The Di-Plast Data Science Toolkit – Enabling a Smart Data-Driven Digital Circular Economy for the Plastics Industry

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I. Abstract

The use of recycled plastic material (rPM) is currently below its potential. Today's main reasons for the low uptake of rPM are lack of information about quality and quantity of the material [4], [7], [8]. In general, the sketched problems originate from a lack of information creation and flow in the markets, as origin, current location and composition of rPM supply are neither traced nor tracked [8]. Information-based digital solutions are hence an essential part of effectively alleviating this situation to increase the rPM uptake [7].

Therefore, data and information needs to be obtained, collected, and analyzed in order to provide insights and knowledge for improving production and supply processes, as well as to enhance specifications and quality key performance indicators (KPIs). This does not only relate to the data types being collected, but also to the overall processes and further tool-based mechanisms for turning data into information and knowledge, in order to improve market transparency for rPM uptake in a sustainable manner. This abstract proposes data-driven solutions, as a set of tools forming a digital toolkit to gain better insights into the quality and available quantity of rPM. The tools provide improvements that lead to a higher rPM uptake, e.g., using prescriptive process analytics and intelligent decision support [2].

The proposed tools are designed for specific processes where rPM is involved. In order to solve quantity and quality issues, the toolkit contains both information and knowledge tools as well as data analytics tools, divided in four separate disciplines (Figure 1). In total, the toolkit contains seven standalone tools that, if desired, can be combined.

The tools in the disciplines *Measuring Process* and *Process Analytics* aim to contribute in improving the quality of rPM material, while the tools in the disciplines *Optimizing & Forecasting* and *Matching Product Requirements* mainly address improving the available quantity of rPM, as knowledge-based tools potentially utilizing feature-rich network structures [5]. The *Quality Control* and *Forecasting* tools are directly linked to the field of data analytics and machine learning. The *Quality Control* tool will assess the quality of the recycled plastic material that machines produce. These machines will be analyzed by detecting anomalies and trends in the data. A variety of data mining, machine learning and deep learning applications will be deployed on the gathered machine data [6], [9]. The *Forecasting* tool focuses on collecting and combining data of material and product flows from multiple companies, enabling the analysis of rPM supplies on a larger geographical scale, which leads to forecasting future quantities of rPM [1], [3], [10].

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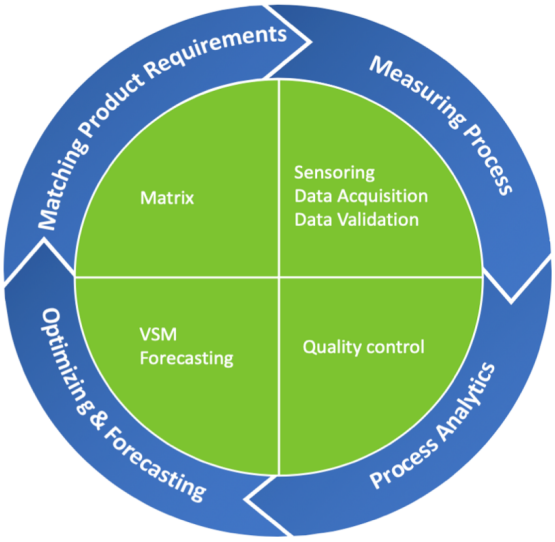

Fig. 1.
Overview of the Di-Plast Toolkit.

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