Development of a Smart Connected Product-Service-System (PSS) for the Waste Management Ecosystem

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Abstract

The project aims to exploit the potential of digitalization for the waste management ecosystem in Switzerland. To accomplish this, 1) a sensor and connectivity module for waste bins and 2) corresponding data analysis and 3) cross-company service processes within connected systems are developed and validated. The analysis and planning phase of the ongoing Innosuisse funded project is completed, and the next step is the validation in an extensive field test. This paper presents the conceptualization of the smart waste management ecosystem platform, the development phases of the project, how the sub-work packages proceeded in the analysis and planning phase, and the main results thereof.

Keywords

Waste management, internet of things, case study, platform, ecosystems, smart cities, digital twin, smart services

1. Introduction

The goal of the project is to design a digital waste management ecosystem in Switzerland. The basis is the dense network of existing waste bins, which are equipped to measure different data on their own condition (e.g. fill level) and the environment and transmit them to different ecosystem actors for analysis and process optimization. Several papers have already proposed efficient solutions for implementing smart connected waste bins. Hong et al. [1] developed a successful IoT-based smart waste system to reduce the amount of food waste in Seoul, Republic of Korea. The smartbin system by Folianto et al. [2] is designed to collect and transmit data through a wireless mesh network and was implemented in a field test. Existing proposals are either mainly focused on the implementation and testing of a centralized waste management system in an outdoor environment or on the conceptual architecture in smart cities. Others such as Kyriazopoulou [3] give an overview and discuss the key technologies that have been proposed. The project presented in this paper follows a holistic approach, combining technology and process development for a smart waste management ecosystem in Switzerland. This will increase the effectiveness and efficiency of multiple processes in the ecosystem and generate significant economic, ecological, and social added value for Swiss society.

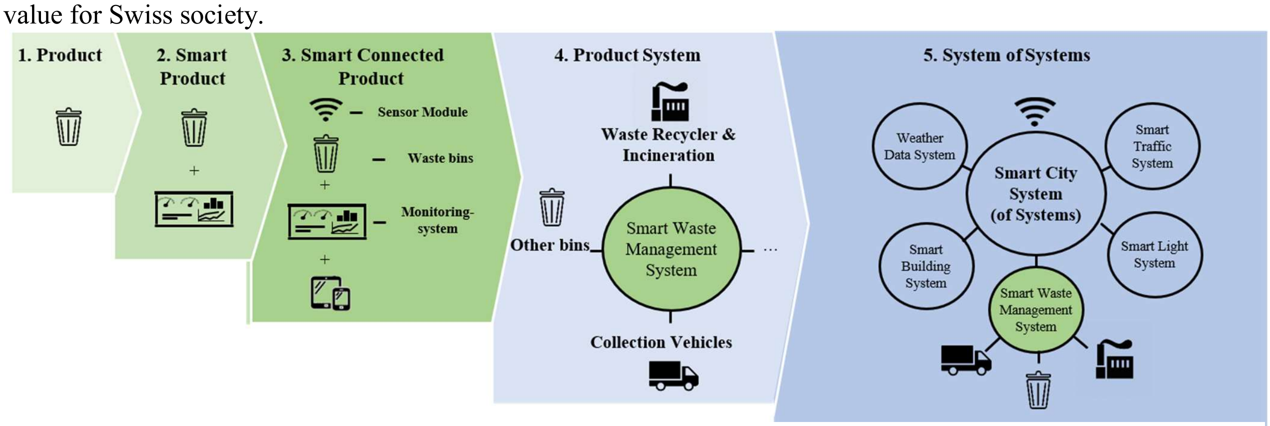

Figure 1: Development of Smart Connected Products into System-of-Systems in the Waste Management context [4],[5].

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To realize this goal, a new, smart product-service system (PSS) is developed and validated, which can digitally map, analyze and optimize cross-company processes in waste management. Starting from the initial situation, 1) the technical measurement in the waste bins (raw data collection by means of sensors), 2) the processing and analysis processes of the generated data (processing the data into information and 3) the associated cross-company decision-making and service processes must be redesigned with regard to the needs of the stakeholders and actors in the ecosystem.

The focus is put on existing processes regarding the management of waste collection bins, their maintenance, the emptying or collection, and the recycling of municipal and commercial waste. However, by taking a holistic view of the waste management ecosystem, further innovation potentials regarding the integration into subsequent and higher-level systems such as smart cities are also taken into account and advanced (Fig. 1).

2. Project procedure

The project procedure was structured along the ideal-typical procedure for marketing-oriented tasks, hence divided into the four phases of A) analysis, B) planning, C) implementation and D) control [6] Phases A and B were completed at the end of May 2021, but some MVPs still need to be finalized. According to the plan, phase C will run for seven months from September 2021. The total project duration is 21 months.

A. Analysis

The analysis phase focused on the requirements engineering for the smart waste management ecosystem in Switzerland and the analysis of the current Product-Service-System (PSS). This phase consisted of the following main work packages: 1) Analysis of the waste management ecosystem, identification and evaluation of the main stakeholders, 2) analysis of present PSS, current service processes and capabilities and challenges with raw data collection and data processing, 3) capturing of the requirements of the strategic stakeholders for a smart PSS and 4) analysis of technical alternatives for data collection and processing.

B. Planning

During the planning phase, the new smart PSS for the waste management ecosystem in Switzerland was designed and developed. This phase consisted of the following main work packages: 5) Design of value propositions, 6) design of services and processes, 7) design of the platform, 8) consolidation of requirement specifications of the PSS, 9) definition of the PSS system specification for the minimum viable product (MVP) validation and 10) development and realization of MVPs of the new PSS.

C. Implementation

The main goal of the implementation phase is the demonstration and validation of the new PSS by testing MVPs with selected customers. This phase consists of only one main work package, 11) PSS validation with MVPs in the field. However, the field test is divided into several phases in which the number of different bins, as well as the total number of bins, will be gradually increased.

D. Control

The final phase contains the adaptation of the specifications and requirements for a marketable PSS based on the insights and findings from the field test in phase C. The main work packages are thus 12) monitoring, analysis, and documentation of the processes and values generated by the new PSS and 13) updating the requirements and specifications for a marketable PSS.

3. Vision of a smart waste management platform

In the planning phase, the vision of a smart waste management platform was developed (Fig. 2). The goal was to exploit the synergies and network effect of the ecosystem in a holistic way to create value for mainly involved stakeholders. To achieve this goal, as seen in the left part of the figure, a wide variety of Smart Connected Products (SCPs) from different providers must be connected to one platform. Therefore, the platform must be able to connect SCPs with different connectivity solutions and communication protocols via a standardized data gateway. The data collected in this way on the IoT-core from various sources must now be stored, structured, and processed, as seen in the middle section. The data can then be interpreted, resulting in the services ultimately creating value for the stakeholders. The interpretation of the data can be automated in the core, or the data can be optimized for interpretation by human users. The services are delivered, and/or the interpretation takes place via the applications that represent the interfaces to the human users, as seen on the right side of the figure. These are specialized for different user categories with different tasks in the smart waste ecosystem.

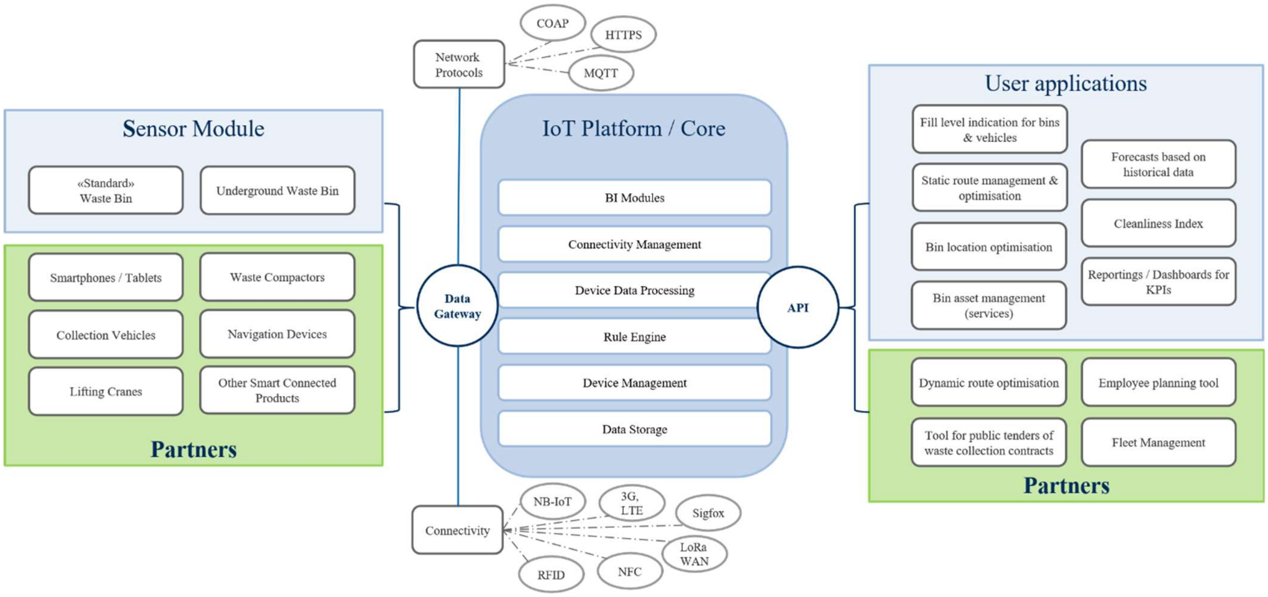

Figure 2: Vision of a Smart Waste Management Platform.

A. Sensors and connectivity

In order to obtain high-quality raw fill level data from the prototype sensor module in the new smart PSS, the following main problems with raw data collection identified in commercially available sensor modules had to be addressed: occasional large variations in measured fill level with only small associated changes in the true fill level, systematic fill level errors due to interference caused by waste bins with small diameters and random fill level errors due to interference with wrinkled or sticking together / twisted bin liner bags.

In initial lab tests, multiple sensors were tested with the aim to address the above-mentioned problem points and to fulfil other performance requirements such as fill level accuracy in the cm-range, a maximum measurement distance of 2.5 m and low energy consumption. Tests were carried out with mid- and long-range ultrasonic Time-of-Flight (ToF) sensors, multiple short-range radar distance sensors operating in the 60 GHz unlicensed ISM frequency band and two invisible laser ToF sensors using typical public waste bins with waste volumes of 60 L and 150 L filled at pre-determined fill levels with a mix of paper, plastic wrappers and aluminium cans as waste materials.

The investigated ultrasonic sensors TDK CH101 [7] and CH201 provide fill level measurements with very low energy consumption (< 20 µJ) and a reasonable mean accuracy of 6.9 cm in the lab. However, the Field-Of-View (FOV) of the sensors had to be narrowed to 30° and 40°, respectively, using appropriately designed acoustic housings to reduce the interference caused by small bin diameters and wrinkled liner bags. It was observed that large variations in the measured fill level with only small associated changes in the actual fill level become less likely when the whole range-reflected power profile of the ultrasonic sensor is used for fill level determination, which is possible with the two selected ultrasonic sensors.

As an alternative to the ultrasonic sensors, the investigated STMicroelectronics VL53L1 ToF sensor has a FOV of 27° [8], making it well suited to reduce unwanted interference. Furthermore, the 16 available individual Regions of Interest (RoI) permit the measurement of the fill level at multiple points on the waste surface, which is expected to lead to more accurate fill level measurements for waste surfaces with irregular height. The measured mean accuracy of the fill level was 2.4 cm. However, this higher accuracy comes at the cost of significantly higher energy consumption of 456 mJ for measuring the distance in all 16 RoI, compared to the ultrasonic sensors.

0shows a subset of the results obtained with a 60 L waste bin with bin liner bag, where the ground truth fill level was measured with an optical laser range finder. The distance error is defined as the difference between the ToF sensor measurement and the ground truth of the distance between the sensor and waste surface.

Another advantage of the ToF Sensor over ultrasonic sensors is the high grade of environmental protection offered by using a cover glass, which will provide effective protection from water and dust. However, dust, dirt and condensation on the cover glass can lead to a reduction in measurement range and measurement errors due to reflections at the cover glass surface.

Table 1

ToF Sensor Fill Level Measurements

Fill level and distance error in a 60 L bin with liner bag		
Fill level Ground truth [%]	***Fill level measured TOF [%]***	***Distance error [mm]***
0	6	-42
19	13	37
70	65	27
86	91	-33

To avoid measurement errors with ultrasonic and ToF sensors when the bin liner bag is sticking together or twisted, the possibility of using an additional short-range radar sensor is being investigated. Initial results show that radar sensors can “see-through” a plastic liner bag that is sticking together since the reflectivity is small and therefore avoid this problem, as shown for the range-reflected power profile in Figure 3, where the correct fill level of 0 % can be clearly detected despite the bin liner back sticking together close to the top of the bin. However, radar sensors may not provide strong enough echoes in the case of irregular and dry waste surfaces for accurate fill level measurements.

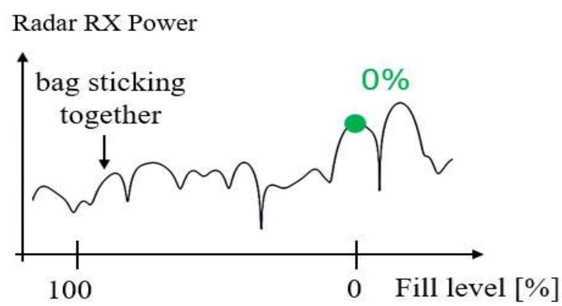

Figure 3: Radar sensor range-reflected power profile in an empty 150 L bin with a bin liner bag sticking together close to the 100 % fill level. The correct fill level of 0 % can be detected clearly.

An advantage of radar sensors is the good environmental protection achieved by using a cover material (e.g. ABS plastic). Strong condensation on the cover, however, was found to have a significant impact on the measured range-reflected power profile.

For the prototype implementation of the sensor module, it was decided to employ all three types of sensors (ultrasonic, ToF and radar) to get a thorough understanding of their performance in the real-world application. Additionally, a camera will be used to measure the true fill level (i.e., labelled data) for the subsequent data processing during the field tests (Fig. 4).

The connectivity of the prototype sensor module will use the NB-IoT wireless technology, which is available in many 4G (LTE) mobile networks. NB-IoT has a very good link budget, which is required when the sensor module is installed in metallic waste bins with relatively small openings. Furthermore, the energy-saving features of NB-IoT make it well suited for the occasional transmission of small amounts of data using battery-powered devices [9].

Figure 4: Trail cam picture of waste bin content (left) that was used for manually determining accurate filling levels. On the right, the setup with both trail cam and fill level sensor is visible.

B. Data processing

We here present the first results for the data processing unit that is going to be developed for the waste bins during the project. Fundamentally, abundant data have been collected in the past, many waste bins (several dozens) have been equipped with sensors and connectivity for more than 2.5 years with a continuous hourly data stream. The challenge, however, lies in the fact that only the noisy sensor data were recorded, bar any information on true fill levels, impeding any powerful statistical analysis. Hence for a small, explorative study, some bins were equipped with trail cameras that automatically shot a picture of the waste every 15 minutes (Fig. 4). From these, gold standard fill labels were determined by manual labour. In this paper, we present results for a 150-liter waste bin situated at Zurich Airport, for which a time series with hourly measurements of sensor and gold standard labels was available (1223 observations, ranging from Sep 25, 2020 to Nov 16, 2020).

Manual assessment of trail cam pictures proved unsustainable on a larger scale, even within the project for development purposes. In order to generate labelled data on a larger scale, image recognition algorithms based on Convolutional Neural Networks [10] architectures were tried. We observed very high accuracy with an R-Squared of 98% between the predicted and manually labelled filling levels. Hence, these algorithms provide a base for acquiring larger amounts of precisely labelled data for developing purposes. For real word application, however, the trail cameras are not suitable, they are not robust enough with, e.g., the lens being soiled too quickly. The focus in data processing therefore lies in smoothing and robustifying the sensor signal.

The display in Figure 5 exemplarily shows the issues with the sensor signal. There are cases where near-maximal fill levels are indicated while the bin is nearly empty.

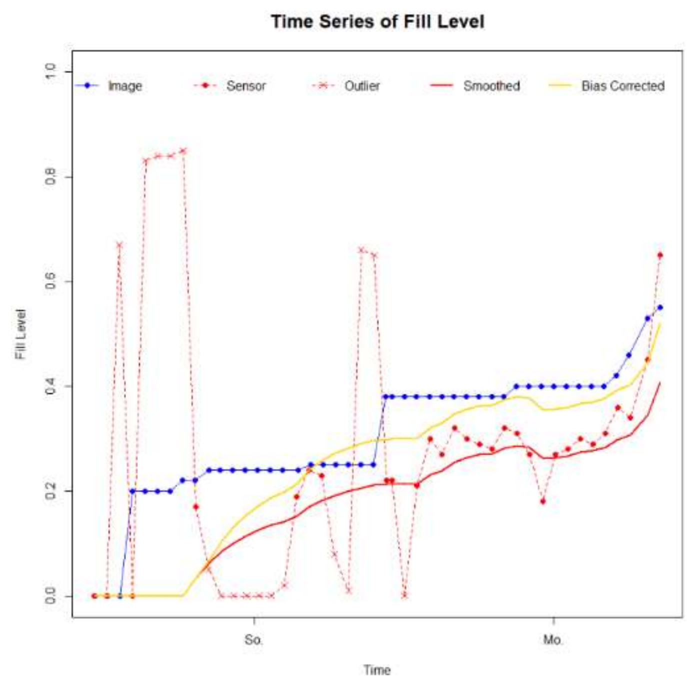

Figure 5: Time Series of true (=image based) and measured (=sensor based) fill levels of a 150L waste bin for one cycle from emptying to emptying. Some observations (marked “x”) were rejected as outliers and not used for computing the smoothed signal. Finally, a bias correction for the signal was implemented.

This is caused by reflections of the wrinkled or twisted plastic bag liner. On the other hand, outliers with zero readings while the bin is filled more than 20% exist as well. Furthermore, the sensor signal is wiggly even during periods where no additional waste is thrown into the bin. And finally, the sensor filling level shows a downward bias. All these findings are confirmed as systematic by the second plot in Figure 6. The data processing module tries to overcome these shortcomings with the following measures:

1. *Smart outlier detection and rejection*
2. *Denoising*
3. *Bias correction*

It is important to note that all measures for improving the signal quality need to be implementable in a real-time nowcasting fashion, meaning that they can only be based on the values prior to the observation. The outlier detection and rejection are based on multiple pillars. First, it comprises of simple heuristics that exclude or downweigh observations where fast increase and especially decrease of the fill level is observed. Further confidence in the untrustworthiness of these observations can be gained from training statistical regression models that predict average fill levels based on calendar data. This is an effective way of exploiting the large base of sensor signals that are fundamentally available. Furthermore, a pooling of signals from spatially adjacent waste bins can further boost the reliability of the regression approach.

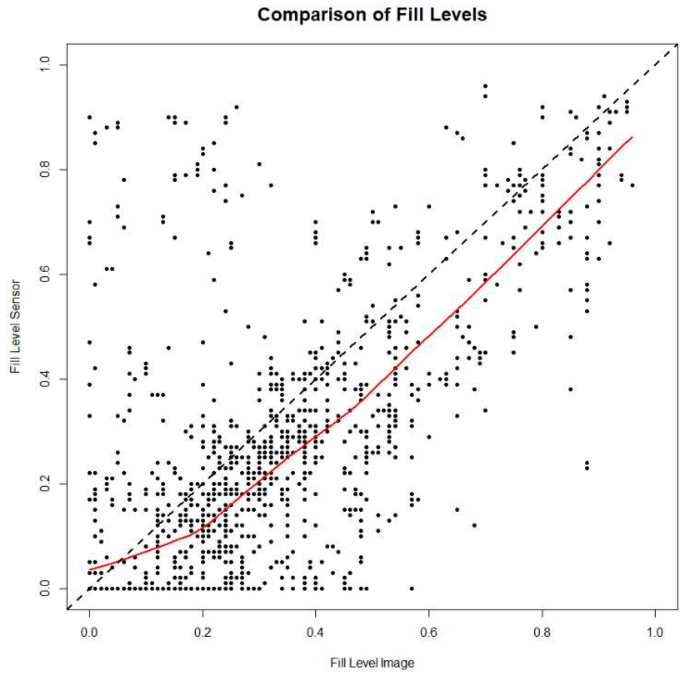

Figure 6: Systematic comparison of fill levels between true and measured values over a period of 7 weeks, comprising 20 emptying cycles with the red smoother highlighting the bias in the sensor signal.

Once outliers are removed or down-weighted, the time series can be denoised by approaches of varying sophistication [11]. For our purposes, simple approaches such as moving averages or exponential smoothing proved reliable enough. However, when filtering or smoothing a monotonically increasing signal, a technical downward bias is introduced. This is coupled with a further measurement bias of the sensor technology. In order to provide fully accurate filling levels, heuristics are employed for a final correction of the values. An empirical out-of-sample study confirms the success of our data processing approach. While the raw sensor signal shows a mean absolute error of 15.9% with respect to the image-based gold standard, the multi-head correction achieves a mean error of only 6.7%, where especially large deviations were strongly reduced. This is a promising basis for an extensive field study where the processing of sensor signals will be further improved on a larger data basis.

C. Service innovation

We identified and evaluated the main stakeholders to map the smart waste management ecosystem in Switzerland by means of desk research and interviews. To capture the requirements of the main stakeholders, we firstly analyzed the status of their processes by observing and interviewing them during their daily work. We documented the main processes as flowcharts in an online tool, allowing us to conduct workshops with several participants from the same stakeholder group. In the workshops, the prepared process flowcharts were validated and, if needed, completed or corrected. In the next step, we used the value proposition canvas framework [12],[13] to identify the pains and gains along these processes, which functioned as the “customer jobs”. The pains and gains identified in this way were subsequently assessed and prioritized by categorizing them in a Kano-model inspired framework [14], [15] along two axes. One of the axes was divided into “can”, “should”, and “must” sections, while the other axis spanned a continuum from "slightly annoying" / "nice-to-have" to "extremely troublesome" / "very inspiring" (Fig. 7).

As we conducted several workshops with different stakeholder groups (e.g. cities, municipalities, companies from the private sector), we had to consolidate the findings, requirements, and priorities in a single PSS requirements document. To further structure the requirements, we divided them into the categories “functional”, “technical”, “system/platform”, “usability” and “economic/business”. In a further step, we assigned the requirements for the PSS that had been collected, prioritized, and grouped to the relevant processes in the ecosystem and translated the added values which had been created along these processes into concrete services. These services were then further detailed in several iteration steps, and the business partners decided whether they wanted to offer the applications themselves or leave them to other platform partners (cp. Fig. 2). The following section explains the services only roughly for reasons of space and IP reservations.

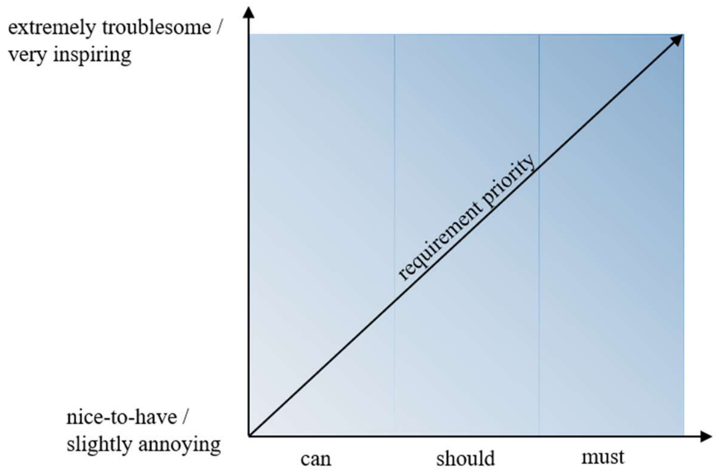

Figure 7: Kano inspired requirements priority matrix.

The applications that will be realized on the “Shark Island” are a) directly linked to the bins and their lifecycle processes and b) of high requirement priority. While the measurement of the fill levels of the bins and the collection vehicles provides the basis for many other services, their indication itself is a demanded service. Especially when combined with a forecast of the time the bin and vehicles will reach the critical fill level, route planners and collection coordinators are provided with valuable information to optimize a wide variety of processes. The forecasts are based on historical data of the individual bin as well as learnings from other bins, even of other customers, to predict the impact of, e.g., seasonal or weather factors. Most users do not want to have their standard routes, which usually matured over many years, adjusted automatically by considering just fill levels. But they would like to have a tool to manage them and to be able to adjust these standard routes for the specific collection day by considering the current fill levels, the forecasts thereof and the newly developed cleanliness index value. For the cleanliness index, the employees are simply given the opportunity to record insufficient cleanliness of the bin or its surroundings. This makes it possible to calculate a cleanliness index that provides information on how quickly and severe a particular location becomes dirty. This value can be more relevant than the fill level when deciding whether or not to schedule a particular bin in a tour. Another process group which will be optimized by a set of services is the asset management of the bins and other related infrastructure, which can also be recorded and managed on the platform. The services range from detailed step by step instructions on how to repair the equipment to long term schedules of recurring maintenance. Another category of services can be grouped around the long-term planning of waste collection systems, e.g. proposing the optimal location and size of waste bins, including calculations of the expected benefits. Displaying the added values, savings, and other key performance indicators (KPI) of the waste management system with an individually customizable dashboard is another central service.

As the service processes for the maintenance of the waste bins require the application of both human (for emptying, cleaning, or repairing) and machine resources (vehicles, refill bags, spare parts etc.), scheduling the service tasks often turns out to be of high complexity and pursuing divergent goals [16]. In particular, there are two constellations in which a quantitative assessment of the impact of the smart connected bins on the service processes add significant value to the ecosystem:

1) A local community (e.g., a city) needs to make an investment decision whether to upgrade their bins from the traditional version to the smart connected one [17]. What will be the impact on the service level, their cost, and their ecological impact? How would they have to reorganize their service processes?
2) A community with an existing installed base of smart-connected bins wants to optimize its service level, its operational costs, or its ecological impact, in particular for the case of unforeseen events. These may be, e.g., social events with an exceptional load on the system, such as cultural or sportive leisure events.

For both cases, a digital process model allowing for simulation-based scenario [18] analysis and resulting decision support services is developed in the project – so-called service process twins [19]. The first viable models of this twin are currently available and tested in user feedback iterations and are foreseen for deployment in the field test (Fig. 8).

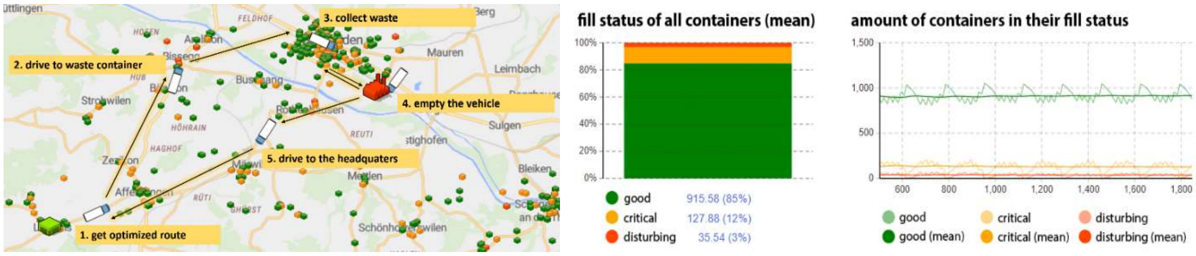

Figure 8: Digital service process twin application example. The main jobs done by the waste collection vehicle on the map with waste bins locations and diagrams with the filling status of all bins over the simulation duration.

Not all value-added and commercially interesting applications can be offered by the platform operator itself. Similar to providers of smartphone operating systems, ecosystem platform providers must also make their platform and the data on it available to partners and third parties by means of appropriate interfaces. In addition to the partner services mentioned as examples in Figure 2, many other potential services were identified in the workshops, and more will emerge through a dynamic exchange between users and providers on the platform. Additionally, the advantages and disadvantages of different access and governance policies for the platform were analyzed and evaluated by means of desk research and interviews. This has shown that a platform basically benefits from as many providers as possible, but for security and data protection reasons, certain restrictions on the use of the platform are necessary and reasonable.

For some of the requested and crucial services in a smart waste management ecosystem, powerful partial solutions already exist on the market, some of which have already been implemented by the existing and potential users of the platform. Therefore, the platform must also be able to provide data-as-a-service to authorized external systems via standardized and customizable interfaces. Within the project, we will only be able to realize connections to other applications already installed in certain customers systems, e.g., for dynamic route optimization using collection vehicle-specific map data. In the long run, the platform could have an open API to deliver data-as-a-service to any actor, whether or not they are providing services themselves via the platform or to the customers from which they obtain the data. However, in order to be able to implement such a vision, in addition to a sophisticated billing model between the data owners, the users and the platform operator as an intermediary, questions regarding the valuation of data as well as a number of contractual issues still need to be clarified.

D. Discussion

The combination of 1) collecting high quality operational raw data by means of sensors, 2) processing and analyzing them to information and 3) offering value-creating decision support services based thereof will enable service managers of the smart waste ecosystem to achieve an improved service level (e.g., no dirty or overfilled bins) while managing the operational costs for doing so. This is beneficial both from a social and an economic perspective. Additionally, optimizing the number of vehicle rides and its accompanying positive ecological impact positions the smart waste ecosystem as a relevant factor in the concept of the triple bottom line.

During a ten-week test phase with a predecessor version of the system newly developed in this project, the optimized emptying routes reduced the working time by 14% and total cost by 16% [20]. In addition, CO2 savings of 17% were achieved due to the savings in fuel and waste bags. These already remarkable results are expected to be higher with the new PSS and holistic process optimization, especially when the Smart Waste Management processes are well established after the implementation phase.

E. Conclusion and Outlook

The smart waste ecosystem discussed in this paper makes apparent that there is considerable potential in managing an ecosystem by the application of smart, connected equipment that is integrated into a comprehensive service platform. The digital interconnection of the ecosystem represents a catalyzer for the service value flows across the system. It also becomes obvious that obtaining, analyzing, or even forecasting condition information from the equipment alone is not sufficient for this value creation. The further processing of the equipment data in the so-called digital service process twins for enabling decision support represents a critical success factor. Only by this, the digital infrastructure can unfold towards service value with benefits in economic, ecological and social terms.

Future research directions will both improve the data quality of the sensor, of its analysis, and further integrate the ecosystem, e.g., taking into account additional contextual information, like weather forecasts or data about the usage intensity in public areas.

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