A Physics-Informed Soft Sensor for Real-Time Ore Hardness Estimation in SAG Mills

A residual-based architecture combining the Morrell mill power model with Extra Trees regression, delivering a continuous, SCADA-only hardness signal suitable for MPC feedforward.

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ABSTRACT

Ore hardness drives SAG mill power draw, throughput, and downstream particle size distribution, yet plants typically infer hardness only through periodic Bond Work Index or SPI laboratory tests at intervals of hours to days. The latency between hardness change and operator response is the single largest source of avoidable variability in comminution. This paper sets out a two-method architecture for real-time hardness estimation from existing SCADA infrastructure, without requiring additional instrumentation. Method 1, the SCADA-only reference implementation, uses the Morrell mill power model to compute the power the mill *should* draw and treats the residual against actual power as the hardness signal. An Extra Trees regressor is trained on this residual together with engineered features and periodic Bond Wi or SPI labels, yielding a continuous hardness estimate that updates every DCS scan cycle. Method 2 extends the architecture to a geospatial mine-to-mill digital twin, fusing blast block models, shovel GPS, and stockpile blending into a thirty-minute look-ahead forecast that serves as the prior in a Kalman filter, with the physics residual as the measurement update. The architecture is sensor-light, physically grounded, and directly consumable by Model Predictive Controllers as a feedforward signal.

KEYWORDS

Soft sensor, ore hardness, SAG mill, Morrell model, Extra Trees regression, Kalman filter, mine-to-mill, geospatial digital twin, MPC feedforward.

1. Introduction

The economic performance of a mineral processing plant is dominated by the comminution circuit, both in energy intensity and in its determination of the particle size distribution presented to flotation. Among the variables that drive comminution behaviour, ore hardness is simultaneously the most consequential and the least directly observable. Plants commonly characterise hardness through SAG Power Index or Bond Work Index assays, but the laboratory turnaround between sample and result, measured in hours to days, makes these labels operationally retrospective. By the time hardness is known, the ore has moved.

The cost of this latency is variability. When a hardness transition arrives at the mill unannounced, operators discover it through reduced throughput, increased mill load, or departures in cyclone overflow particle size. The corrective adjustments to feed rate, mill speed, or water addition come after the disturbance has propagated through the circuit. Where supervisory or Model Predictive Control is in place, the controller is forced to react to its own state estimates rather than to a leading indicator of the incoming ore. Variance reduction at the mill therefore requires that hardness become a measured, or at least estimated, real-time variable.

This paper presents a two-method soft sensor architecture for real-time hardness estimation. The architecture is designed around two non-negotiable constraints. First, no additional instrumentation is required beyond what a typical SAG mill installation already provides through its Distributed Control System. Second, the output must be a continuously updated, physically interpretable signal of a form that can be consumed directly as a feedforward input by an MPC or Advanced Process Control layer. The architecture is the SCADA-only reference (Method 1) followed by a geospatial extension that adds look-ahead (Method 2).

2. Method 1, the SCADA-Only Reference Implementation

2.1 Physics layer, the Morrell mill power model

The Morrell (1996) C-model expresses the gross power drawn by a tumbling mill as a function of geometric and operational variables that are independent of ore hardness:

$$P_{calc} = K \cdot D^{2.5} \cdot L \cdot \rho_c \cdot J_c \cdot \phi \cdot f(\phi)$$

where D and L are mill diameter and length, ρ_c is the charge density, J_c is the fractional charge filling inferred from bearing pressure, ϕ is the fractional speed expressed as a fraction of critical, and K is a calibration constant capturing liner and lifter geometry. The model is well established in the comminution literature and is the standard against which mill power is reconciled in plant design and audit.

The interpretive move is the residual. Once geometry, charge, and speed are accounted for, the difference between the actual power drawn and the model prediction is dominated by the energy required to break the ore. Harder ore breaks at higher specific energy; softer ore at lower. The residual therefore serves as a continuously available, physically grounded hardness signal:

$$P_{residual} = P_{actual} - P_{calc} \rightarrow \text{ore hardness contribution}$$

2.2 Feature engineering and the prediction model

The hardness residual alone is informative but noisy. The full feature vector presented to the regression layer combines the residual with engineered process features that capture the temporal dynamics of the mill. The hardness residual P_actual – P_calc is the principal feature. A normalised load term, computed as bearing-pressure-derived load divided by the square of mill speed, decouples mass from velocity and stabilises the residual against speed transitions. Specific-energy lag windows at five, ten, and thirty minutes capture the hardness trend over operationally relevant timescales.

The prediction model is an Extra Trees regressor (Geurts, Ernst & Wehenkel, 2006), chosen for its noise robustness, its insensitivity to feature scaling, and its ability to handle the skewed residual distributions characteristic of mill power data. The model is trained against the periodic SPI or Bond Wi laboratory labels available from the plant. The training target is a calibrated hardness index in the units of the available label, with held-out validation requiring an R^2 of at least 0.85 before the sensor is signed off for control use.

2.3 Output and integration with control

The output of Method 1 is a continuous, scalar estimate of ore hardness that updates every DCS scan cycle, typically one second. The signal is presented to the MPC layer as a measured disturbance, allowing the controller to adjust feed rate, mill speed, and water addition in anticipation of the hardness change rather than in reaction to its downstream consequences. The sensor is sensor-light by design: it requires only signals already present on every modern SAG mill installation.

3. Method 2, the Geospatial Mine-to-Mill Digital Twin

3.1 Motivation, the look-ahead horizon

Method 1 estimates hardness from the present state of the mill. It cannot estimate hardness that has not yet arrived at the mill. For circuits where the residence time from blast to mill is long enough that a look-ahead horizon adds value, typically thirty minutes to several hours depending on stockpile management, the architecture extends naturally to a mine-to-mill digital twin.

3.2 Geospatial fusion layer

The fusion layer combines three upstream data streams. The blast block model provides lithology and Rock Quality Designation by block identifier from pre-classified drilling. Shovel GPS, typically at RTK accuracy of ten to thirty centimetres, gives the real-time location of mass extraction. The geometallurgical database supplies SPI, Bond Wi, and ore density per block. For each conveyor segment between the loading point and the mill, the residence-time model computes the temporal lag $\Delta t = L \div v$, and a stockpile blending model tracks the resulting multi-shovel mass packets first-in-first-out through the stockpile. The output is a forecast hardness vector for the ore that will arrive at the mill in the next T+n minutes.

3.3 Kalman filter and hybrid state estimate

The geospatial forecast is the prior in a Kalman filter; the physics residual from Method 1 is the measurement update. The Kalman gain K weights geological uncertainty against real-time SCADA evidence at every scan cycle. Where the geospatial signal is confident, for example shortly after a well-characterised blast, the forecast dominates and the controller receives a clean look-ahead hardness signal. Where the geospatial signal is uncertain, for example through complex stockpile reclaim, the measurement residual dominates and the architecture degrades gracefully to Method 1

behaviour. The controller never loses its hardness input.

4. Architectural Position in the Axiom Control Stack

The hardness soft sensor sits in the third layer of the Axiom control hierarchy: above the healthy DCS, above the anomaly detection layer that flags sensor dropout and sticky-valve behaviour, alongside the other physics-informed soft sensors that generate feedforward signals for the Advanced Process Control layer. The APC layer, a hybrid of Fuzzy Logic Control for constraint management and Model Predictive Control for multivariable coordination, consumes the hardness signal as a measured disturbance. The AI Optimisation Layer above the APC computes the economic setpoints into which the hardness feedforward is embedded. The contribution of the soft sensor is therefore leverage on every layer above it, not a standalone output.

5. Conclusion

Real-time ore hardness estimation is achievable from existing SCADA infrastructure without additional instrumentation. The architecture presented in this paper combines the Morrell mill power model with Extra Trees regression to convert the unexplained portion of mill power draw into a continuous, physically grounded hardness signal. Where the upstream mine and stockpile management are sufficiently instrumented, the architecture extends naturally to a thirty-minute look-ahead forecast through Kalman fusion of geospatial and physics signals. In both forms, the output is a feedforward signal directly consumable by the APC layer above it. The cost of hardness latency becomes addressable.

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