AI, Labor, and Economy Case Studies In-Brief

# Tata Steel Europe

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**Tata Steel Europe (TSE), a leading European steel manufacturer with major operations in the Netherlands, has faced industry challenges, volatile earnings, and increasing customer demand for higher-quality products in recent years. In response, the management team began exploring ways to find sustainable long-term profits and lay a new foundation for the company's future. As artificial intelligence (AI) gained a foothold across the manufacturing industry, the leadership of TSE launched an AI-focused strategy in 2016. This initiative was referred to internally as the Advanced Analytics (AA) program and its goal was to transform production and increase profitability at its largest integrated steel plant, located in IJmuiden, Netherlands.**

# Case background

The global steel industry is highly competitive, offers thin margins, and involves highly capital-intensive operations; the industry is also considered to have excess production capacity as of 2018, meaning there is a global overproduction of steel relative to market demand. Steel-making operations have undergone significant changes over the past few decades, with a shift toward physical automation - driven by a combination of challenging working conditions (e.g., safety and health), intense industry competition, and ongoing technology improvements. As a result of these changes, the steel industry has also experienced declining employment over the past few decades. For TSE in particular, contextual factors such as labor unions and labor regulations continue to influence its employment decisions, such as the viability of further workforce reductions: At TSE's IJmuiden plant, an estimated 35 percent to 40 percent of workers — largely members of the production crew — are unionized.

As part of its search for sustainable long-term profits, management at TSE decided to launch its Advanced Analytics program, driven by three key business challenges: 1) The constant pressure to improve low margins and profitability in a highly capital-intensive and competitive market; 2) Shifting customer demand in favor of higher-quality products and strict delivery timelines; and 3) An aging workforce, with the likely possibility of lower labor supply for its steel plant in the future.

In the initial phase of the program, the company prioritized 15 analytics use cases, each focusing on a different part of the production process. These use cases included energy reduction, product quality improvement, and raw material savings. Use cases relied upon a variety of techniques, ranging from more simple linear regressions, to random forest and gradient-boosted decision trees, to the early testing of neural networks in more mature use cases. Each use case was developed by cross-functional teams of project managers, data scientists, data engineers, and business "translators" over a span of roughly 10 weeks.

# Key observations and findings:

- **Implementation challenges:** TSE made a deliberate decision to prioritize its existing employees. For instance, TSE invested in and re-trained the required technical talent from within the company, which the company believes has proven successful. Roughly 200 technologists, plant managers, and executives have been trained in the development and implementation of AI-related technologies as part of TSE's Advanced Analytics program.

  > As an executive noted, *"The company is in the business of steel-making, not of developing the most advanced AI models and competing with the largest tech companies. As such, the company needs employees who understand the technical side of AI, while also intimately understanding the steel production process."*

  Additionally, TSE emphasized the importance of gaining employee buy-in throughout the implementation process for successful change management. For instance, within various production crews, some operators understandably showed resistance to the introduction of a new way of doing things. Because this posed a major hurdle for TSE, the company developed key strategies to mitigate these challenges, including increasing the use of data visualization tools to aid the explainability and interpretability of AA models, obtaining executive sponsorship to create momentum, and ensuring collaboration across teams from early stages of the implementation process. For example, AA project managers hosted "office-hours" to discuss models with plant operators.

- **Business and productivity impact:** TSE's internal assessments show that the AA program increased productivity, delivering roughly 13 percent higher EBITDA[1] (a common proxy for cashflow) with the same production staffing levels. In the first year of the program, TSE stated that all implemented AA use cases had substantial positive EBITDA impact for the IJmuiden plant. TSE found that the program broke even overall on its investment (e.g. system development, training, and data infrastructures) within one to two years of launching, and that use cases offered a higher return on investment (ROI) than more capital-intensive plant upgrades or physical automation over the same time period. The economic benefits from the AA use cases typically came in the form of raw material savings, yield improvement, or margin improvement from higher-quality products. Some use cases had more financial impact than others. For example, TSE found one of the most successful implementations that focused on process stability improvement contributed to about 20 percent of the total benefits of the AA program. Because raw materials were the plant's largest cost driver (consuming 63 percent of the IJmuiden plant's revenues), projects that could improve the efficiency of raw material usage (yield from raw materials) had a particularly significant impact on profitability. As a project manager reported, "What used to take data analytics teams two to three months to build now takes about 30 minutes, due to the improvement of models, analytical skills, and availability and quality of production data."

- **Workforce and labor impact:** While no immediate workforce reduction was observed from the AA program, it is likely that there will be job loss in the medium- to long- term. However, this workforce reduction should be contextualized within the steel industry's decades' long trend of decreasing labor requirements. Twenty-five years ago, a similar plant might have employed 23,000 full-time equivalents (FTEs[2]) and produced 3 million tons of steel. TSE's current production is 7 million tons, but with only 9,000 FTEs.[3]

[1] Earnings before interest, tax, depreciation, and amortization (EBITDA) is a common proxy for a company's cash flow. This metric can be sensitive to both company-specific volume changes (producing more steel), as well as industry pricing levels (higher steel price-points), and thus comparing directly across time periods can have limitations.

[2] FTE refers to full-time equivalent employees at the company. The term is a business acronym and is a conventional unit of measure to compare workloads across different business contexts. Because labor may be undertaken by part-time employees, it is useful to standardize work amounts across full-time equivalents, rather than total worker counts.

[3] Reported data from management interviews

To date, TSE has not used AI explicitly as a means of workforce reduction, but rather has focused on realizing economic benefits through raw materials savings, yield uplift, and quality improvements. TSE's decision to deploy AI solutions and avoid immediate worker layoffs may be attributed to strong union representation and the company's interest in providing a positive example of corporate leadership. Though the AA program has not directly reduced employee count, it has had other effects on the composition of TSE's labor force: AA use cases are complex, driven by plant operators' heuristics or domain expertise or requiring specialized focus on processes with more variables. The ratio of higher- to lower- trained employees will likely continue to increase as the company continues its work with AA and hires or trains the required staff. TSE believes this approach produces the best results, as it believes its steel engineers' knowledge of steel production makes for better AA models and analysis compared with hiring data scientists who may have no steel industry experience. However, although TSE was able to source labor internally by training the company's existing engineers in data science, the danger of disproportionate impact of eventual job losses on unskilled and low income labor forces exists for companies in industries that might not prioritize domain expertise.

# Conclusion and lessons learned

Since the launch of the Advanced Analytics Program at the IJmuiden plant, TSE management has viewed AA as another step in pursuit of continuous improvement in their business and a way to differentiate and stay competitive in the highly commoditized and capital-intensive steel industry.

In highly-regulated industries, such as steel and manufacturing, contextual factors such as unions and regulations may influence managerial decisions about AI-related efforts: For instance, the AA program at TSE was designed to focus on non-labor levers of value, so it specifically avoided workforce reduction.

Additionally, the case study of TSE demonstrates that Advanced Analytics or AI more generally is not a panacea — it is a particular analytics tool suited for specific types of problems, such as process improvements, and could not immediately resolve all challenges at the plant. The best use case candidates for AA have been multivariate or complex problems, such as understanding the influence of hundreds of factors throughout the production process on the chemical properties of steel. In the past, these types of processes had been monitored through a heuristics-driven approach, using the learned experience of a plant operator over many years working in the plant. While plant operators still rely heavily on their domain expertise, it appears that some of that knowledge is being codified or replaced by analytical models and automated processes - an example of improved efficiency that can (but will not always) arise from AI systems. The implications this has for job losses in the future remain to be seen. Some within TSE believe that there will likely be reductions in labor in the coming years as a result of the AA program. It is difficult to isolate, however, AA's exact contribution to this potential outcome, as the AA program is admittedly not the only change taking place within the organization and must be contextualized within a longer-term trend of automation and labor reduction in the steel industry overall.

# Open questions and future research

One question of note is the likely progression for labor as Advanced Analytics use cases become more mature: For instance, in one system, what began as a predictive early-warning tool for operators' use has evolved to a fully autonomous system, in which an operator does not intervene. As the AI-related technologies at TSE mature, it is likely that they will start to intersect with existing automation programs or expand to further use cases outside of production (e.g., use cases in procurement, finance, HR), which may lead to job loss, or may allow employees to focus on other areas of the company's operations.

Complicating these dynamics is TSE's aging workforce: If TSE does not reduce its dependence on labor, how might the company be affected in coming years by lower availability of workers? Will there be further economic savings in the form of raw materials and yield, or will the AI wave look similar to the physical automation wave of the past few decades, leading to reductions in the workforce? It is unclear what these questions will mean in sum for the future of work at TSE's IJmuiden plant and for incumbents of older industries in general as they adopt AI to remain competitive.

# Appendix

## Definitions and terms used

While we acknowledge that there is no consensus on the definition of terms such as AI and automation, we would like to explain how these terms are used in the compendium:

**Artificial intelligence/AI** is a notoriously nebulous term. Following the Stanford 100 Year Study on Artificial Intelligence, we embrace a broad and evolving definition of AI. As Nils J. Nilsson has articulated, artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment. (Nils J. Nilsson, *The Quest for Artificial Intelligence: A History of Ideas and Achievements,* Cambridge, UK: Cambridge University Press, 2010).

Our definition of **automation** is based on the classic human factors engineering definition put forward by Parasuraman, Sheridan, and Wickens in 2000: https://ieeexplore.ieee.org/document/844354, in which automation refers to the full or partial replacement of a function previously carried out by a human operator.[4] Following Parasuraman et al.'s definition, levels of automation also exist on a spectrum, ranging from simple automation requiring manual input to a high level of automation requiring little to no human intervention in the context of a defined activity.

**Explainable AI** or **Explainability** is an emerging area of interest in communities ranging from DARPA to criminal justice advocates. Broadly, the terms refer to a system that has not been "black-boxed," but rather produces outputs that are interpretable, legible, transparent, or otherwise explainable to some set of stakeholders.

In this compendium, a **model** refers to a simplified representation of formalized relations between economic, engineering, manufacturing, social, or other types of situations and natural phenomena, simulated with the help of a computer system.

[4] Our definition draws on the classic articulation of automation described by Parasuraman, Sheridan, and Wickens (2000): https://ieeexplore.ieee.org/document/844354

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