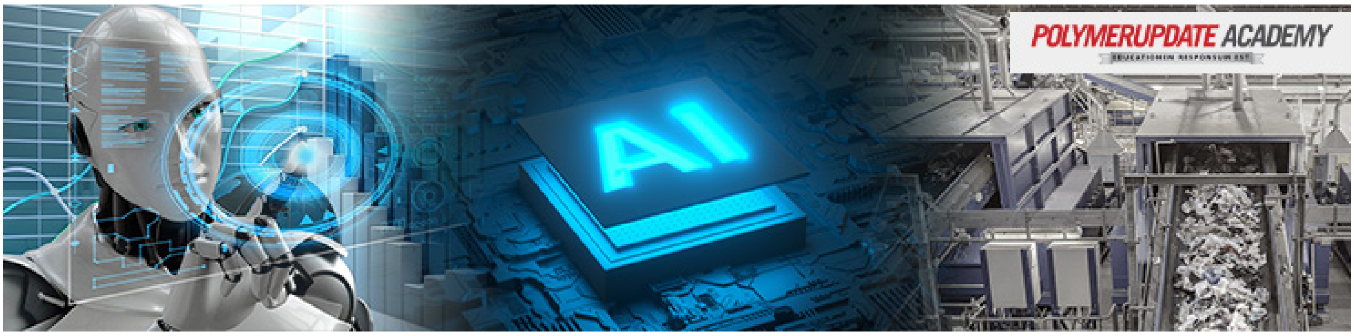
USING AI/ML FOR SUSTAINABILITY IN THE PLASTICS INDUSTRY



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Using AI/ML for Sustainability in the Plastics Industry

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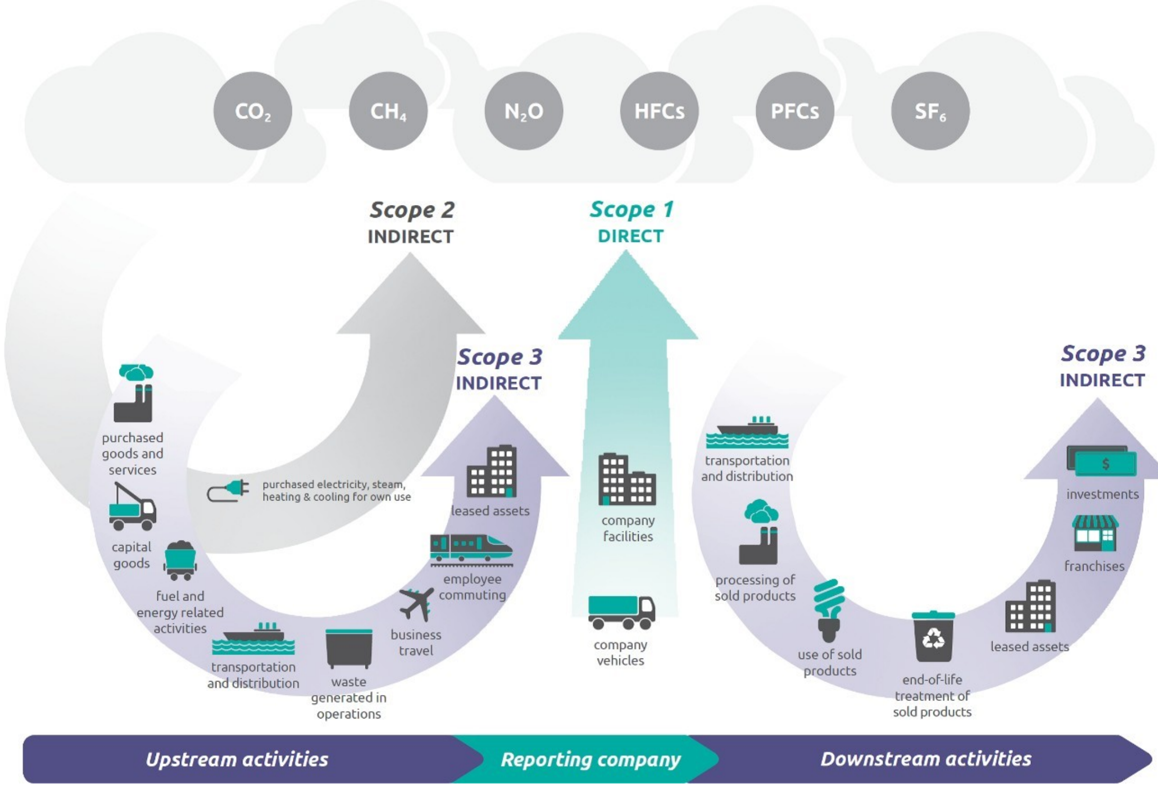
Plastics have an increasingly key role to play across a multitude of industries, given their various properties around strength, efficiency, and resilience. However, with the importance of mitigating environmental and pollution impacts, there is a renewed focus on the sustainable and responsible lifecycle of plastic across the spectrum of industries that employ its myriad of uses (1).

In order to make tangible impacts to the reduction and mitigation of Scope 1, Scope 2 and Scope 3 emissions (2) (3)(4), digital transformation of the entire lifecycle starting from production of raw materials, by products creation, packaging & distribution, waste management & recycling, secondary lifecycle, to name a few, is key to provide metrics-based insights at every step of the lifecycle and value-chain (5).



Source Credit:WRI/WBCSD Corporate Value Chain (Scope 3) Accounting and Reporting Standard (PDF), page 5.

With Industry 4.0 and 5.0 driven digitization (6) and the resulting availability of digital data (7) in the plastics industry, there is an exponential set of business opportunities to address the problem statements around sustainability in the plastics industry. This is where the techniques of Data Science, expanding into Machine Learning (AI/ML) and Deep Learning take root as key components of the entire digital value chain and in addressing the various scope-based categories of emissions mentioned earlier. This article will focus primarily on AI/ML usage for Scope 1 and Scope 2 emissions. A companion article will explore the use of AI/ML for Scope 3 emissions.

Scope 1:

Scope-1 emissions in the plastic industry result in the direct or indirect emissions of CO2e i.e. a range of Green House Gases (GHG's) whose Global Warming Potential (GWP) is measure relative to CO2 – hence CO2 equivalent or CO2e in short (8) (9). The role of AI/ML in Scope 1 emissions could be as follows:

- Develop AI based models of the plastic production process taking into account all the key input parameters (X), the key production output parameters (Y) which also include emissions data such as measurement of GHG's (e.g. ppm/g/kg/hr of CO2/CH4), particulate matter (e.g. g/m3), cooling/effluent waste water (e.g. litres/hr) etc.
- These models developed fall into two categories of estimation and forecasting.
- The estimation models predict the output Y(t+N) where N > 0 and is the estimate of the output at time "t+N" (which includes production throughput and emissions), based on all the inputs X(t, t+N-y) where y>0 i.e. all the input variables along the process line at various time stages (since this is a continuous production line) just upto the time "t+N". Typical ML algorithms used to build models here could range from a Support Vector Machine (SVM) Regressor to a Deep Neural Network (10).
- Similarly the forecasting models predict the output Y(t+N+M) where N, M > 0 and is the forecast of the output at time "t+N" to "t+N+M" at "M discrete time points (which includes production throughput and emissions), based on all the inputs X(t -P, t+N-y) where y>0 i.e. all the input variables along the process line at various time stages (since this is a continuous production line) just upto the time "t+N" for "P" historical samples. Typical ML algorithms used to build models here could be Encoder-Decoder Long short-Term Memory (LSTM) Neural Networks (11).
- All the models above assume the availability of processed historical data over a period of time that considers all seasonal variations that may occur due to environmental or business reasons. It is entirely possible that the modelling may be segmented into time of year specific models owing to the inability to converge on suitable accuracy or explainable insights for a single model set.
  Once the estimator and forecasting models have been built, the value of these AI/ML based models is to be able to leverage them to determine the optimal input parameters at times from "t" to "t+N- y" that can help maintain the output throughput of production at time "t+N", while keeping the emissions (which is also an output) as low as possible at time "t+N". This constrained optimization problem leverages the estimator built to help determine these optimal inputs, and, using AI/ML algorithms like Particle Swarm Optimization (PSO) (12) one could determine the set of X(t, t+N-y) that keep the output for emissions Y(t+N) at a minimum. However, this approach has obvious limitations, and instead if we have a forecaster model, we can use it in similar fashion but over a larger input time series set to get the minimal output time forecasts for emissions.

It is feasible to determine a number of What-If scenarios once the above AI/ML model approaches have been fleshed out to determine what algorithms works best – the above suggestions are only representative.

Scope 2:

Scope-2 emissions in the plastic industry are usually on account of indirect GHG emissions owing to consumption of electrical power from the grid, which could be powered by coal or fossil fuels. In this scenario what becomes imperative is the active monitoring of power intensive equipment as part of the industrial process flow w.r.t. their efficiency (e.g. current drawn from the grid and the output power produced). The role of AI/ML in Scope 2 emissions could be as follows:

- Develop AI based anomaly classification models of key electricity-powered equipment in the plastic production process considering all the key input parameters (X), with the target output being the power characteristics (current, voltage) drawn by the equipment)
- The anomaly classification models predict the occurrence of an anomalous current being drawn by a piece of equipment from the grid at time "t+N"where N>0 based on all the inputs X(t, t+N-y) where y>0 i.e. all the input variables along the process line at various time stages (since this is a continuous production line) just upto the time "t+N". Typical ML algorithms used to build models here could range from a Support Vector Machine (SVC) Classifier to a Deep Neural Network (10).
This classification model can potentially be integrated with the Scope 1 emissions forecaster above (e.g. PSO based) to eliminate input vector combinations X(t, t+N) that could result in an anomalous current event drawn by the piece of equipment. This way we could potentially address both the Scope 1 and Scope 2 emissions together.

Conclusion:

With accelerating Climate Change and the urgent need for Sustainability across industries, the examples above provide insights as to how AI/ML can be used to address the issue of emissions at source, augmenting any future process line improvements or industry technology improvements.

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