

## **GREEN STEEL AS THE BIG CHALLENGE OF THE EUROPEAN INDUSTRY: CONTRIBUTIONS FROM THE INDUSTRY 4.0**

**J. Ordieres-Meré<sup>1</sup> and M. Gutiérrez<sup>1</sup> and J. Branderburger<sup>2</sup>**

1. Industrial Management Department at Universidad Politécnica de Madrid. José Gutiérrez Abascal 2, 28006. Madrid {j.ordieres,miguel.gutierrez}@upm.es
2. VDEh- Betriebsforschungsinstitut, Sohnstraße 65, 40237 Düsseldorf, Germany jens.brandenburger@BFI.de

### **ABSTRACT**

Global steel production is currently dependent on coal and capital-intensive production facilities with long economic lifetimes, whereas the Paris Agreement implies that carbon neutrality must be reached globally by 2050–2070. As far as steel industry is a key provider for many other businesses as construction of buildings, ships, automotive, food and retailing sectors, it is not only significant that nowadays coal-based steel production accounts for around 8% of global energy-related CO<sub>2</sub> emissions, but it also stands out for its wide impact on society products. When the whole value chain is considered, it has good recyclability properties, yet still emission reduction remains a challenge. This paper looks to emphasize the direct and indirect benefits provided by cross-sectional technologies such as Industry 4.0 and Internet of Things when applied to the steel production. In particular, this paper emphasizes how technology enables a more accurate accountability for emissions than the averaged figures that are usually considered when these aspects are discussed, and on the other hand how they enable a much higher level of granularity. Such approach could potentially lead to a different business model by considering a fee for the CO<sub>2</sub> emissions inside the cost of each product.

*Keywords:* Green Steel, Energy monitoring, Internet of Things, Modelling Energy Performance

### **1 INTRODUCTION**

The European Union (EU)'s Green Deal goal of becoming climate neutral by 2050 is putting enormous pressure on the European Continent's steelmakers. Those unable to swiftly decarbonize are risking to get swallowed by rivals. They will also face competition from Asian steelmakers, which are aggressively promising to slash their greenhouse gas emissions. Reduction of carbon emissions is a key challenge for the steel industry, since it is particularly intensive in coal-based production while subject to an increasing demand [1], [2]. To comply with the Paris Agreement, experts advocate for net-zero carbon emissions by 2045-2055 to limit warming to 1.5°C (and by 2070-2085 at most to limit warming to 2°C) [3].

World Steel Association members have agreed on a common framework to work towards reducing their carbon footprint, including [4]–[7]:

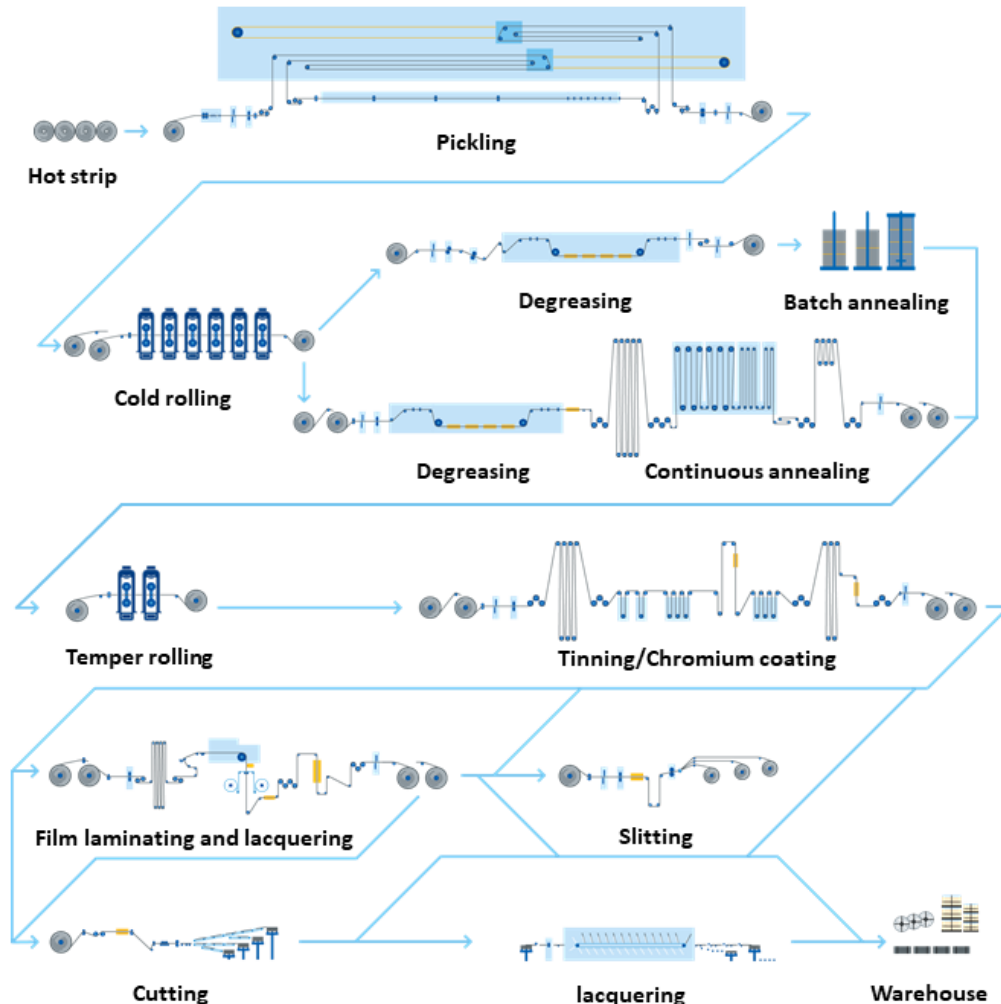
- the development and application of new steels to improve the energy efficiency of steel-using products in society;
- expenditure on research and development to identify breakthrough steelmaking technologies with the potential of reducing steel's CO<sub>2</sub> emissions significantly;
- improving plant performance through benchmarking and technology transfer;
- and a common measurement and reporting system for steel plant CO<sub>2</sub> emissions.

The rate of innovation in carbon mitigation related technologies in steel has been increasing over the last decades. At European scale, for the steel industry the Paris Agreement means it must undergo large-scale technological change. Public funding for research and demonstration projects has been successful in nurturing a variety of technology innovation projects, such as projects aiming to use renewable hydrogen in the direct reduction process, or to produce chemicals from steel off-gases via carbon capture and utilization [2], [8], [9].

Rethinking the technology Europe uses to make steel and encouraging the use of more scrap steel instead of making the virgin product, can have big impacts on the industry's carbon footprint. Out of 160 million tons of crude steel produced in the EU in 2019, only about 40 percent came out of electric arc furnaces, according to the most recent statistics from industry group Eurofer [10]. The rest was made in old-school blast furnaces, most of which run on coking coal — a big part of why global steel production generates between 7 percent and 9 percent of the world's greenhouse gases [11]. While the most efficient blast furnace process

produces 1.9 tons of CO<sub>2</sub> per ton of steel, melting down 100 percent scrap in an electric arc furnace produces 0.4 tons of CO<sub>2</sub> per ton of steel — dropping to 0.1 tons of CO<sub>2</sub> if the electricity is carbon-free. Obviously, generation of CO<sub>2</sub> depends on the specific plant and steel production involves several of them, grouped in upstream and downstream phases [11]. In this work we ground our proposal based on data from a flat rolled steel coil products manufacturer, therefore Figure 1 presents an example of production plant sequence for flat products.

Figure 1: Downstream steel plants for flat products. Source: [12]



In spite of the source for the energy used in any production plant, there is a second level factor linked with emissions and waste generation which is not always well understood. It refers to process efficiency, by making sure that used energy is properly tracked and reported.

Transparency mechanisms become critical for such endeavour as they provide emission accountability both, per plant and per product. Based on such data, not only precise estimations can be provided, but also better analysis for variance in energy consumption can be carried out. As a consequence, better process routing and resource assignment decision-making processes can be implemented, since in this kind of industry alternative process plans are possible due to some degree of redundancy for different plant types, as well as the existence of alternative production routings.

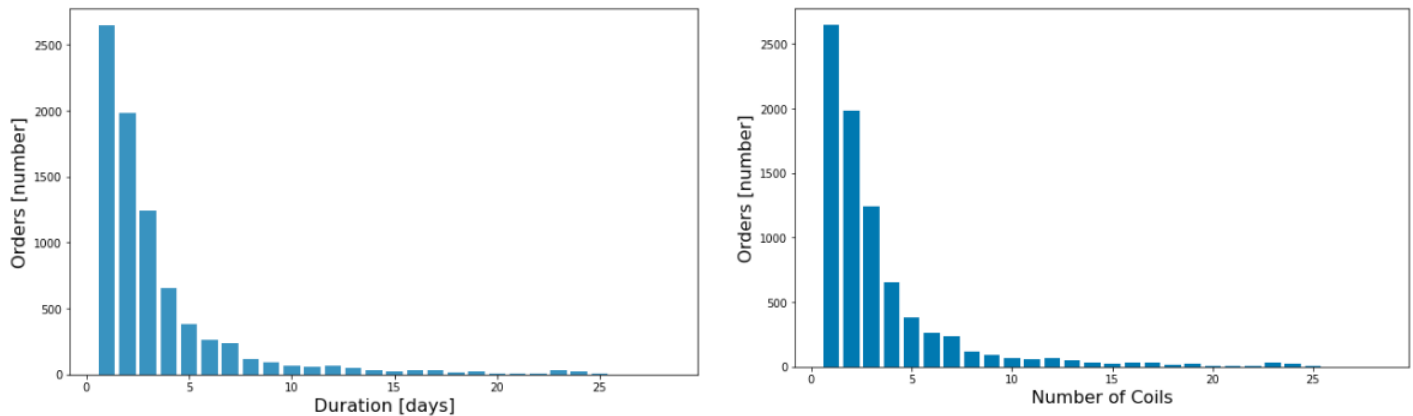
This industry operates in a make-to-order basis. Customers place orders, each of them involving different number of products (coils, strips, and sheets), which trigger production and process planning. Each product is scheduled through production lines according to different policies depending on customer requirements (quality, deadlines, etc.), meaning that different products of the same order can be produced in different plants (see Table 1).

Table 1: Orders involving different products and plants

Order ID.	Energy [w*15min]	Num. Products	Order StartTime	Order EndTime	Plant ID	Order Duration [min]
359558	124619.11	1	2020-11-05 00:51:46	2020-11-05 01:09:05	[P04]	17.32
360292	163342.20	1	2020-09-28 18:18:01	2020-09-28 18:36:55	[P04]	18.91
360788	166377.80	1	2020-11-27 01:08:18	2020-11-27 01:26:39	[P04]	18.35
362350	843025.39	8	2020-09-30 05:02:24	2020-10-02 18:59:37	[P02, P02, P02, P02, P02, P02, P02]	3717.22
362373	858736.27	6	2020-10-03 14:59:02	2020-10-05 10:50:02	[P02, P03, P02, P02, P03, P02]	2631.01

Figure 2 shows illustrative distributions of time to completion of customer orders (left) and size of the orders (right), where data have been taken from a real factory kept anonymized because of confidentiality reasons.

Figure 2: Distribution of Durations and Number of products of different orders.



The aim of this paper is to analyse to what end a transparency mechanism for energy usage at plant and product level can help to apply carbon reduction policies in a wider context, through the added value chains. As detailed in section 2, new possibilities offered by the emergent Industrial Internet of Things (IIoT) and Industry 4.0 paradigms open the way to assess not only plant-based performance, but also carbon footprint at product level [13], [14]. Section 3 summarizes relevant results thrown by our proposal, whose main conclusions are detailed in Section 4.

## 2 ENERGY INFORMATION AT PRODUCT LEVEL

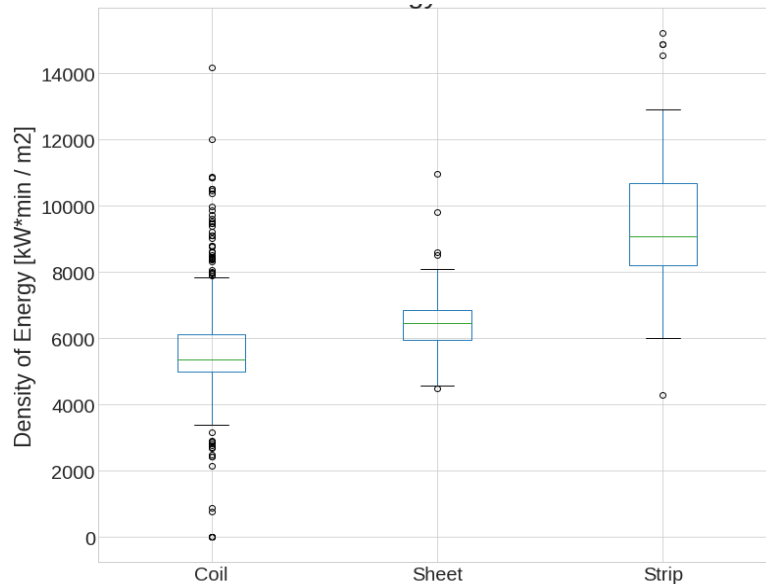
IIoT technologies allow to develop a real-time online system to assess the energy performance. However, only global energy demanded within distributed time periods (15 mins, etc.) is measured, without considering which items were manufactured at the individual plants. The measurement system is based on Non Invasive Load Monitoring (NILM) technology that allows to determine the current intensity, current voltage and phase angle as well as to calculate the active and reactive power used at different sections of the plant in such a way that integration within the previously defined time periods and summation as per plant section is carried out by the Data Energy Monitoring System (DEMS).

Then, an imputation mechanism has been established, by collecting information from the Data Production Monitoring System (DPMS) and crossing it against the DEMS in order to derive the amount of energy devoted to every single product. Density of energy, measured as Energy used per surface unit and period of time, is selected as the KPI (Key Performance Indicator) for the assessment.

In order to gain insights of the information to be included in the system, firstly we carry out a statistical characterization of the Density of Energy distribution at each plant both in a monthly basis and type of product basis. In Figure 3 the obtained distribution is presented for one of the finishing plants under study. Although, the total amount of products processed in this plant is not homogeneous, it becomes clear that there exists a significant variability in the density of Energy per type of product, suitable for smarter decision making when Energy behaviour is considered.

Although the implemented method was designed for Energy monitoring, it can be extended by considering other relevant dimensions, such as Data Quality Monitoring System (DQMS), in such a way that non only efficiency can be analysed, but effectiveness as well.

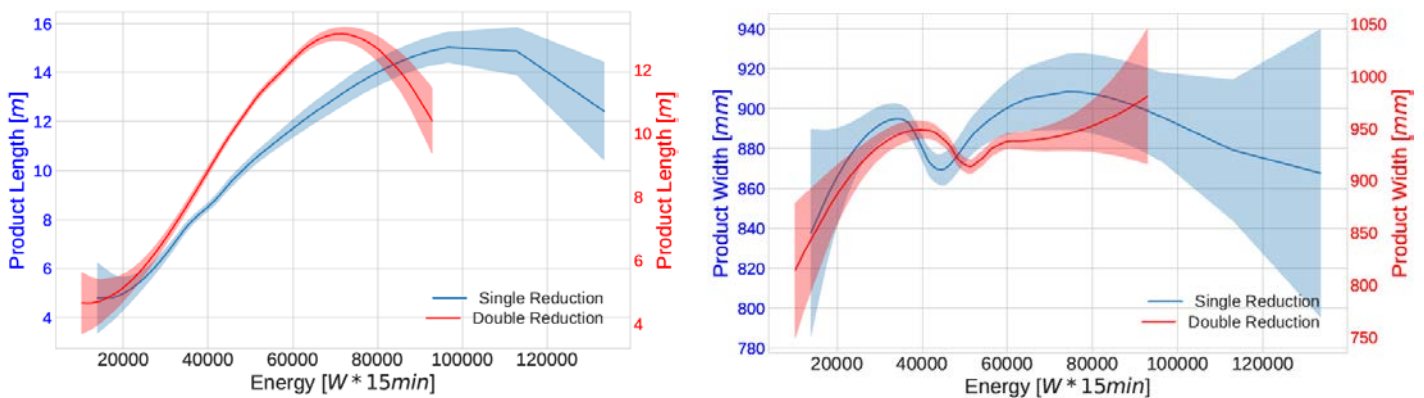
Figure 3: Density of Energy per type of product and Plant.



### 3 ANALYSIS

In order to develop the proposed energy assessment system, we performed a deep analysis of relevant factors affecting energy consumption as per product type and plant. Therefore, different factors have been considered, such as product length, width, area, production speed, and other production related factors.

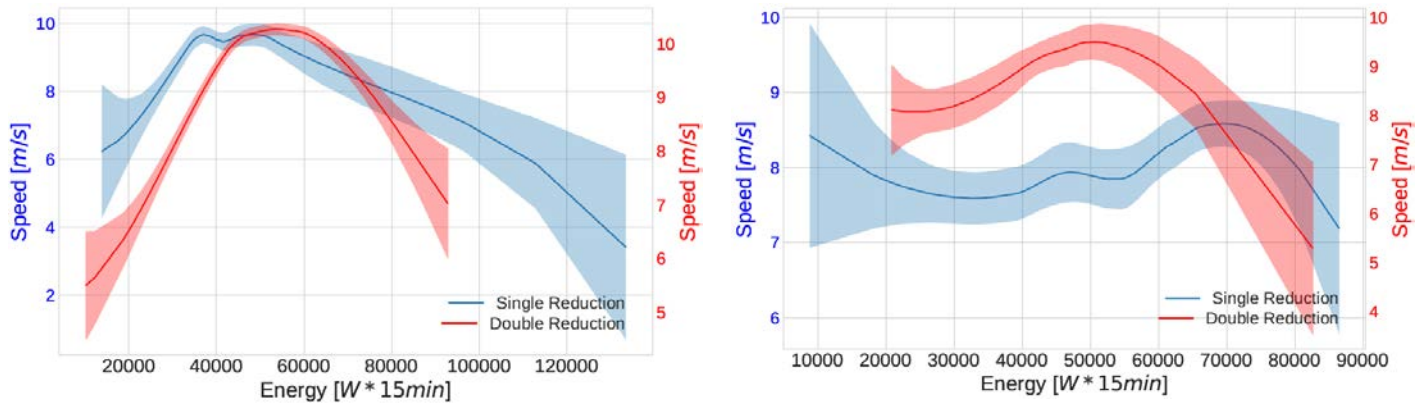
Figure 4: Density of Energy for Coil products at finishing plant depending on Length or Width



Analysis of Energy demand depends on the different parameters when different types of flat products were considered (among Coils, Sheets and Strips) but also when different operations were considered, such as product with no reduction, single or double reduction.

Different dependencies can be derived, such as strong dependency for product length (see Figure 4), and much less intensity when product width is considered (see Figure 5). Product speed has also limited impact in energy demand, while multidimensional dependency does exist.

Figure 5: Energy for Coils (left) and Strips (right) at finishing plant depending on Speed



Another relevant aspect that can be observed is the significant level of uncertainty which accounts for additional identification of factors able to contribute to explain variability of energy demand.

#### 4 DISCUSSION AND CONCLUSIONS

Steel is part of a broader Horizon Europe partnership on energy-intensive industries. Under Horizon 2020, the steel sector was part of the public-private partnership Sustainable Process Industry through Resource and Energy Efficiency (SPIRE). In this framework, energy efficiency is a major trend, and increasing it requires higher level of transparency and accountability. The proposal of this paper was to use digitalization strategies to increase the accountability for Energy consumption per product and production step. The performed analysis carried out and presented in this paper allows,

- By combining production and energy accountability, to assign energy consumption to processed item (coil, strip, etc.), hence to orders as well.
- This information can be incorporated as a Key Performance Indicator (KPI) (at aggregated level) to aid production control managers.
- Energy/length [kW\*min/m] can be adopted as a relevant KPI at item level, and it can be averaged according to weights at order levels. Of course, such KPI will depend on some parameters, such as material class or processing configuration, which must be under consideration as well.
- Such KPIs will collect impacts from order deviations, such as rerouting, quality failures..., and they can provide extra accountability in terms of management decisions.
- Environmental footprint (at least regarding energy dimensions) for steel products could start to be incorporated as reliable information per product according to its specific production route, as a key dimension to integrate in the existing labelling system coherent with some others already existing for EU consumers based on the EU Directive 92/75/EC [15], but it can also be used as crude numbers, because it is used in business to business market.
- The relationships found suggest that it could be possible to develop sophisticated models able to better forecast the energy demand of the forthcoming items, and with this information support management decision.

The latest aspect, related to the capability to predict the energy consumed by the next type of product at one specific plant based on its status, provides pre-assessment capabilities that both production and quality managers can use to re-schedule products at local level. This strategy can be implemented in addition to other more structural decision focused in reducing energy consumption variability that occurs because no information is provided and then, no particular policies are enforced to this end.

The final message is that it is worthy to consider the relevant capacity that NILM and IIoT technologies, in cooperation with advanced data management technologies, to improve the energy behavior at steel production facilities, both by considering stronger policies with higher level of transparency as backend, as well as because of the construction of a predictive system able to estimate the energy being demanded for the next product in a specific plant.

Additional added value for the implementation of these technology-based transparency systems is to provide a framework considering additional linked dimensions to the deadline, as relevant for making decisions. Energy efficiency is understood as a powerful instrument contributing to the industrial decarbonization.

Further research will require to progress in prediction methods making it possible to implement advanced decision-making strategies, out of the measuring mechanisms providing evidences for product labeling.

## ACKNOWLEDGEMENTS

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