steel})$ is the equilibrium concentration of refractory component i, for the refractory in contact with the steel. Similarly,

$X_i^{eq,slag}(T, X_j^{slag})$ is the equilibrium concentration of refractory component i, for the refractory in contact with the slag. These solubilities depend on composition and temperature.

The solubilities will normally increase with temperature. The controlling temperature controlling this is found at the slag/refractory or metal/refractory interface. This means that higher refractory and higher metal temperature will increase refractory erosion. To find an accurate surface temperature for the refractory surface the heat transport balance must be solved. The refractory is normally more soluble in the slag, resulting in larger erosion rates where high temperature slag is available. The mass transfer coefficient will depend on the Schmidt (Sc) and the wall shear stress caused by the slag and metal flow. The Sc number is expected to increase moderately at elevated temperature. The wall shear stresses (steel, slag) depend on fluid viscosity and bulk velocities. Increase gas flow rates (bubbling) will increase the mass transfer due to stronger mean flow but will also generate surface waves that have a very strong effect on the mass transfer. The wave contribution to the mass transfer coefficients will depend on wave amplitude and frequency. Larger amplitudes and frequencies will increase the mass transfer.

Accordingly, large flow velocities due to high gas injection from the bottom, and surface waves generated by the bubble plume, will both enforce large mass transfer coefficients and thereby increase refractory consumption. The model above can be written out in detailed. The closure models and thermodynamic data, fluid properties and other relevant data and supported by machine learning to enable explanation of the measured data. Based on this action for improvement can be taken.

3.4 Innovation

1) Since the brick degradation pattern is not uniform along the height of the ladle, it was suggested we may need to have different models for the first 10 rows of bricks (slag line) in the ladle and a different model for the ones below. Because the slag on top of the molten steel can cause more damage than the bulk of the solution.
2) The next approach could be to check the temperature along the outer walls of the ladle after the ladle has been emptied to the tundish. Regions in the outer walls of the ladle with higher temperature can mean the bricks in the inner walls have worn out more than in other regions. This is because thinner the inner brick layer, higher the outside wall temperature in that specific point.
3) Texture analysis on images of the emptied ladle can also be a promising idea. Areas in the lining with bricks that have worn out will have craters or have a different texture compared to normal brick lines.

3.5 IoT platform and architecture in use

Currently SIDENOR does not have any digitalisation setup specifically for this section of their production process. The conditions of the brick ladles are checked manually and decisions about brick replacement is also done by SIDENOR's technicians.

3.6 Current data analytical models in use

The data model to be developed in the frame of COGNITWIN project is based on data mainly from two data sources. One of those sources will be the measurements of the refractory remaining thickness measured during the repairing and demolition phase of the ladle.
The second data source will be obtained from all available steelmaking parameter measurements. For example, time of the ladle with liquid steel, steel quality vacuum time, time in burners, among others. These data are composed different measurements from the processes that are provoking ladle refractory wear but are heterogeneous and must be treated adequately to obtain the information about the manufacturing conditions of each heat.
A deep analysis of those data is required to perform an intelligent/systematic treatment for every heat process and a priori knowledge of the critical processes is important to collect data efficiently. There are 2 types of process data:

- Acyclic data which describes commented process parameters data for individual heats (heat by heat basis).
- Cyclic data which describes time-series data for individual heats (1 seg)

Finally, both sources will be coupled to set up the data set. The data model will seek effects from changes in the process data over the wear measured in the bricks. The short-term prediction will work as an advisory system recommending ladle repair when residual thickness gets below a safety level. The central concept of this approach is that the combination of the many data captured from ladle's histories will be able to explain the rich data obtained with the manual measurement of the ladle profiles.

On the other hand, refining process parameters are monitored heat by heat, and their influence on the refractory wear, analysed in depth. Despite all of the parameters being stored in the database, experience and basic regression models have demonstrated that 4 of them have more influence on the wear of the refractory wear lining:

1. % Sulphur in the steel composition (after vacuum)
2. Electric consumption in refining (kWh)
3. Total lime added (kg)
4. Time that the ladle is full (min)

feprod	ncuch	nusos	ncol	S Vacío	kwh_RR	cal total	tiempo_llena	Alumina _RR	s al vuelco_RR	mecheros_RR	Tiempo_vacio	gases	caf total	acero_liquido	formato	v_desulfuracion	t_calentando	escoria_land	mn_vuelco
03/01/2019	1	1	203007	0,004	6153	1598	177		25	1	19	44	94	129,4	185185	0,32	30	0,9	311
03/01/2019	1	2	203012	0,003	9323	2152	171		55	0	23	54	201	125,9	185185	0,90	40	0,7	439
03/01/2019	1	3	203017	0,003	6020	1943	149	150	22	0	22	39	283	116,3	185185	0,27	29	0,0	508
04/01/2019	1	4	203022	0,003	5278	1831	161		35	0	17	48	393	132,8	185185	0,68	22	0,9	403
04/01/2019	1	5	203027	0,003	8368	2053	202	100	37	0	28	58	208	133,7	350470	0,80	37	1,1	418
04/01/2019	1	6	203032	0,003	11721	2091	239		30	0	26	105	271	128,3	350470	0,71	46	0,2	475
04/01/2019	1	7	203038	0,002	8350	1846	222		27	0	32	127	205	116,7	185185	0,51	35	1,5	429
05/01/2019	1	8	203044	0,001	6472	1806	192		34	0	22	63	277	132,3	185185	0,56	26	0,7	402
05/01/2019	1	9	203050	0,003	7814	1845	215		22	0	31	67	186	130,4	350470	0,25	31	0,0	433
05/01/2019	1	10	203055	0,003	6136	1806	167	150	30	0	21	40	198	118,0	185185	0,65	26	1,6	493
05/01/2019	1	11	203060	0,003	6153	1820	159		33	0	17	46	224	121,1	185185	0,82	25	2,3	348
05/01/2019	1	12	203066	0,002	7718	1827	190		19	0	26	70	377	144,1	350470	0,29	33	2,4	414
06/01/2019	1	13	203072	0,003	7482	2744	197		27	0	34	51	317	135,0	350470	0,31	29	1,4	442
06/01/2019	1	14	203078	0,003	5255	1821	152		32	0	17	49	144	119,8	240240	0,73	21	1,4	411
06/01/2019	1	15	203084	0,002	8470	2093	153	150	33	0	23	87	202	147,9	240240	0,59	35	2,4	447
07/01/2019	1	16	203090	0,004	6120	1954	161		32	0	20	36	153	107,9	240240	0,45	26	1,6	358
07/01/2019	1	17	203095	0,006	6266	1656	151		35	0	22	38	143	152,3	240240	0,63	27	1,5	432
07/01/2019	1	18	203100	0,003	5723	1832	174		26	0	30	64	236	131,4	240240	0,58	24	1,0	444
07/01/2019	1	19	203105	0,003	7517	1750	173		30	0	18	56	201	135,5	240240	0,52	35	0,6	408
07/01/2019	1	20	203111	0,003	6788	2315	164		32	0	22	41	404	116,5	240240	0,40	32	3,8	442
08/01/2019	1	21	203116	0,003	7665	1907	190		43	0	18	80	166	155,9	240240	0,84	31	1,4	430
08/01/2019	1	22	203122	0,006	8142	2131	194	100	44	0	27	71	160	125,9	350470	0,68	33	1,8	450
08/01/2019	1	23	203128	0,003	8184	2170	170	150	28	0	25	67	201	152,7	240240	0,52	33	0,1	264
08/01/2019	1	24	203134	0,003	6759	1831	191		38	0	26	57	200	99,6	350470	0,44	30	0,2	416
09/01/2019	1	25	203140	0,004	4834	2161	151		31	0	16	48	153	139,0	240240	0,74	20	5,0	529
10/01/2019	1	26	203148	0,002	9848	1946	217		22	1	35	101	279	126,9	240240	0,47	41	2,2	440
10/01/2019	1	27	203153	0,003	6695	1847	163		26	0	23	52	236	118,3	240240	0,60	28	1,0	492
10/01/2019	1	28	203159	0,003	5207	1936	150		47	0	18	49	169	102,9	240240	1,17	21	1,0	501
11/01/2019	1	29	203165	0,003	4495	1989	157		26	0	15	82	261	149,5	240240	0,76	20	0,4	490
11/01/2019	1	30	203171	0,001	10942	1917	225		14	0	30	97	398	127,5	350470	0,23	46	1,9	415
11/01/2019	1	31	203177	0,001	12193	2341	244		38	0	57	107	417	134,1	240240	0,68	50	1,2	472
11/01/2019	1	32	203183	0,003	7931	1696	183		30	1	17	53	202	96,0	240240	0,69	34	0,9	522
12/01/2019	1	33	203190	0,003	8497	1819	193		20	0	32	68	326	137,9	350470	0,27	36	1,3	474
12/01/2019	1	34	203196		7631	2362	168		27	0	27	65	201	129,0	240240	0,53	32	0,8	481

Table 1: A snippet of the process parameters monitored for the steel production.

With the combination of the information coming from the ladle brick remaining thickness measurement, and the process parameters, SIDENOR makes decisions and prepares a ladle plan every week, in order to optimise the life of the ladles

sidenor

PLAN DE CUCHARAS

CICLO: 18/04/19 - 24/04/19

Fecha edición:	18-abr.-19	Ju	Vi	Sa	Do	Lu	Ma	Mi	
Día	Estado	18	19	20	21	22	23	24	
Coladas previstas	inicial	16	24	24	25	25	24	3	Observaciones
Nº1 RHI	0					1	4	1	
	0	0	0	0	0	1	5	6	
Nº2 RHI	11	3	4	4	4	4	4		
	11	14	18	22	26	30	34	34	
Nº4 RHI	30	3	4	4	4				RETIRAR LUNES
	30	33	37	41	45	45	45	45	REPARAR MIERCOLES
Nº5 RHI	0								
	0	0	0	0	0	0	0	0	
Nº8 RHI	44+0	3	4	4	4	4	4	1	
	44	47	51	55	59	63	67	68	
Nº10 KELSEN	0		1	4	3	4	4		
	0	0	1	5	8	12	16	16	
Nº11 RHI	51+19	3	4	4	3	4	4	1	
	70	73	77	81	84	88	92	93	
Nº12 RHI	45+27	1	4	4	4	4			RETIRAR MARTES
	72	73	77	81	85	89	89	89	CAMBIO EJE -CONSTR. VIERNES
Nº14 RHI	45+0				3	4	4		
	45	45	45	45	48	52	56	56	
Nº15 RHI	39	3	3						RETIRAR VIERNES
	39	42	45	45	45	45	45	45	REPARAR MARTES
		0	0	0	0	0	0	0	
Cucharas en ciclo y reserva		6	7	6	7	7	6	3	
	coladas/día	Contadas en el vuelco del HEA de 6:00h. A 6.00h							

		Ju	Vi	Sa	Do	Lu	Ma	Mi	
	Estado	25	26	27	28	29	30	1	
	inicial	16	25	25	12	24	3	0	Observaciones
Nº1 RHI	6	1	4	4	2	4			
	6	7	11	15	17	21	21	21	
Nº2 RHI	34	3	4	4	1				RETIRAR DOMINGO
	34	37	41	45	46	46	46	46	REPARAR JUEVES
Nº4 RHI	45+0								
	45	45	45	45	45	45	45	45	
Nº5 RHI	0								
	0	0	0	0	0	0	0	0	
Nº8 RHI	44+24	3	4	5	3	4	1		RETIRAR MARTES
	68	71	75	80	83	87	88	88	CONSTR. VIERNES
Nº10 KELSEN	16	3	4	4	2	4			
	16	19	23	27	29	33	33	33	
Nº11 RHI	51+43	3	2						RETIRAR VIERNES
	93	96	98	98	98	98	98	98	CONSTR. MARTES
Nº12 RHI	0					4			
	0	0	0	0	0	4	4	4	
Nº14 RHI	45+11	3	4	4	2	4	1		
	56	59	63	67	69	73	74	74	
Nº15 RHI	45+0		3	4	2	4	1		
	45	45	48	52	54	58	59	59	
		0	0	0	0	0	0	0	
Cucharas en ciclo y reserva		6	7	6	6	6	3	0	

Cuchara secando

Preparada

Cuchara retirada

Table 2: Snapshot of the weekly ladle condition monitoring and maintanance log.

In this ladle plan, the reparation and teardown of the ladles are scheduled, as well as the number of heats that each ladle will be in operation every single day.

3.7 Description of Data available

Possible parameters that affect the refractory wear in the ladle were commented: Tapping temp, Slag carry over, Stirring practices, Steel grades, Secondary metallurgy needs (de-sulfurisation, degassing etc.), Types and methodology of alloys and fluxes additions of tap, Steel contact or residence time, electrical consumption KWh and taps used at ladle furnace, Thermal cycles ladle is submitted to, thermal shock, reliability of ladle, Drying curves, slag treatment and slag fluxes.

3.8 Measurable KPIs and Final impact

The idea is to find a balance between being over precautious and being reasonable in deciding whether to take a ladle out of production to a complete replacement. If let's say they increase the average number of heats per cycle from 69 to 81 before which they need to perform a complete replacement, this will translate to significant financial savings for SIDENOR (approx. 600,000 Euros per annum).

In other words, using the model developed within the COGNITWIN, it should be able to predict if the ladle's lining will last for the next heat or not while not compromising on the safety (due to leakage, as mentioned earlier). This decision today is done manually by a technician. The new model, to start off should be at least be as accurate as the visual inspection method. We then improve from there.

4 NOKSEL – Pilot

4.1 Introduction to NOKSEL & Process description

NOKSEL is one of the leading steel pipe manufacturers of Turkey with its plants located in Iskenderun at the region Hatay and in Hendek at the region Sakarya since 1987. Noksel serves domestic and international markets by manufacturing spiral welded steel pipes for petroleum, gas, water and piling industries.

Turkey is the biggest producer in Europe with production capacity of 5.2 million tons of steel pipe per year. NOKSEL is 97th biggest company in Turkey and the second largest in steel pipe industry. Besides NOKSEL Turkey, Noksel España S.A. was established in Spain in 2008. All manufacturing plants of NOKSEL are planned mainly for the production of the pipes in API standard, also manufacture pipes in accordance with AWWA, DIN, BS, ASTM, ISO, EN, UNI and AFNOR to serve the petroleum, gas, waterline and construction industries. With a full commitment to superior performance, the Company constantly strives to ensure that its quality policies and principles are in full compliance with all national and international regulations and standards. To optimize the management of information, NOKSEL has been using the SAP system for its own business operations and MIS systems since 2005 and continues to invest in digitalization of its premises.

Noksel's pilot case aims to the development of Digital Twin for the production process of Spiral Welded steel Pipes (SWP). The digital twin will collect, integrate and analyse multiple sensors' data streams in real-time, and enable predictive maintenance by a smart condition monitoring system. Real-time data acquisition, communication networks for monitoring, and automated recommendation generation are among the key innovative features of this pilot.

Smart components that use sensors to collect in real-time condition of the equipment's and their position will be connected to a cloud-based system that processes the collected data streams. Theses inputs will be analysed against business and other contextual data through smart visualization systems. The digital twin models will allow joining the physical and the virtual worlds to create a new networked layer in which intelligent objects interact with each other to virtualize the steel pipe manufacturing process on the SWP machinery shown in below Figure 12: Schematic lay out of SWP Machinery and Figure 13: Photo of SWP Machinery.

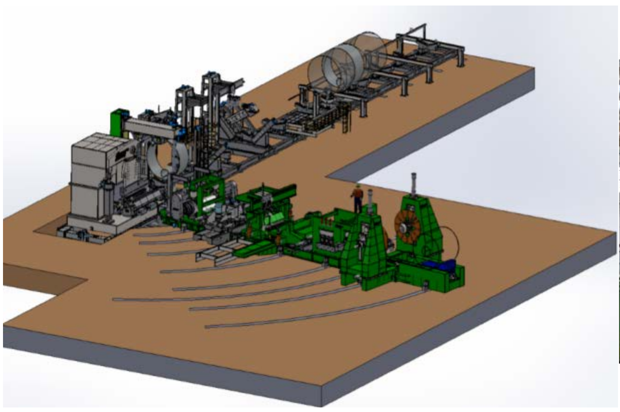


Figure 12: Schematic lay out of the SWP Machinery

Figure 13: Photo of the SWP machinery.

SWP machinery is used in the production of spirally welded steel pipe. In these machines the hot rolled sheets are combined by turning at a certain angle or flatly using the submerged arc welding (SAW) method. The general name of this process is spirally welded steel pipe production process, in Figure 14.

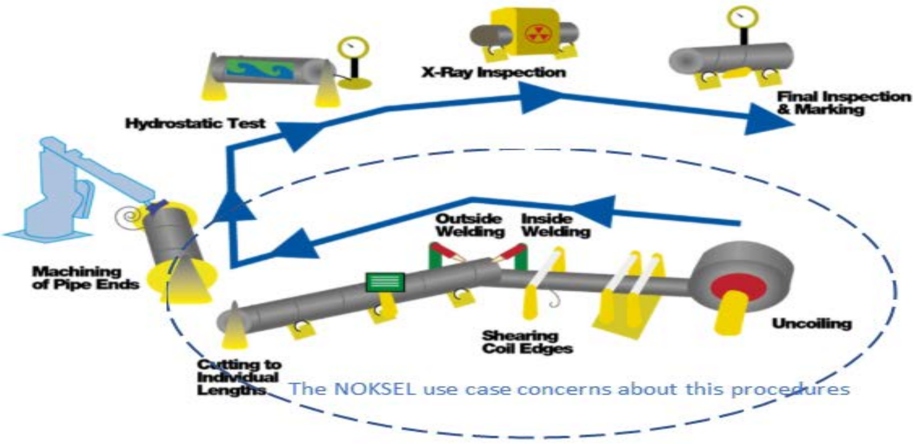


Figure 14: NOKSEL's use case processes

SWP is a multi-step, manufacturing process that consists of the following steps:

1) Preparation of hot rolled coils,
2) Coil ends welding, (skelp end welding)
3) Edge preparation of the coils,
4) Transforming the coils to pipe, (pipe forming)
5) Welding operations,
6) Pipe production,
7) Pipe cutting,
8) Repair welding,
9) NDT(Non-Destructing) testing,
10) Acceptance of the pipes,
11) Coating and lining,
12) Final testing and acceptance of the pipes.

4.2 Current challenges

The difficulties that may be encountered during the project activities are as follows:

- Monitoring condition with the existing system is a challenge due to the SWP machinery very large size and high complexity of the system made of a large number of components (e.g.: no less than 100 motors used)
- Selection and positioning of the right sensor type, number of sensors and position selection for the machine,
- Machine's preparation of maintenance and relations among the parameters,

-The need for grouping and arrangement due to the different scope and content of the data to be made meaningful for the machine,

- Lack of technical documentation and sample applications due to the fact that technical sub-parts of the project to be developed include new technologies,
- Lack of 3D models of the machines and devices that need to be virtualised into Digital Twin,
- Machine learning methods are not at the desired level of predictive performance,
- Selected machine learning methods remain slow and inadequate compared to data generation speed.
- Suboptimal working time due to the lack of effective prediction of machines breakdowns

4.3 Pilot specific aim

The aim of the pilot case is to improve the predictive maintenance capabilities and thus increase the total equipment usage performance by analysing operational and automation data received from different sensors with digital twin supported condition monitoring platform to be developed in serial production of steel pipes.

Steel pipe sector is a sector where operation run on 24/7 basis. The cost of machines breakdown is very high. Due to the multi-step nature of the process (Figure 14) if a section stops due to a malfunction, the entire production is stopped. An efficient Predictive Maintenance approach has the potential to increase the machine uptime. Hereby, equipment availability, performance and quality are expected to be increased. It also supports reduction in maintenance times, maintenance and operational costs and operator risks. Flexibility, agility, profitability and competitive advantage in production are provided.

4.4 Innovation

The main innovation is the development of a Digital Twin for the SWP in steel pipe production. The digital twin will collect and analyse multiple sensors’ data in real-time and enable a smart condition monitoring system for predictive maintenance. Real-time data acquisition, communication networks for monitoring, and automated recommendation generation are among the key innovative features of this pilot.

Smart components that use sensors to gather data about real-time status, working condition, or position will be connected to a cloud-based system that receives and processes all the data the sensors monitor. This input will be analysed against business and other contextual data through smart visualization systems. The digital twin model will allow joining physical and virtual worlds to create a new networked layer in which intelligent objects interact with each other to virtualize the steel pipe manufacturing process on the SWP machinery.

4.5 IoT platform and architecture in use

Currently the SWP Machinery is tracking by NOBİS System (Delphi based special software created by NOKSEL and machinery adjustments are made by terminals with installed TEKNOPAR’s software. NOBIS is also integrated with the SAP system.

The digitalisation architecture is closely related to the processes of the SWP machine. At NOKSEL, involved processes are; Pre-delivery, rough levelling, end cutting and butt welding, precision levelling, fraises, main delivery, forming by inner and outer welding, forming, V support, ultrasonic testing and length cutting. Figure 15 displays the current processes of SWP at NOKSEL:

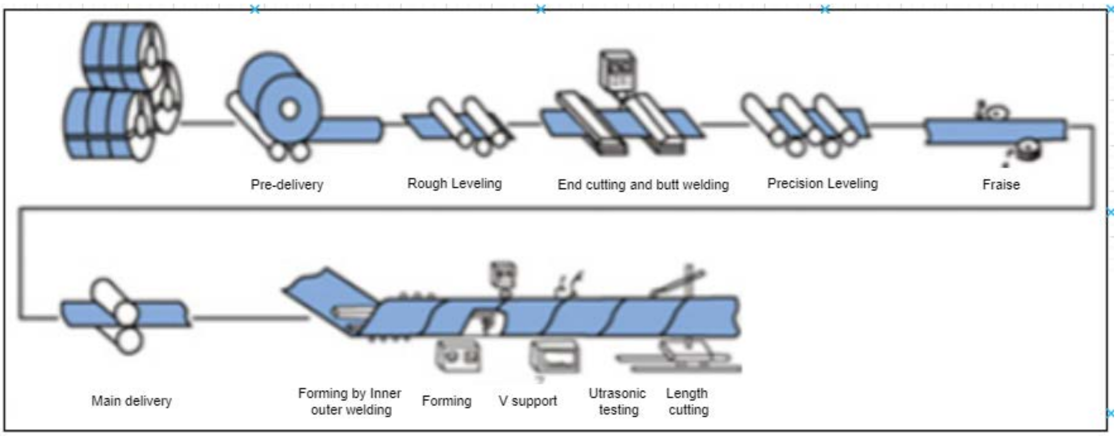


Figure 15: Steps in the SWP process at NOKSEL.

The existing architecture at NOKSEL's pilot facility is referred as AS-IS architecture and the planned future architecture is referred as TO-BE architecture Figure 16 presents the AS-IS architecture.

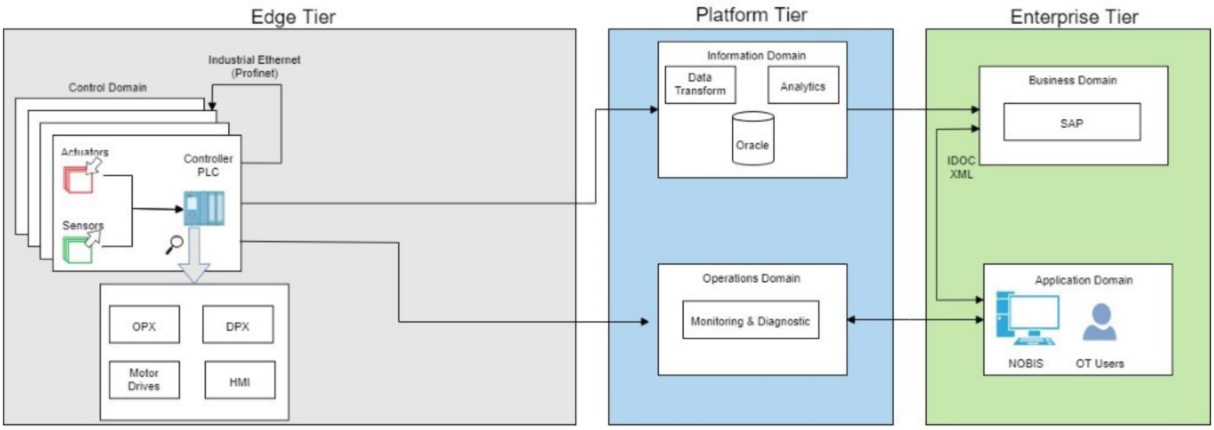


Figure 16 : AS-IS: Existing Architecture at NOKSEL

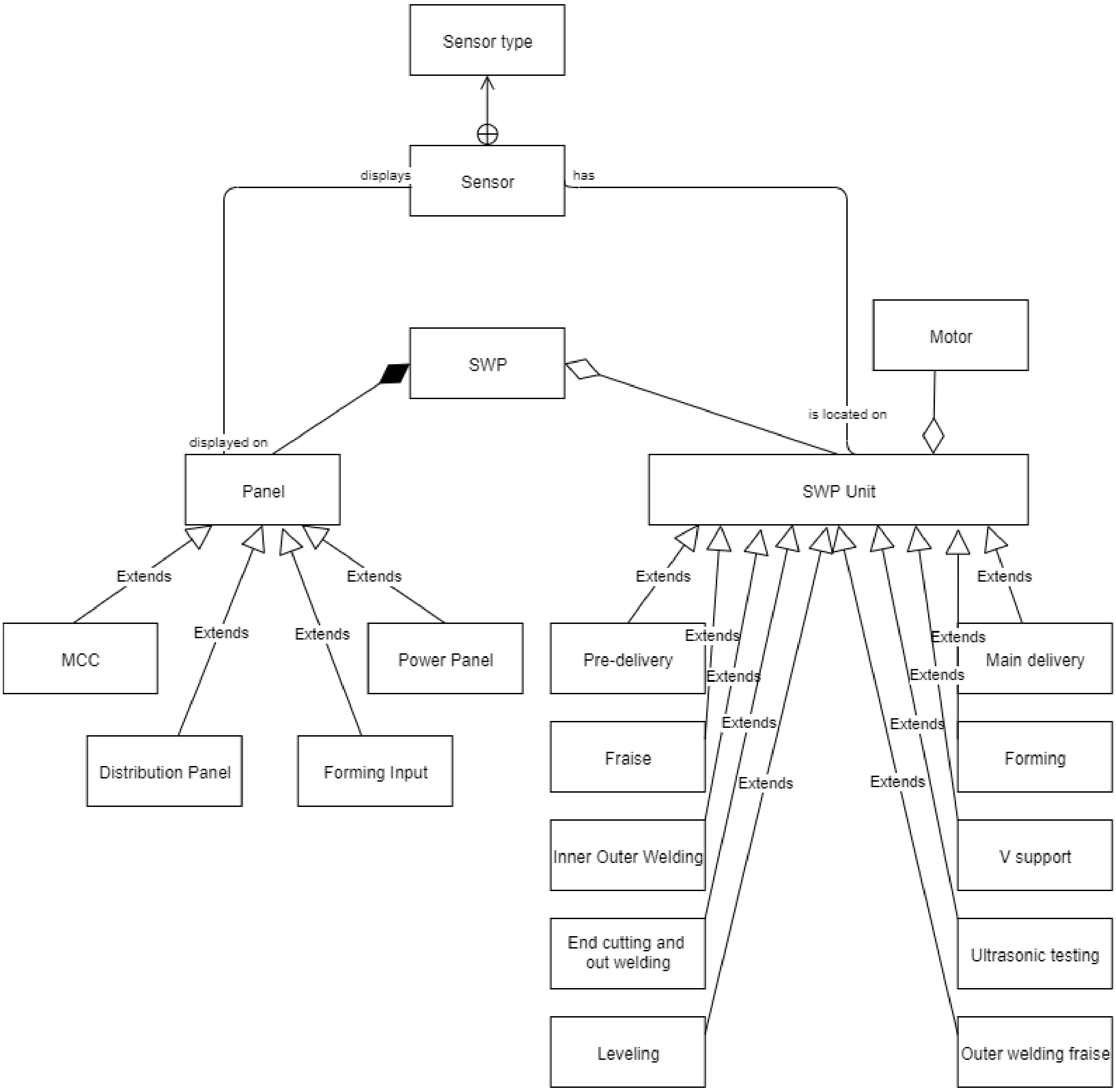


Figure 17 : System's Generic Static View of the Architecture at NOKSEL

SWP is associated panels and is composed of different SWP units. The SWP units at NOKSEL are as follows: pre-delivery, fraises, inner outer welding, end cutting and out welding unit, levelling unit, main delivery, forming, V support ultrasonic testing and outer welding fraise. On these units, there are limit sensors located. These sensors are displayed on the existing panels, which are MCC, distribution panel, forming input panel and power panel. In a UML class diagram, Figure 17 presents a top-level generic architecture of the SWP at NOKSEL from a static point of view.

Currently, there is an IoT platform where the machine is monitored with SCADA systems on the shop floor. The existing sets of sensors are composed of limit sensors:

- Direction limit sensors of carrier cars (forward and backward limits)
- Right/Left roll handler limit sensors (in out limits)
- Pre delivery up location limit sensors
- DP1-DP5 limit sensor list

Note: We have the complete list of existing sensors and their specifications at NOKSEL. We do NOT present the list and sensor specs in this document for confidentiality reasons.

At NOKSEL, three types of motors (AC, DC and servo motors) exist (Figure18). The motors are associated with the drivers that are specific to the associated motors.

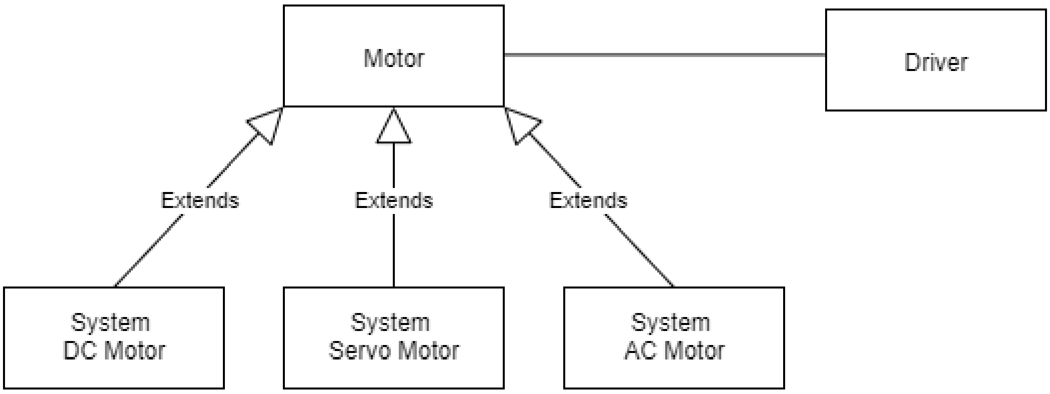


Figure 18 : Engine Types at NOKSEL

Currently, panels at NOKSEL are classified into two main groups; Distribution panels and Operator panels. There are five distribution panels at NOKSEL's existing IIoT platform (Figure18).

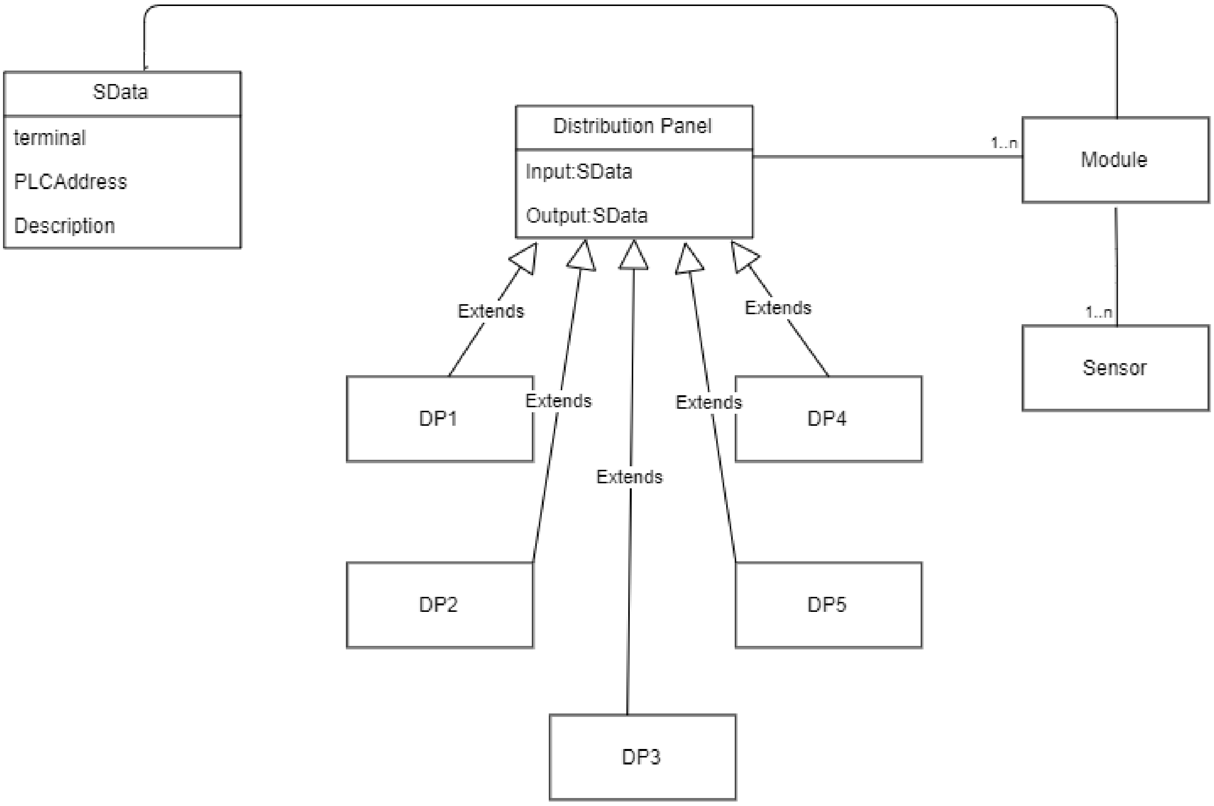


Figure 19 : Existing Digitalization at NOKSEL: Distribution Panels

Each distribution panel (DP) is associated to sensors and switches via modules. Table 3 displays the DP's and their associated types of sensors and switches at NOKSEL's existing IIoT platform.

Panel	Type of System Sensor/Switch	Number of Sensor/Switch
DP1	Proximity End. Sensor	19
DP1	Pressure Switch	4
DP2	Proximity End. Sensor	15
DP2	Pressure Switch	1
DP3	Proximity End. Sensor	15
DP3	Laser Photosensor	6
DP5	Proximity Sensor	9

Table 3: AS-IS: Existing Digitalisation at NOKSEL: System Sensor/Switches and Distribution Panels.

At NOKSEL, there are ten operator panels, each of which is associated to different units of SWP. The units that are associated with the existing sensors are listed in Table 4.

Name	Unit	Number of Modules	Number of Butons/Keys
OP1	Pinch Roll	2	48
OP2	Pre-delivery	3	64
OP3	End Cutting and Butt Welding	3	66
OP4	Fraise	2	48
OP5-6	Main delivery Forming, Inner Welding, GAP Control	4	80
OP7	Length Cutting	2	48
OP9K	Forming by Inner Outer Welding	4	36
OP10K	Inner Outer Welding	3	56
MOP	Main Operator Panel	4	96
KMOP	Welding Main Panel	5	80

Table 4: AS-IS: Existing Digitalisation at NOKSEL: Operator Panels.

4.6 Current data analytical models in use

The IoT system components and tools used are given in detail in template tables filled for D4.1. Briefly current IoT system has its components like PLC hardware and software, analogue/ digital modules, communication modules and SCADA system installed in the production plant. Establishing the necessary infrastructure to communicate with the intermediate module software (OPC server) and streaming from PLC to cloud through sensor network are under development

4.7 Description of Data available

Current tracking system provides downtimes periods and types, total working durations, effective working durations, number of produced pipes, meters of produced pipes, weight of produced pipes, which pipe produced of which labelled raw material which shows the quality of raw material.

Only daily electrical consumptions have been started to be recorded since November 2019. Before then, electrical consumptions are recorded monthly in 2019.

4.8 Measurable KPIs and Final impact

- Type I Error in Anomaly Detection: Currently there is no such system. The target in this project is to achieve zero error of Type I. Type I error occurs when the system states that a case is an anomaly when in reality it is not.

- Type II Error in Anomaly Detection: Currently there is no such system. The target in this project is to achieve zero error of Type II. Type II error occurs when the system states that a case is not an anomaly when in reality it is an anomaly.

- Reduction in energy Consumption by % 10
  By decreasing number of downtimes, our aim is to decrease number of start/stop of the SWP Machinery so that energy consumption amount during starts which requires more energy will be prevented. Moreover by enabling efficient running of SWP machinery (with lower number of downtimes) the project will increase production amount so that energy consumption produced by electrical systems of the SWP Machinery will also be prevented which results in total energy consumption decrease and at the same time increase in production amount
  Electric consumption data has been started to be recorded daily since November 2019. Before this date, electric consumption data was recorded monthly. Therefore; the current figure is set from SWP Machine real recorded data.

  Let X be the current energy consumption of SWP to produce 1 ton of steel pipe in one hour before COGNITWIN and let X' be the energy consumption of SWP running in one hour with COGNITWIN project to produce 1 ton of steel pipe. For both X and X' the unit of measurement is MWatth/ton.

- Reduction in shifted average duration of downtimes by %10
  With new system COGNITWIN will provide predictable downtimes so that required measures could be taken timely preventing the duration of undesired downtimes.

5 Summary

SAG analyzed the initial situation in the Nauweiler rolling mill and identified lacking sensors and required actions. To ensure the correct and automatized identification of billets upon entrance into the mill train, an improved billet identification system was installed. The more demanding task of providing a seamless tracking of billets in the blooming train will be addressed in close collaboration with technology partners by means of a Computer Vision tracking system. To this end, 3 FullHD cameras were installed overlooking the entire blooming train.

In SIDENOR initial industrial starting point for ladles information has been assessed. The relevant process data and type of available measurement of the ladle profiles were also established considering the requirements of the rest of the partners for the tasks to be developed. The definition of the data requirements has been started and firs data set has been provided to the technological partners.

NOKSEL conducted a gap analysis to identify requirements for the cognitive digital twin of SWP machinery. The current system architecture was studied. The data needed to observe and evaluate contributions and impact of the new system was collected and analyzed. The current sensors of the SWP machine were listed. The desired new sensor installations will be integrated into the current plant's system. At the end, the predictive maintenance system supported by the cognitive digital twin for SWP system will be built up.