qoncept

CASE STUDY REPORT
VERSION 1.0
08.2026

SELF-LEARNING RAW MATERIAL OPTIMIZATION

FROM SCRAP UNCERTAINTY TO COST LEADERSHIP

How EAF Producers Reduce Production Cost with Self-Learning Raw Material Optimization

SELF-LEARNING SCRAP COMPOSITION AND YIELD

Replace static scrap quality assumptions with self-learning raw material quality derived from actual production data.

REDUCTION OF OFF-SPECIFICATION HEATS

Accurately predict melt composition and stay within target composition at minimum production cost.

REDUCED ENERGY COMSUMPTION WITHOUT PRODUCTIVITY LOSSES

Optimize electrical and chemical energy together with chemistry, yield, slag formation, and productivity requirements.

FOREWORD

In electric arc furnace (EAF) steel production, production cost is highly linked to the cost of raw materials and electrical energy, which are both governed by market prices. The more decisive question is whether the chosen scrap mix will actually behave as expected in the furnace. For many producers, this is still managed through static scrap data, fixed recipes, and conservative dilution strategies after a heat has been out of its target chemical specification. Production continues, but the plant pays a hidden premium for uncertainty.

That premium appears in different forms. It appears in the use of cleaner and more expensive scrap than would theoretically be necessary. It appears in avoidable dilution, wider safety margins to tramp element limits, unnecessary electrical energy consumption, unstable metallic yield, increased slag volume, and the recurring need to compensate for raw material behavior that was not sufficiently understood before charging. In such an environment, charge planning is no longer a routine technical preparation step. It becomes one of the most important economic decisions in the entire melt shop.

This is precisely why conventional approaches are reaching their limits. Traditional charge calculators and isolated optimization routines were developed for a more stable industrial reality. They assume that material properties are sufficiently known, that raw material behavior can be represented through static master data, and that optimizing purchase cost or target chemistry is enough to steer production economically. In today's steelmaking environment, these assumptions are no longer robust. Scrap quality changes over time. Metallic yield is not constant. Non-metallic burden affects slag, energy, and productivity. Energy prices fluctuate. Product specifications remain tight. The result is that many plants still operate with planning methods that look structured but are economically weaker than they appear.

The key issue is not that steel producers lack metallurgical competence. On the contrary, many plants run with a high level of operational know-how and practical experience. The real limitation is that experience alone cannot fully resolve a dynamic raw material system with constantly shifting inputs and incomplete transparency at the moment of planning. What is required is a connected decision model that can continuously learn from actual production results, reflect the real behavior of the available raw materials, and convert that knowledge into better decisions for the next heat.

This whitepaper explains why EAF steel producers often overpay for certainty and why static scrap assumptions create hidden cost throughout the melt shop. It also shows how a software system called "qontrol MAPS" addresses this problem by replacing fixed raw material assumptions with a self-learning, metallurgically grounded optimization system that evaluates the real cost of a heat rather than the theoretical cost of a recipe. The strategic message is simple: the future of steelmaking is not about buying ever safer raw materials. It is about making better decisions with the raw materials that are actually available.

Most EAF plants don't pay for scrap only, they also pay for uncertainty regarding its quality, safety margins, corrections, excess slag and unnecessary energy consumption.

Dr. Stefan Griesser
Head of Sales at qoncept technology GmbH

PIONEERING TECHNOLOGIES

MAKING INTELLIGENT PRODUCTION A REALITY

Software and engineering solutions that increase process efficiency, optimize raw material use, and increase operator safety in steelmaking.

GLOBAL FOOTPRINT

15+	5	60+	19	40+	9
Software Projects	Countries Software	Equipment Projects	Countries Equipment	Consulting Projects	Countries Consulting

PRODUCT PORTFOLIO

SOFTWARE & HARDWARE

qontrol MAPS
Raw material management & charge optimization

qontrol L2
Level 2 automation & digital twins

qontrol MES
Manufacturing execution system

qontrol LMS
Ladle management system

qurve AI
Operator terminals & camera systems

EQUIPMENT & DEVICES

qouplerG
Automatic gas coupling system

qouplerM
Patented multi-media coupler

qouplerD
Automatic slide gate coupling, globally unique

Bins & Silos
Complete industrial silo systems

Engineering Services
Custom mechanical design & revamps

CONSULTING & STUDIES

Metallurgical Process Consulting
Measurable improvements in melt shop operations

Digitalization & Software Strategy
Feasibility studies and transformation roadmaps

COMPANY HISTORY

2018 — FOUNDATION

Founded in Leoben, Austria, by metallurgists with strong industrial backgrounds.

Establishment of the internal software architecture creating the scalable foundation for modular qontrol integration.

2020 — MARKET READINESS – qouplerM & FIRST PRODUCT DEPLOYMENT

qouplerM, an automatic multimedia coupler, reached market readiness and was patented.

Implementation of the first productive scrap tracking system, marking the transition to operational digital steel production.

2022 — PATENT AND FULL STEELMAKING INTEGRATION

Patent granted for the automatic slide gate coupling system qouplerD. This expanded the portfolio into automated slide gate actuation and signal integration.

Implementation of the first productive steel plan management system (Level 2) on full scope.

2024 — NORTH AMERICAN EXPANSION & PLATFORM SCALING

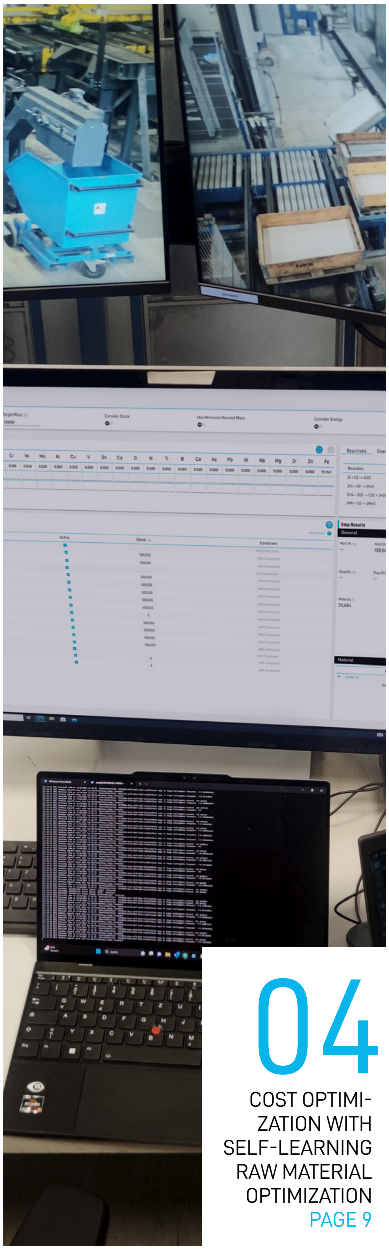
Establishment of qoncept Americas Inc. to support North American customers.

Functional specialization of the qontrol platform with dedicated modules for heat optimization, ladle tracking, and advanced scrap yard management.

TODAY — 100+ PROJECTS WORLDWIDE

Active operations across Europe, the Americas, and Asia.

CONTENTS



01 WHY SCRAP UNCERTAINTY IMPACTS PRODUCTION COST

EAF steel producers often operate under a structural contradiction. On the one hand, they depend on low-cost secondary raw materials such as end-of-life scrap, shredder scrap, and other heterogeneous scrap streams in order to remain economically competitive. On the other hand, these same materials introduce uncertainty in chemical composition, metallic yield, non-metallic burden, slag behavior, and energy demand. The industrial response to this contradiction is often not to eliminate uncertainty, but to buffer it.

These buffers are deeply embedded in the daily logic of the melt shop. Producers maintain distance to specification limits instead of operating close to them with confidence. They dilute uncertain scrap with cleaner, more expensive materials. They rely on recipes that reflect accumulated experience, but that are only loosely connected to the current behavior of the material base. They compensate for uncertainty through conservative decisions that protect production stability, but at the same time reduce the economic efficiency of the process. What looks like operational prudence is often, in financial terms, a recurring cost of caution.

This matters especially in EAF production because the raw material decision influences far more than the purchase price of the charge. It influences whether chemical composition limits can be met without excessive correction. It influences how much of the charged material actually becomes liquid steel. It influences how much slag is formed, how much electrical energy is required, and how much process variability the plant must absorb later. If these factors are not considered together, the producer may believe that the charge was economically optimized while in reality only one part of the cost structure was minimized.

In this sense, many steelmakers are not truly optimizing scrap usage. They are optimizing their tolerance for uncertainty. The cost is rarely visible as one dramatic failure. It accumulates quietly through small daily inefficiencies: a slightly more expensive scrap mix than necessary, a slightly lower metallic yield than assumed, a slightly higher slag burden, a slightly more conservative alloying strategy, a slightly wider margin to the chemistry limit. None of these individual effects is necessarily catastrophic, but together they can represent a substantial structural disadvantage.

The problem is therefore not simply that heterogeneous scrap is difficult to manage. The deeper problem is that uncertainty is still too often handled through static assumptions and safety margins rather than through continuously improving knowledge. As long as this remains the standard approach, steel producers will continue to pay for raw material uncertainty instead of converting it into competitive advantage.

02 THE HIDDEN COST OF USING STATIC MASTER DATA

The core weakness of conventional charge planning lies in the use of static scrap assumptions in a non-static raw material environment. Heterogeneous scrap streams do not have one fixed chemistry, one fixed metallic yield, or one stable process value. Their effective behavior changes over time due to supplier changes, lot-to-lot variation, non-metallic contamination, differing source materials, and shifts in market availability. Yet in many plants, planning still treats these materials as if one stored analysis and one stored yield value were sufficient to represent their actual industrial behavior.

This creates a false sense of certainty. A scrap grade may appear economically attractive in the planning system while behaving very differently in the furnace. Tramp element input may be underestimated. Metallic recovery may be overstated. Energy demand may be treated as a downstream operational issue instead of a direct consequence of the raw material decision. In such a case, the recipe may look correct on paper while already containing the seeds of higher real production cost.

Scrap-based EAF steel production is particularly exposed to this problem because some steel grades are subject to strict chemical specification limits for residual elements. In these cases, even relatively small deviations in the effective contribution of individual raw materials can significantly change the risk profile of a heat. When the plant does not know with sufficient confidence how a given scrap mix will contribute to the next melt, it is forced into conservative behavior. That conservatism is rational in the short term, but expensive in the long term. It increases dependence on cleaner scrap, larger dilution volumes, and wider operating buffers.

The same logic applies to metallic yield and non-metallic burden. Heterogeneous scrap may carry oxides, dirt, coatings, and inert fractions that reduce metallic recovery and increase slag formation. Because such effects are rarely captured accurately in static master data, a material that appears cheap in purchasing terms may generate more slag, consume more fluxes, require more electrical energy, and reduce overall process efficiency. A conventional cost-only view cannot capture this adequately. It transfers cost from the purchasing perspective into the production process, where it appears later in a more diffuse and less transparent form.

This is why static scrap assumptions are not merely a data quality issue. They are a structural economic weakness. They reduce the accuracy of the planning basis and force the organization to compensate through experience, manual intervention, and conservative decision-making. The plant continues to operate, but it does so on a weaker decision foundation than necessary. Over time, this leads to avoidable cost, avoidable instability, and avoidable dependence on raw material buffers that could be reduced if the true behavior of the material base were known more accurately.

In practical terms, the hidden cost of static scrap assumptions is that the cheapest scrap on paper is often not the cheapest heat in production. The real economic outcome of a charge depends on how the materials behave in the melt shop, not on how stable the master data looked at the moment of planning.

03 TRANSFORMING STATIC MASTER DATA TO REAL-TIME SCRAP COMPOSITION

The decisive step toward better raw material decisions is to replace static scrap assumptions with a dynamic, plant-specific model of actual material behavior. This is where qontrol MAPS fundamentally differs from conventional charge planning logic. Instead of assuming that a scrap grade always behaves according to one predefined analysis and one fixed metallic yield, the system continuously determines the effective contribution of each scrap type based on real production data and actual heat outcomes.

This self-learning approach is particularly relevant for EAF production because often heterogeneous scrap is not only variable, but economically central. The system evaluates how charged materials actually behave heat by heat and continuously refines its understanding of their effective chemistry and metallic yield. This applies to non-oxidizing tramp elements such as copper, tin, and nickel, but also to oxidizing elements such as silicon, manganese, and chromium, whose behavior depends on furnace practice, oxygen input, and slag reactions. The result is not a generic scrap database, but a time-resolved material model that reflects the actual industrial behavior of the material base in this specific plant context. **Figure 1** shows the result of the self-learning scrap quality model for shredded scrap and how it changes its properties (i.e. chemical composition and metallic yield) within one week of production.

A static scrap database cannot capture how heterogeneous raw materials drift within a single week of production, requiring a dynamic, plant-specific model of actual material behavior.

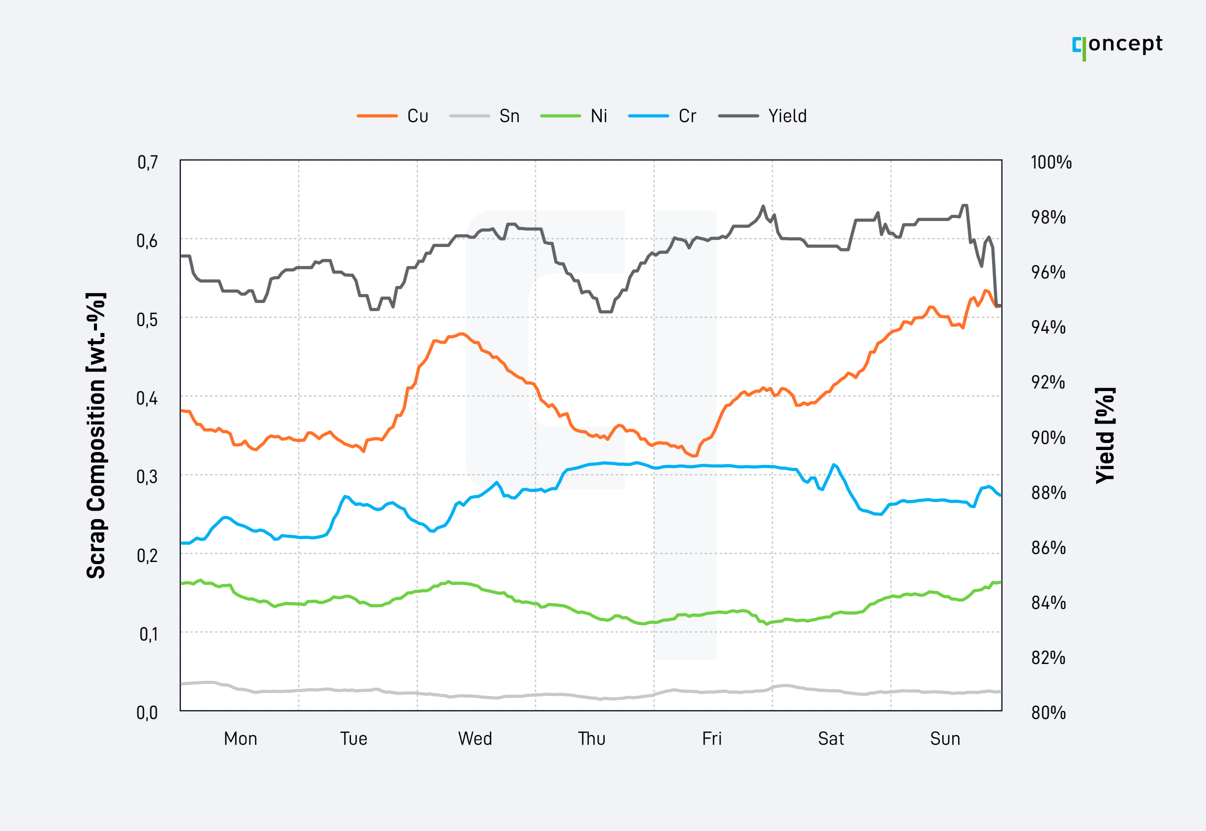
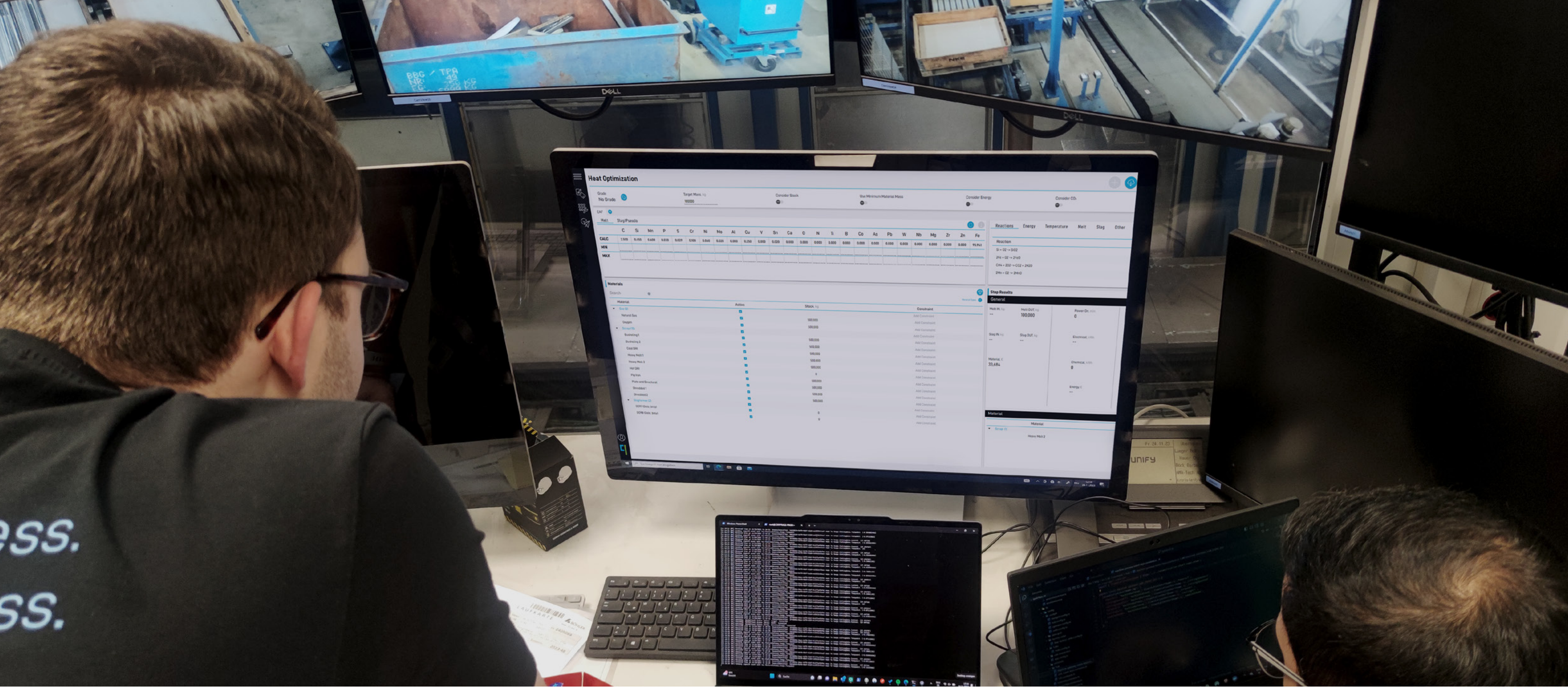


Figure 1: Real-Time Scrap Composition and Yield of Shredded Scrap Determined by the Self-Learning Model.

This changes the nature of raw material planning in a fundamental way. Scrap is no longer treated as a static assumption that the plant hopes will be "close enough." It becomes a learning object inside a continuously improving decision framework. Supplier shifts, lot variation, and drifting scrap quality no longer remain hidden behind frozen master data. They become visible through production feedback and can be used as decision-relevant information in subsequent heats. Over time, this reduces uncertainty not by eliminating heterogeneous scrap, but by understanding it more accurately.

From an economic perspective, this is crucial. In steelmaking, the main challenge is not only to calculate a charge that is formally valid. It is to predict with sufficient confidence how that charge will behave before it is melted. A self-learning scrap model improves exactly this decision basis. It enables the plant to move away from broad safety margins and toward more precise, more informed, and more economically effective material decisions. What was previously handled through conservatism can now increasingly be handled through knowledge.

This also has strategic implications beyond individual heats. Once the producer begins to build a continuously improving model of the real material base, raw material management itself becomes more mature. The plant gains better transparency into how materials actually perform over time, which suppliers or streams drift, where hidden costs originate, and how purchasing, production, and quality assurance can align more effectively around one evolving picture of material reality. In that sense, self-learning scrap characterization is not just a technical feature. It is the foundation of a more truthful raw material management system.



04 COST OPTIMIZATION WITH SELF-LEARNING RAW MATERIAL OPTIMIZATION

qontrol MAPS is not a conventional charge calculator. It is a connected raw-material decision system that combines self-learning material characterization, metallurgical process logic, and multi-constraint optimization in one industrial framework. Its purpose is not simply to identify a mathematically cheap blend, but to determine the best executable charge under current plant conditions with predictable results.

The first component of this framework is the continuously updated understanding of the available raw materials. Because the system learns the effective chemistry and metallic yield of the scrap base from actual production behavior, it works with a more realistic planning basis than static recipe logic can provide. This is essential because the quality of any optimization result depends directly on the quality of the input data. A sophisticated algorithm working with frozen or inaccurate assumptions cannot produce consistently superior industrial decisions. qontrol MAPS improves the optimization result by improving the input data itself. **Figure 2** compares the predicted copper content of 200 consecutive heats in a 100 t EAF based on static master data (blue) and the self-learning scrap model (green) with the copper content measured in the EAF sample (red). The black line indicates the applicable maximum copper specification for each steel grade. While the master-data prediction remains largely static and is deliberately held below the grade-specific maximum by a fixed safety buffer, qontrol MAPS predicts the measured variations in melt chemistry with much greater accuracy.

> qontrol MAPS does not select the cheapest scrap mix. It selects the lowest-cost executable heat after chemistry, yield, slag, energy, availability and operational constraints are considered together.

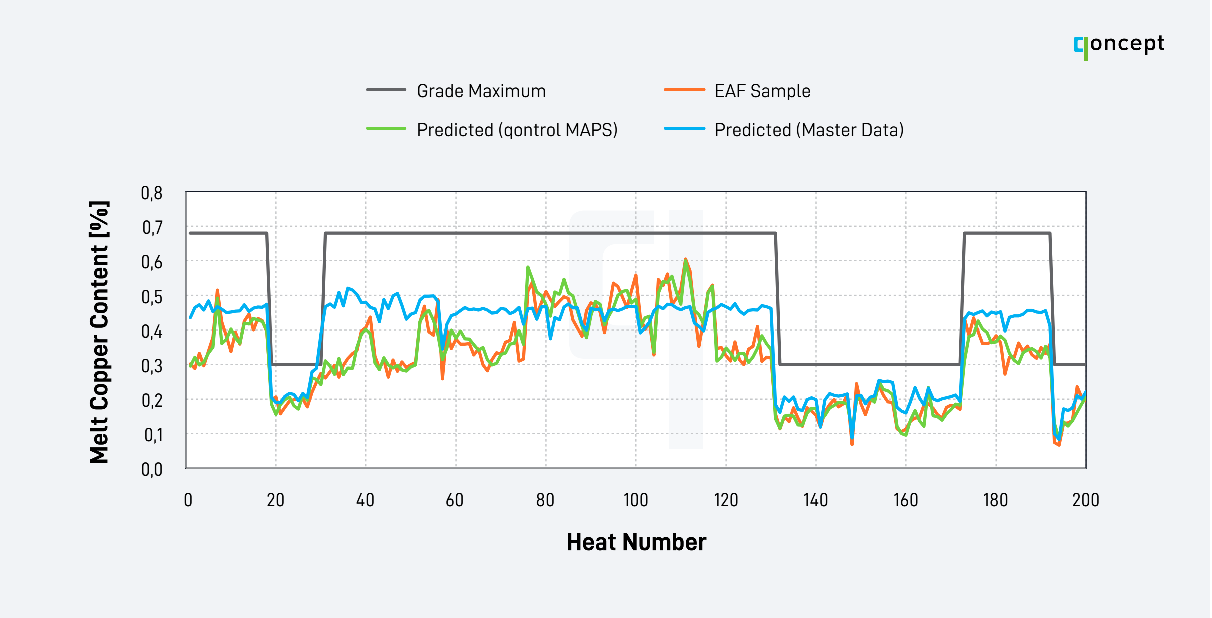


Figure 2: Prediction of Melt Composition for 200 Heats Using Master and Real-Time Scrap Data.

The second component is metallurgical grounding. A cheap-looking charge has no practical value if it cannot be run robustly in the furnace. qontrol MAPS therefore evaluates candidate charge mixes not only against target chemistry and purchase cost, but also against the relevant process realities of EAF steelmaking. These include the effect of raw material composition on metallic yield, slag formation, as well as the impact on electrical and chemical energy. This ensures that optimization remains anchored in actual furnace behavior rather than abstract numerical cost minimization.

The third component is economic optimization under real constraints. Instead of minimizing scrap cost alone, qontrol MAPS evaluates the real cost of the heat. This includes raw material prices, target melt composition, metallic yield, slag burden, hot heel impact, energy demand, availability limits, and operational constraints. The result is that the best charge is often not the one with the lowest purchase cost. A slightly more expensive scrap may still be preferable if it improves yield, reduces energy consumption, lowers slag formation, or decreases the need for dilution with clean materials. The system therefore optimizes production economics as a whole rather than one cost category in isolation.

An important practical consequence of this approach is proactive quality assurance. Because the system predicts the effective contribution of the chosen charge before melting, it enables producers to operate closer to specification limits with greater confidence. That reduces the need for broad chemistry buffers and emergency corrections after charging. In tramp-element-sensitive grades, this is not a secondary benefit. It is one of the main economic levers, because every unnecessary tonne of clean scrap or primary iron used for safety represents real cost. Better prediction quality therefore translates directly into better cost performance.

What makes qontrol MAPS particularly strong as an industrial solution is that it does not stop at theory. The system is designed to operate in the background, integrate into real production environments, and provide executable results without additional manual workload for operators. This matters because industrial value depends not only on whether an algorithm can optimize, but on whether the plant can actually use the result directly in its daily decision process. qontrol MAPS therefore optimizes the heat, not just the recipe. It improves the quality of the raw material decision in a way that is both economically meaningful and operationally practical.

05 WHAT CHANGES ON THE SHOP FLOOR

When raw material decisions become more accurate, the operational consequences are immediate. The plant gains the ability to use low-cost heterogeneous scrap more confidently because the behavior of that scrap is better understood. The dependence on conservative dilution with cleaner and more expensive materials can be reduced. Melt chemistry can be predicted more reliably. The probability of unpleasant surprises after charging decreases. And the daily logic of production begins to shift from reactive correction toward proactive control.

This does not mean that steel production becomes simple. The process remains inherently complex, and raw material variability does not disappear. But the plant's relationship to this complexity changes. Instead of absorbing uncertainty mainly through experience, local workarounds, and wide safety margins, the producer begins to manage it through a more structured decision framework. That framework is not based on abstract theory alone, but on a continuously improving picture of how the plant's own material base actually behaves in practice. The effect is greater control, greater confidence, and a more stable operating model with detailed instructions for the operators.

One of the most important changes is consistency. In many operations, raw material decision quality depends strongly on the experience and judgment of specific individuals. That knowledge is valuable, but it is also difficult to scale across shifts, teams, and time. When qontrol MAPS is introduced, relevant knowledge becomes increasingly embedded in the system itself. Better decisions no longer rely exclusively on the person currently making the call. They are supported by a shared, continuously updated model of material behavior and process economics. This improves robustness across the organization and reduces variability caused by differing individual assumptions.

Another important change is transparency. Once raw material behavior is linked to actual production results, the plant gains a clearer view of where cost and instability truly originate. The conversation changes. Instead of discussing whether a recipe "usually works," the organization can increasingly evaluate which materials behave differently than assumed, where yield losses are occurring, how much slag burden is associated with a given scrap stream, and how purchasing and production decisions influence one another. This helps create stronger alignment between melt shop operations, quality management, and raw material procurement.

The biggest operational gain is therefore not automation for its own sake. It is decision confidence. The plant becomes more capable of making the next charge decision on the basis of actual plant reality rather than static assumptions. In an environment with tight margins and variable scrap quality, that shift alone can have major economic significance.

> Instead of correcting the melt composition from an uncertain scrap mix after melting, operators can rely on an accurate prediction of the resulting melt quality before the bucket is charged.

06 WHY DECISION QUALITY IMPROVES HEAT BY HEAT

One of the strongest differentiators of qontrol MAPS is that its value does not remain static after go-live. It continuously adapts to real production conditions with each heat. Because the system links charge planning, actual charging data, and production results in one feedback loop, every heat contributes to a better understanding of the plant's raw material reality. The next optimization is therefore not based only on current prices, inventory, and target chemistry. It is also based on a more refined and more truthful model of how the available materials actually behave in this specific furnace and process environment.

This creates a compounding effect that conventional static systems cannot deliver. A traditional charge tool remains bounded by the quality of its initial assumptions. If the underlying scrap data are incomplete, outdated, or too generic, the result will continue to reflect that limitation. A self-learning system behaves differently. It continuously reduces uncertainty by updating its material knowledge from real production outcomes. The plant becomes less dependent on conservative assumptions because the basis for future decisions becomes progressively stronger.

For steel producers, this learning effect is strategically important. The economic challenge in this segment is not a one-time optimization task. It is a recurring challenge of making robust decisions under uncertain raw material conditions. A system that becomes more accurate heat by heat therefore creates a fundamentally different kind of value than a static optimization program using constant master data. It does not simply support today's decision. It improves the quality of tomorrow's decision as well. That is why the benefit of qontrol MAPS should not be understood as a one-off software effect, but as the establishment of a stronger and more mature operating model.

The consequence is greater competitiveness. As the system learns the plant's material base more accurately, the producer can use heterogeneous scrap more intelligently, reduce unnecessary buffers, and move closer to the true economic optimum. This is especially relevant in volatile raw material markets, where the ability to adapt quickly to changing quality, availability, and cost conditions becomes a real strategic differentiator. Decision quality becomes an asset that compounds over time.

In this sense, the competitive advantage is not only better optimization today. It is better raw material knowledge tomorrow. That is a much stronger foundation for cost leadership than any static recipe system can offer.

> Every completed heat improves the model used for the next one. Changes in supplier quality, lot composition and scrap behaviour no longer remain hidden behind fixed values.

07 INDUSTRIAL DEPLOYMENT WITHOUT DISRUPTING PRO-DUCTION

Industrial value depends not only on the quality of the optimization logic, but also on how well the system fits into the real workflow of the plant. Even a technically advanced solution will fail if the result reaches operators, planners, and production managers in a form that is difficult to interpret or awkward to execute. That is why qontrol MAPS is designed as an industrial software solution that integrates into existing plant structures and supports operations without creating additional manual workload.

This is an important distinction because many optimization narratives remain too theoretical. They describe what a system can calculate, but not how that result becomes part of actual daily decision-making. In a real melt shop, the decisive question is whether optimization output can be translated directly into actionable charge decisions that fit existing operating logic and can be executed reliably. qontrol MAPS is built around this requirement. It is meant to function as a practical decision layer inside the production environment, not as a parallel analytical world that operators must reinterpret on their own.

A further advantage is that implementation can be staged. The system does not require the plant to wait for one large disruptive transformation before value is created. Instead, relevant data sources, learning logic, and optimization workflows can be connected step by step in a way that reflects the maturity and reality of the operation. This incremental approach supports organizational acceptance and makes the project easier to embed sustainably. In industrial environments, systems that respect existing workflows and improve them progressively usually deliver better long-term adoption than systems that demand a complete behavioral reset from day one.

For steel producers, this is particularly valuable because the economic effect of better raw material decisions can emerge relatively quickly once the learning loop is established and optimization begins to operate on a more truthful material basis. The project is therefore not best understood as a disruptive software rollout, but as the gradual establishment of a better raw material operating model: first improve the data basis, then strengthen the material model, then connect the improved decision logic directly to execution.

A better raw material model only creates value when it fits the real melt shop. That is why practical usability, integration quality, and operator acceptance are not secondary considerations. They are part of the economic logic of the solution itself.

08 CONCLUSION

Steel producers can no longer afford to manage heterogeneous scrap with static assumptions. The traditional response to uncertainty, cleaner dilution materials, conservative recipes, wide chemistry buffers, and reactive correction, may protect short-term production stability, but it weakens long-term competitiveness. It is a cost of caution that many plants still accept as normal, even though it arises not from metallurgical necessity alone, but from insufficient decision quality at the moment of planning.

qontrol MAPS offers a fundamentally different path. By continuously learning the true behavior of scrap, combining that knowledge with metallurgical process logic, and optimizing against real plant constraints, the system enables producers to make better raw material decisions under uncertainty. This reduces total melt cost, improves quality stability, and strengthens the economically effective use of low-cost secondary raw materials. The result is not just a better recipe. It is a better decision system for the raw material reality of modern EAF steelmaking.

The strategic implication is clear. The next generation of steel production will not be defined by who buys the safest scrap. It will be defined by who understands the available scrap best, who learns fastest from production reality, and who can convert that knowledge into the most economically effective heat decision. In that sense, the real lever is not more conservatism. It is better decision quality.

> The next generation of EAF steel production will not be defined by buying better scrap, but by responding faster to changing raw material quality and turning real production feedback into economically optimized heat decisions.

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