Carbon Footprint Reduction of a Petrochemical Process Supported by ML and Digital Twin modelling

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DOI:10.34658/9788366741928.23

Abstract. *This article aims to present a concept of an Artificial Intelligence application in the form of pre-trained Machine Learning modules to reduce the carbon footprint of a chemical recycling process.*

Chemical recycling of plastic is energy-consuming as it requires relatively high temperatures and calibration cycles based on a constantly changing structure of raw materials. Due to that fact, complex process parameters must be tuned to allow the production of the required fraction of gasoline. In general, the designed IoT system enables a massive collection of technology and environmental data and the processing of parameters to feed the Digital Twin of a petrochemical plant.

The scientific part of the project consists of Digital Twin modelling, experiments, simulations, and training of machine learning modules to predict the optimal set of production line parameters based on the specific structure of raw materials to reduce the number of calibrations and lower energy consumption indirectly which will lead to carbon footprint reduction. There is an here is an estimate that that deployed solution will allow reduction of energy consumption on a monthly level of 10-15% which could generate direct savings on a cost of energy but also savings in a field of carbon emission and

related credits. The project also includes the evaluation of predictions supported by machine learning modules, training techniques and comparison to expert settings to assess the quality of the application.
Keywords: *Internet of Things, Digital Twin, Machine Learning, Carbon Footprint*

1. Introduction

As an industrial environment, the petrochemical plan consists of many specialised systems which have never been integrated. Moreover, some areas are still managed by simple tools such as spreadsheets and document templates, which limits automation and seamless dataflow related to complex production processes. However, the proposed Smart Refinery solution integrates the most important ones.

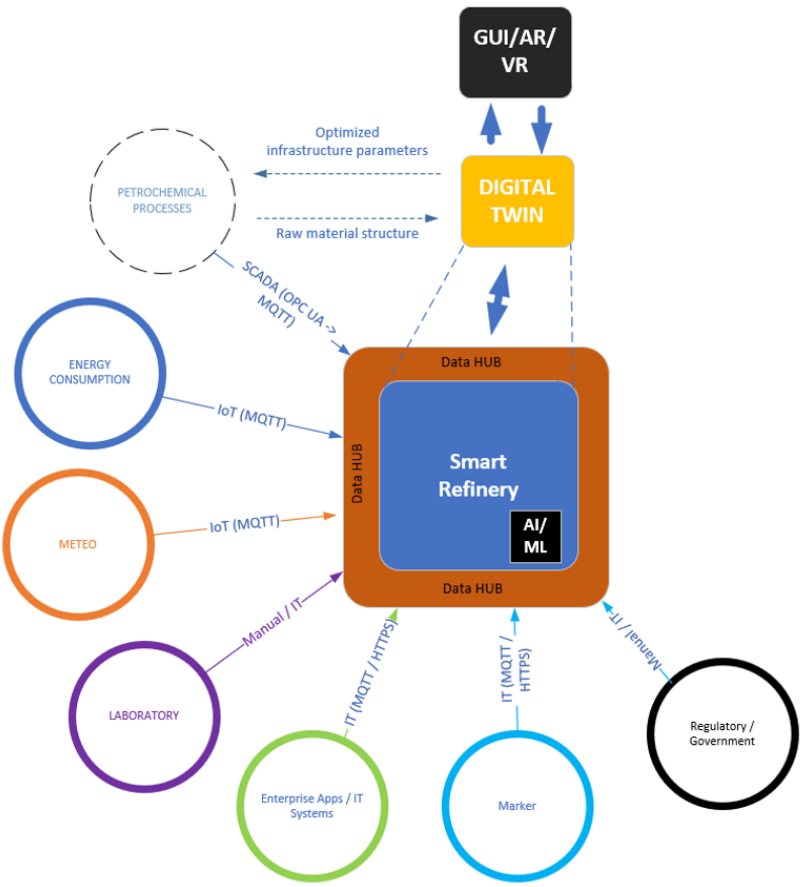

Figure 1. High-Level overview of data sources and integration considerations. Source: own work.

It enables data exchange, processing, storing and visualization to enable insights, improvements, optimization, and carbon footprint reduction through controlled and reduced energy consumption supported by Machine Learning modules. Increased monitoring, better control and optimization over energy consumption allow reduction on a monthly level of 10-15%. The following diagram presents a high-level view of data sources integrated into a Smart Refinery system which is in a designprototyping phase. Additionally, it indicates the simulation capabilities of a Digital Twin based on exact laboratory and hypothetical data. (Figure 1).

2. Data processing and ML application

Machine Learning and Digital Twins [1, 2] require a constant data feed through designed interfaces connected to a data hub and stored in a time-series database as metrics and events (Figure 2).

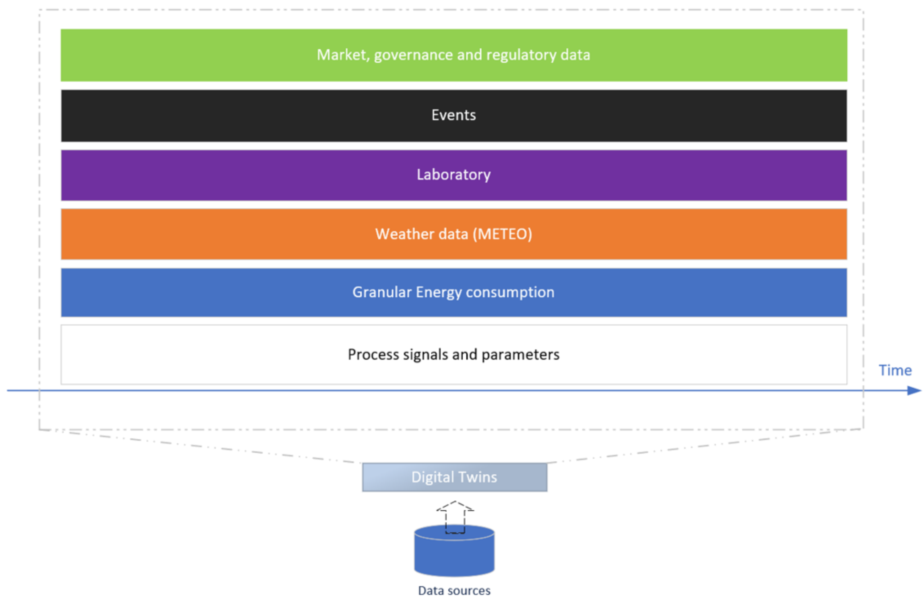

Figure 2. Multidimensional context of enterprise data in the form of stacked timelines. Source: own work.

Collected and prepared data is used to create a multidimensional analysis supported by pre-trained Machine Learning modules to identify patterns, trends, anomalies, and cross-dimensional contrast to find undiscovered dependencies and areas for optimisation [3, 4]. Each layer depicted below consists of a dataset enriched by time signatures which enables contextual research on the recycling process, its parameters and phases, the structure of raw materials, environmental data, and events. In most cases, applied Machine Learning features will be based on the following algorithms:

- Linear and Logistic Regressions,
- Decision Tree,
- Gradient Boosting and AdaBoosting.

Yet another area of ML application is prediction of process parameters based on a current and forecasted weather data. In this specific case a petrochemical plant is large on-air installation of pipes, distillation towers and tanks which are sensitive on environmental conditions (Figure 3).

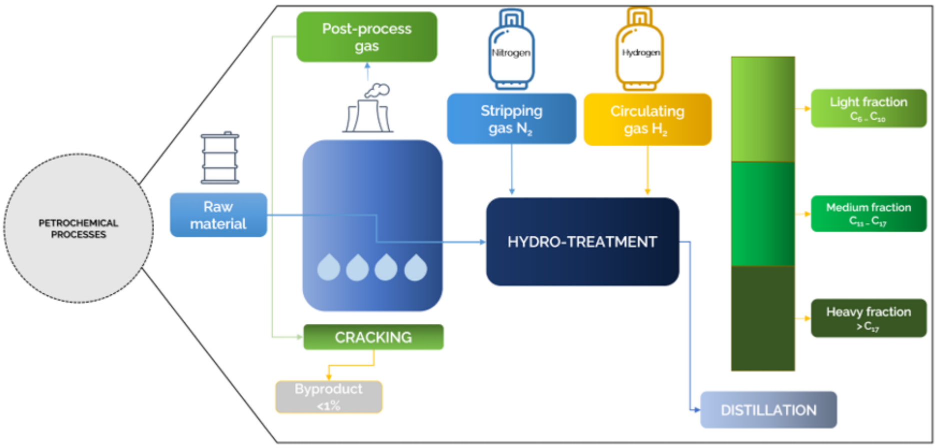

Figure 3. High level overview of petrochemical process. Source: own work.

Outdoor temperature, pressure and humidity have a direct impact on a process parameters such as flows, installation pressure and temperatures and overall processing time and differs on specific season of a year. Considered ML modules will adjust mentioned process parameters based on weather forecast collected from a weather API and current data from weather station. Historical process parameters and whether data will be used to create a dataset to train and evaluate a ML module in the cloud [5]. Once trained and evaluated specific ML module will be deployed on Edge in a form of web service as presented below (Figure 4).

3. Conclusions

The latest, the 4th Industrial Revolution, requires an efficient ability to convert data into information which is the only way to build market advantage, competitiveness, and sustainability. According to market research conducted by widely recognized consulting companies [6], and details described in article [7]:

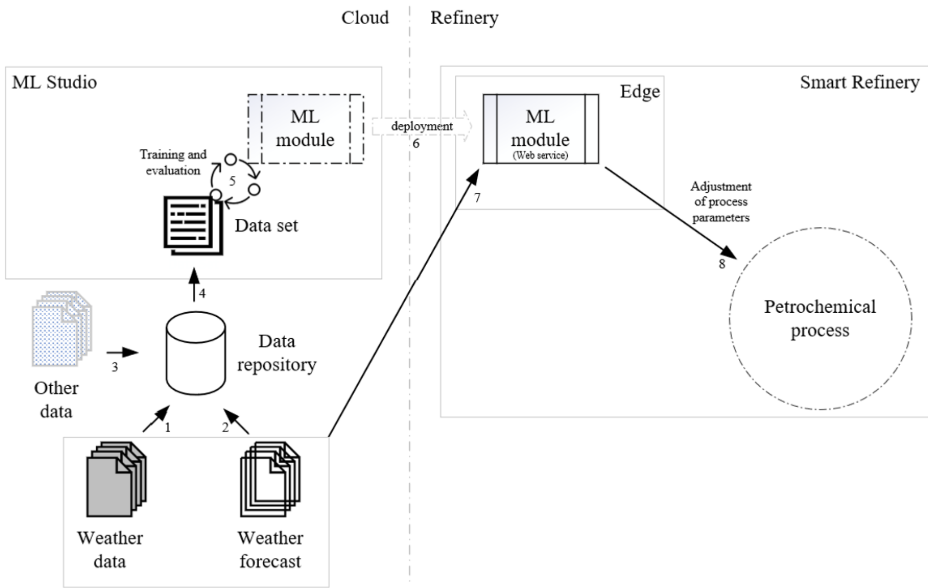

Figure 4. ML application example including training and deployment – weather conditions compensation ML module. Source: own work.

- almost every second organisation does not know how to use the collected data to manage the company better properly,
- on the other hand, 88% of corporate data is not used to manage the organisation better.

Above results lead to a statement that the amount of collected data makes human perception inefficient at that scale and complexity. Application of AI in a form of specialized Machine Learning modules is crucial to achieving expected goals related to 10-15% reduction of energy consumption in a monthly basis what's a field of studies, researches and evaluations defined on a project level.

Acknowledgment

This research and development are conducted as a part of the 6th edition of the Implementation Doctorate program financed by the Polish Ministry of Education and Science. As part of the research consortium project will be funded by Atos R&D partners and, in addition, by EU and NCBiR grants.

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