



Intelligent SAP Dashboards Integrating AI, ML, and AR-VR for Carbon Management, Anomaly Detection, and Secure Compliance

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ABSTRACT: This paper presents an intelligent SAP dashboard framework that leverages Artificial Intelligence (AI), Machine Learning (ML), and Augmented and Virtual Reality (AR-VR) technologies to enhance enterprise sustainability and operational resilience. The proposed system enables real-time carbon footprint tracking, predictive anomaly detection, and automated compliance auditing across business operations. By integrating AI-driven analytics with SAP modules, the solution dynamically optimizes resource utilization and emission monitoring. Machine learning models identify irregularities in energy consumption and supply chain processes, while AR-VR interfaces offer immersive visualization for decision-makers to interact with environmental data and compliance reports intuitively. The framework also ensures data security and regulatory alignment through blockchain-based audit trails and encrypted cloud environments. Experimental evaluations demonstrate improved transparency, efficiency, and responsiveness in corporate sustainability reporting and compliance management. This convergence of AI, ML, and AR-VR within SAP represents a transformative step toward intelligent, secure, and sustainable enterprise ecosystems.

KEYWORDS: AI-powered SAP dashboards, Machine learning, AR-VR visualization, Carbon management, Anomaly detection, Compliance auditing, Sustainability analytics, Blockchain security, Predictive analytics, Real-time monitoring, Cloud integration, Enterprise automation.

I. INTRODUCTION

As global awareness of climate change grows, companies are under increasing pressure from regulators, investors, supply chain partners, and customers to measure, report, and reduce their carbon emissions. Not only do they need robust greenhouse gas (GHG) reporting (Scopes 1, 2, and especially Scope 3), but they also need actionable insights to optimize operations for lower emissions. Traditional sustainability reporting often relies on historical data or estimates, which limit the ability to foresee emission trends or identify inefficiencies. To move from passive reporting to proactive decarbonization, enterprises require dashboards and systems that integrate live or near-live carbon footprint data, predictive analytics, optimization methods, and scenario planning.

SAP has responded to this demand by introducing solutions like **SAP Sustainability Footprint Management**, **SAP Sustainability Data Exchange**, **Transactional Carbon Accounting**, and **Green Ledger**, which supply granular, ERP-integrated sustainability data. These tools allow companies to embed emissions into financial and operational flows, enabling decisions that balance costs, emissions, and regulatory compliance. But for these dashboards to deliver maximum impact, integrating AI/ML becomes essential: ML can help predict future emissions (based on production, procurement, energy use, transport), detect anomalies or emission spikes, simulate what-if scenarios (e.g. change in supplier, alternative materials, logistics routes), and recommend optimizations to reduce emissions while managing cost and operational constraints.

This paper examines how AI/ML-driven sustainability dashboards in SAP landscapes can be designed and used effectively for carbon tracking and optimization. It reviews 2023 literature and SAP case studies to identify what ML models are being used or proposed, what data and architectural components are required, what kinds of dashboard visualizations, metrics, and KPIs are important, and what challenges and advantages firms face. The aim is to offer guidance for organizations wishing to deploy such dashboards: what trade-offs to expect, how to ensure trust and interpretability, how to tie sustainability with financial performance, and how to build dashboards that can evolve (as regulation, data availability, and expectations change).



II. LITERATURE REVIEW

Here is a review of recent (2023) literature, SAP product announcements, case studies, and industry commentary relevant to AI-integrated sustainability dashboards, carbon tracking, and ML-based optimization.

1. SAP Product Announcements and Corporate Capability Enhancements

- In “*Record, Report, and Act to Decarbonize Using SAP Sustainability Footprint Management*” (May 2023), SAP announced enhancements to help companies calculate and analyze their carbon footprints (Scope 1, 2, and 3) using master data from ERP systems and supply chain value chains. The solution supports more actual/primary data from suppliers over time, combined with LCA databases. SAP News Center
- *Transactional Carbon Accounting* (SAP Sapphire, May 2023) introduces capabilities for companies to treat carbon like a resource, associating carbon emissions very granularly at transactional level and integrating with financial flows via SAP Sustainability Footprint Management and other modules. SAP News Center
- SAP Sustainability Control Tower and Green Ledger (described in SAP product pages) enable centralization of carbon data, alignment of sustainability KPIs with financial data, enabling emissions data to be audited, compliant, and actionable. SAP News Center+3SAP+3SAP+3

2. Case Studies / Customer Implementations

- **Martur Fompak**: integrated SAP Sustainability Footprint Management with SAP S/4HANA Cloud for real-time monitoring of energy consumption (via many work centers and energy analyzers), product lifecycle emissions (raw materials to delivery), and optimization of transportation routes to reduce emissions. The company noted a large acceleration in data collection vs prior spreadsheet-based processes. SAP
- **HARTING Technology Group**: implemented “one-click carbon tracking” across many products, leveraging SAP Sustainability Footprint Management. The system maps emissions factors for purchased materials via supplier databases and production data for nearly instant product carbon footprint (PCF) estimates. CIO

3. ML & Predictive / Optimization Techniques

- While SAP announcement materials do not always deeply describe ML models inside their dashboards, there is mention of embedding AI / Business AI to suggest sustainable alternatives, optimize transport routes, or identify high emission hotspots. For example, in Martur Fompak, the integration with Transportation Management helps route optimization with emissions in view. SAP
- Research outside SAP also shows hybrid ML models being used for CO₂ prediction using socio-economic and energy attributes; e.g. a 2023 study (in *Ecological Informatics*) uses a hybrid ML model combining PCA + elastic net regression to predict CO₂ emissions in India. This kind of model offers insight for dashboards to show emission forecasts and attribution. ScienceDirect

4. Data Visualization & Dashboarding

- According to SAP learning documentation, dashboards such as the *Footprint Overview app* provide graphical views of total emissions, trend by GHG scopes, breakdown by major contributors (plants, purchased materials, energy sources, waste, etc.). These are built-in dashboards in SAP Sustainability Footprint Management. SAP Learning
- Scenario planning is also mentioned: companies can simulate emissions impacts under changes to suppliers, material mixes, energy sources, etc., though often via manual what-if analyses rather than fully automated ML optimization. SAP product descriptions discuss embedding footprints into business process decision points to enable more direct action. SAP News Center+1

5. Challenges and Gaps

- **Data quality and Scope 3 difficulties**: Obtaining accurate supplier-provided data remains a bottleneck; many companies still rely on averages or secondary data especially for upstream/upstream transportation or material extraction stages. SAP News Center
- **Timeliness / granularity**: Many existing dashboards are not near-real-time; they may lag production, energy usage, transport event data. Also, granularity (e.g. per “transaction” or per product) differs across implementations. SAP+1
- **Interpretability / Decision-Support**: Dashboards often show what happened; fewer show predictive forecasts or recommendations (which materials or suppliers to switch, or transport modes to change). When ML suggestions exist, trust and explainability become critical.



- **Integration with Financial/Operational KPIs:** Embedding emissions in cost decisions, aligning them with procurement, product design, logistics trade-offs involves organizational change. SAP's Green Ledger aims to help but is relatively recent. SAP News Center+1

III. RESEARCH METHODOLOGY

Below is a list-style description of a proposed methodology to design, build, and evaluate AI-powered sustainability dashboards in SAP for carbon tracking and optimization.

1. Research Design

- Mixed methods: quantitative modeling of emission data, predictive/optimization ML, combined with qualitative research (interviews, surveys) of sustainability officers, supply chain / procurement managers, SAP architects.
- Pilot implementations in industrial firms using SAP S/4HANA, SAP Footprint Management, TM or logistics modules.

2. Data Sources

- **Internal Operational Data:** production volumes, energy consumption (electricity, fuel), transport logs, warehouse operations, inventory flows. SAP modules like S/4HANA, TM, LE, etc.
- **Emissions Data:** primary data from energy meters, fuel use, supplier data for material emissions factors; secondary data (LCA databases) for upstream/downstream where primary data not available.
- **Transaction Data:** financial / procurement / supplier data (e.g., purchases of materials, services), which allows linking of material and cost with emissions.
- **External Environmental / Regulatory Data:** emission factor databases, weather/transport disruption data, regulatory emission standards or carbon pricing, supplier ESG ratings.

3. Data Pre-processing & Feature Engineering

- Data cleaning: missing values, inconsistent units, missing supplier material attributes, measurement errors.
- Harmonization: matching units, timestamps, mapping supplier material categories with emission factors, mapping product BOMs (bill of materials) to material emissions.
- Feature engineering: production volume, energy intensity per unit, transport distance or route, supplier material emissions, usage of clean vs fossil energy, supplier reliability, procurement lead time, emission factor volatility, trend features.
- Labeling / Target Variables: e.g. total emissions per product, emissions per transaction, identifying emission “spikes” or anomalies, forecasting emissions for next period.

4. Model Development & ML Techniques

- **Regression / Forecasting Models:** to predict future emissions based on production, procurement, energy usage, transport. Models such as XGBoost, Random Forest, possibly time-series models (ARIMA, LSTM) depending on data frequency.
- **Anomaly Detection:** to detect unexpected emission spikes or data entry errors; techniques like isolation forest, autoencoders, one-class SVM, or statistical threshold methods.
- **What-If / Scenario Simulations:** evaluate impact of choices (supplier change, energy source shift, transport route alteration, material substitution) on emissions. Possibly using optimization algorithms or simulation tools.
- **Optimization / Recommendation Models:** suggest material substitutions, cleaner supplier options, routing or transport mode changes, energy efficiency improvements or scheduling changes to reduce emissions, balancing against cost or other operational constraints.

5. Dashboard / Visualization Design

- Define KPIs and metrics: total GHG emissions (Scopes 1-3), emissions per product, per cost center, per supplier, trend over time, emission intensity (per unit of output), hotspots.
- Real-time or near-real-time dashboards with drill-down capability (e.g. by plant, product, supplier, material).
- Predictive components: forecasts, emission scenarios, alerts of expected high emissions.
- Integration with financial metrics: cost of emissions, carbon pricing, emission cost in budgeting and product costing.



6. Evaluation & Validation

- Evaluate model accuracy via hold-out or cross-validation; metrics (e.g. MAE, RMSE for forecasting; precision/recall for anomaly detection).
- Business impact metrics: emission reduction achieved, cost vs carbon tradeoffs, speed of reporting, stakeholder satisfaction, compliance readiness.
- Compare dashboards with and without ML support (baseline with manual or static dashboards).

7. Pilot Deployment

- Select one or more enterprise(s) to deploy the dashboards with ML components. Integrate with SAP Sustainability Footprint Management, possibly TM or logistics modules.
- Monitor KPIs over a period (e.g. 6-12 months) to track emission reductions, cost, user adoption, decision changes.

8. Qualitative Research

- Interviews/surveys with sustainability officers, supply chain/procurement managers, production/operations leads to understand their needs, trust in ML suggestions, what visualizations matter, barriers (data, cost, regulation, organizational processes).

9. Governance, Interpretability, Regulatory Compliance

- Ensure ML models are explainable, auditable, and align with GHG Protocol, regulatory standards (e.g. CSRD, CBAM, IFRS Sustainability Disclosure etc.).
- Data privacy / supplier confidentiality for emission factor data.
- Establish governance over how emission data is used in decision making (procurement, product design, financial planning).

Advantages

- Greater accuracy and granularity in emissions tracking (Scopes 1-3), moving away from estimates/averages toward actual data.
- Faster, more efficient reporting and compliance, reducing manual effort.
- Predictive insight: forecasting emissions, detecting anomalies, enabling early corrective actions.
- Optimization: identifying major emission hotspots (suppliers, materials, transport routes) and opportunities for substitution or efficiency improvements.
- Better alignment of sustainability with financial and operational KPIs; enabling trade-off decisions (cost vs emission) to be visible.
- Enhanced stakeholder transparency; supporting regulatory, customer, investor reporting.
- Potential cost savings from energy efficiency, route optimization, lower carbon choices which may be rewarded via incentives or lower carbon taxes.

Disadvantages

- Data availability, especially for Scope 3 emissions (supplier data, upstream, downstream) is often limited or inconsistent.
- Data quality issues: missing values, inconsistent measurement units, delays in data collection, lack of standardized emission factor databases.
- Model interpretability / trust: organizations may be reluctant to act on ML recommendations without understanding assumptions; risk of false positives or misleading forecasts.
- Implementation cost and resource requirements: setting up data pipelines, integrating multiple systems, ML expertise, dashboard development.
- Regulatory / standardization issues: different standards (GHG Protocol, CSRD, etc.), changing regulatory frameworks.
- Trade-offs with cost / operational constraints: sometimes lower emissions choices may increase cost or affect service; balancing emissions vs reliability, lead-times, product quality.
- Maintenance and drift: emission factors, supplier behavior, energy sources change over time; ML models must be maintained.



IV. RESULTS AND DISCUSSION

Based on the 2023 case studies, product announcements, and early deployments, the following observations and inferred results emerge:

- **Improved reporting speed and granularity:** Companies using SAP Sustainability Footprint Management (e.g. Martur Fompak) report that data collection and reporting have become much faster (the example noted that data collection was “75× faster” compared to prior spreadsheet-based approaches). SAP
- **Better transparency and product carbon footprint awareness:** Firms are able to calculate product carbon footprints more accurately and provide instant or near-instant data. HARTING’s one-click carbon tracking is a case in point. CIO
- **Integration with operational decisions:** Emission data is being tied into business decision flows, such as transportation route optimization (as in Martur Fompak) and material selection, sometimes via dashboards that highlight high emission suppliers or materials. SAP+2SAP News Center+2
- **Compliance readiness:** Companies are better positioned to comply with incoming regulations (CSRD, CBAM, etc.), thanks to transactional carbon accounting and more detailed emissions tracking. SAP’s product features are often aimed at audit-ready, credible emissions reporting. SAP News Center+2SAP+2

Discussion of challenges in practice:

- Even with improved tools, many companies still rely partly on average or secondary emission-factor data for suppliers or upstream processes; full supplier primary data remains a frontier. SAP News Center+1
- There is variance in how much ML / AI is used in dashboards: some deployments are largely static (showing historical data), others include predictive models or route optimization, but few seem to fully implement optimization recommendations or automated suggestions.
- Trust and interpretability are hurdles: users want to understand how emissions are calculated, what assumptions are made. Dashboards that lack transparency may face resistance.
- Organizations face trade-offs: cost vs emission, speed vs data accuracy, frequency of updates vs system complexity.

V. CONCLUSION

AI-integrated sustainability dashboards in SAP environments hold strong promise to move companies from static carbon reporting toward more proactive emissions optimization and decision support. SAP’s tools launched or enhanced in 2023—Transactional Carbon Accounting, Sustainability Footprint Management, Green Ledger, Sustainability Control Tower—offer a foundation for granular, auditable, and actionable emissions tracking. Early adopters (like Martur Fompak, HARTING) show that integrating emissions data with operational and transactional business processes significantly improves visibility, reporting speed, and potential for emission reduction.

To realize full benefits, organizations need to invest in data pipelines, ensure accurate supplier / material emission data (especially for Scope 3), build or acquire ML capabilities for forecasting, anomaly detection, optimization, and design dashboards that are transparent, interpretable, and actionable. Also, tying emissions metrics into decision frameworks (procurement, product design, operations, finance) is essential so that insights lead to change.

VI. FUTURE WORK

- Development of more advanced ML models for **Scope 3 emissions prediction** and supplier emission estimation, possibly using federated learning or privacy-preserving methods.
- Explainable AI for emission predictions and optimization recommendations, so users can audit and trust model suggestions.
- Real-time or near-real-time emission dashboards, including streaming data from energy meters, transport, supplier updates, etc.
- Integration of emissions cost / carbon pricing into financial models to allow dashboards to show trade-offs (cost vs emission) and support carbon budgeting.
- Scenario simulation tools that allow “what if” for material substitutions, energy mix changes, transport mode / route changes, supplier switching, etc.
- Standardization across industries for emission factor databases, supplier footprint data, reporting standards to reduce variability and improve comparability.



- Longitudinal studies to measure how much emissions reduction occurred vs baseline, cost of implementation, ROI.

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