Journal of Environmental Management 335 (2023) 117548

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Smart textile waste collection system – Dynamic route optimization with IoT

Antti Martikkala[a,d,*], Bening Mayanti[b], Petri Helo[c], Andrei Lobov[d], Iñigo Flores Ituarte[a]

[a] Unit of Automation Technology and Mechanical Engineering, Tampere University, Korkeakoulunkatu 7, FI-33720, Tampere, Finland
[b] Vaasa Energy Business Innovation Centre, University of Vaasa, Yliopistonranta 10, FI-65200, Vaasa, Finland
[c] Networked Value Systems, Department of Production, University of Vaasa, P.O. Box 700, FI-65100, Vaasa, Finland
[d] Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Richard Birkelands Vei 2b, NO-7034, Trondheim, Norway

ARTICLE INFO

Keywords:
Textile waste collection
Circular economy
Route optimization
Smart bin
Internet of things
Arduino

ABSTRACT

Increasing textile production is associated with an environmental burden which can be decreased with an improved recycling system by digitalization. The collection of textiles is done with so-called curbside bins. Sensor technologies support dynamic-informed decisions during route planning, helping predict waste accumulation in bins, which is often irregular and difficult to predict. Therefore, dynamic route-optimization decreases the costs of textile collection and its environmental load.

The existing research on the optimization of waste collection is not based on real-world data and is not carried out in the context of textile waste. The lack of real-world data can be attributed to the limited availability of tools for long-term data collection. Consequently, a system for data collection with flexible, low-cost, and open-source tools is developed. The viability and reliability of such tools are tested in practice to collect real-world data. This research demonstrates how smart bins solution for textile waste collection can be linked to a dynamic route-optimization system to improve overall system performance.

The developed Arduino-based low-cost sensors collected actual data in Finnish outdoor conditions for over twelve months. The viability of the smart waste collection system was complemented with a case study evaluating the collection cost of the conventional and dynamic scheme of discarded textiles. The results of this study show how a sensor-enhanced dynamic collection system reduced the cost 7.4% compared with the conventional one. We demonstrate a time efficiency of −7.3% and that a reduction of 10.2% in CO2 emissions is achievable only considering the presented case study.

1. Introduction

The textile industry is constantly growing, leading to the increased of environmental burden associated with the production process and waste management. The sector is responsible for climate change impact since it contributes about 1 ton of CO_2 out of 19.8 tons of total CO_2 in the atmosphere (Akhtar et al., 2017a, 2017b). The cost of recycling directly affects the price of the recycled fibers. Normally the price of regenerated fibers is 30% higher than the native fiber (Yan, 2019). Therefore, a decrease in collection costs can play a significant role in making recycling more profitable and in reducing overall costs.

In general, the benefits of circular economy can be evaluated with three indicators as economic, environmental, and social dimensions (Calzolari et al., 2022). The improved textile collection can also benefit people in need. An increase in textile collection increases the amount of good quality textiles to be collected. Accompanied with effective sorting, this reflects the quality and the prices of textiles in secondhand stores as well as the quality of donated textiles. Similarly, the growth of the recycling business with a larger amount of collected textiles increases the need for workforce. Moreover, the social benefits of decreasing environmental burden are clear.

Consumer behavior is one of the key factors affecting the environmental benefit obtained from recycling (Nencková et al., 2020). Statistics indicate that only 25% of the total amount of textiles is recycled (Koch and Domina, 1999). It presents a challenge and opportunity for improvement. A study showed that people will take pro-environmental actions if there is a convenient way to do so (Koch and Domina, 1999). As for textiles, curbside drop-off system is widely employed

* Corresponding author. Unit of Automation Technology and Mechanical Engineering, Tampere University, Korkeakoulunkatu 7, FI-33720, Tampere, Finland.
E-mail address: antti.martikkala@tuni.fi (A. Martikkala).

https://doi.org/10.1016/j.jenvman.2023.117548
Received 7 December 2022; Received in revised form 14 February 2023; Accepted 17 February 2023
Available online 4 March 2023

(Lounais-Suomen Jätehuolto Oy, 2020; Watson et al., 2018). Hence, travel distance between home and the drop-off site should be perceived short (Ramayah et al., 2012).

The irregular accumulation of waste in different bins causes a high variation in bin fullness. This variation, accompanied by some seasonality, leads to inefficiently high emptying frequency to avoid overflow of the bins (Seifert and Messing, 2006). Consequently, there is a need for monitoring the textile collection bins. Without monitoring the textile collection bins are emptied regularly which has numerous drawbacks. The use of smart bins can improve waste collection and prevent the overflow of the bins (Arebey et al., 2012; Goutam Mukherjee et al., 2021). The efficiency of supply chains in textile collection plays a significant role in reassuring high collection rates of discarded textiles. Advanced technologies such as Internet of Things (IoT) and Artificial Intelligence (AI) can offer new opportunities to increase efficiency (Koot et al., 2021).

In general, IoT can play an important role in making world greener, safer, and more efficient (Li et al., 2021). Artificial Intelligence has been used to forecast waste accumulation and optimize waste bin locations and bin sizes (Bakhshi and Ahmed, 2018). The use of AI can decrease collection costs due to optimized route distance, number of collection vehicles, and employees (Hannan et al., 2018). For companies, the costs of IoT technology plays an essential role, and the economic and ecological value of the sensor information needs to be known (Ben-Daya et al., 2019). Moreover, the use of IoT and collected data can improve consumer awareness and thus motivate them to recycle (Concari et al., 2022).

In this regard, this paper presents a technical solution and a proof-of-concept study of implementing a novel system for household waste textile collection.

2. Literature and prior works

Optimization of waste collection with digital technologies has been covered in various scientific publications. For example, an IoT-Enabled waste management system based on battery operated Raspberry Pi's (RP) with ultrasonic distance sensors was tested with 38 bins for ten days % (Bakhshi and Ahmed, 2018). The sensors were connected to public Wi-Fi hotspots which limits the usability of the sensors to specific locations. Further, the use of RP as platforms resulted a high-power consumption of sensors and required battery changes in every two days. The sensor data was used with route optimization, and the results showed an improvement of 18–63.4% in overall efficiency. The average time savings of the collection period were 16 min per day which corresponds an 18% decrease. Also, the driven collection distance decreased by approximately 26%, with a fuel efficiency drop of 46%.

The optimization of waste collection has been proposed in several other scientific publications, and the results are promising. For example, the study with integrated GA with GIS for collection routing showed decreases of 8% in the operating distance, 28% in travel time, and 3% in fuel consumption (Amal et al., 2018). When MLR and ANN models were used to predict the required collection frequency, a 10% decrease in the frequency was observed (Ferreira et al., 2017). In a similar study, a 19% better performance in sustainability and environment load was achieved (Montecinos et al., 2018). Moreover, a simulated optimization of bin collection with genetic algorithms resulted a 15% improvement in waste collection cost savings (Fujdiak et al., 2016).

Despite the existing literature, the benefits of smart bins with route optimization still seems a valid question. Especially in the context of textile recycling, as any scientific research on the topic was not found. The environments and use cases for smart bins are various. For example, textile collection is often done with fever bins than traditional waste collection. Further, textile waste generation can be more difficult to predict as it is affected how consumers empty their closets. Moreover, there is a lack of study regarding the trends of the filling rates of textile waste bins, including the effect of seasonality of people's behavior in disposing of clothes. Consequently, a research gap (i) is found: *what is the reduction in costs by using IoT/route optimization approach for the textile collection.*

Further, a recent extensive literature survey of smart waste managing systems states that there are many theoretical works on this topic, but a lack of pilot projects with a detailed analysis of the results of the implementation of such systems (Sosunova and Porras, 2022). Similarly, in the context of IoT and AI in supply chains, it was also stated that more real industry cases going beyond toy-examples are required to validate the benefits (Koot et al., 2021). Consequently, a research gap (ii) is found: *real-world data is rarely used in research regarding the optimization of solid waste collection.*

The lack of real-world data in research can be attributed to the reason that there is a lack of viable sensors for long-term data collection for research projects. This sets challenging requirements because outdoor conditions vary greatly throughout the year, and the sensors should be operable without mains power and maintenance for several months. Further, the measured data should be collected wirelessly from various bin locations.

More support for this hypothesis is found with a literature review of 56 most relevant publications in IEEE database related to search words "IoT bin". These 56 papers were screened by employing ATLAS. ti software by tagging the interesting parts with codes that were used for analysis. More detailed results of the literature review are presented in the table in appendix 1. From the review, it was observed that most of the research projects are adopting Arduino compatible development platforms as Arduinos and ESP's. The low entry barrier, flexibility, and low costs of these tools are the main reasons for their popularity. The flexibility comes from standardized hardware and software interfaces and from the hardware that can be easily reprogrammed for different use cases. Low cost in this context means prices of no more than tens of euros. In this paper, such tools will be further called as flexible low-cost tools or flexible low-cost hardware when explicitly referring to hardware tools.

The results of the review correspond to the findings that flexible low-cost tools can be used to develop new IoT solutions, although more proof of their reliability is needed to be seriously taken (Martikkala et al., 2021a, 2021b). According to the literature review, it is evident that these tools are widely used in research in the context of smart bins. However, as stated, the reliability for long-term data collection seems to be an issue. Issues such as a need to improve power efficiency and extend the system to ascertain the design capability of advanced waste collection systems are specified (Bakhshi and Ahmed, 2018). Similarly, the power optimization of the developed sensors was stated as a challenge (Nirde et al., 2017). The rapid developments in the area and the thoughtful combination of tools can create solutions that fulfill the requirements. However, their viability should be proven. Consequently, a research gap (iii) is found*: the viability of flexible low-cost tools needs to be proven/improved.*

From the surveyed publications, only five papers were adopting wireless technologies such as LoRa, NB-IoT, and Sigfox, which are suitable for long-range and low-power wireless communications. Such technologies are crucial for long-term data collection from bins spread over large areas. Similarly, most of the proposed implementations were adopting sensors such as HC-SR04 ultrasonic distance sensors that are not waterproof, which is likely an issue for long-term outdoor use. Further, the use of hardware platforms with high power consumption is a clear obstacle for a battery-operated wireless sensor. In general, IoT is characterized by low resources in terms of both computation and energy capacity (Atzori et al., 2010), which has not been the case in many of the developed sensor systems in the literature Consequently, it is acknowledged that if these shortcomings are found in the proposed sensors, they should not be considered suitable for long-term data collection. Finally, the four most relevant developed sensor systems for long-term data collection found in the review are described in more detail.

Garbage Zero (Garb0) is a wireless sensor for outdoor garbage bins and aims at developing a power efficient IoT-based real-time solid waste monitoring solution (Chavan et al., 2021). The module is based on an ARM cortex STM STM32L083cz microcontroller and deploys ultrasonic, temperature/humidity and GPS sensors. It uses LoRa for wireless communications with 1-year battery life and is enclosed in IP67 compliant enclosure. The used ultrasonic sensor Maxbotix MB7137 is IP67 proof and better quality than the sensors used in most projects, which is reflected in its high price.

Trash Bin Level Measurement Unit (TBLMU) is a fullness monitoring sensor built on a specifically designed circuit board (Ramson et al., 2021). The module is based on Atmel ATmega 2560 microcontroller and deploys ultrasonic and GPS sensors. It uses LoRa for wireless communications, is enclosed in IP67 compliant enclosure, and has extended battery life with a solar panel, which is sufficient to recharge the battery. The used MB1010 LV-Maxsonar-EZ1. It is a low-cost, high-performance, and stable ultrasonic range detector with quality beam features, but it is not waterproof, which somewhat neglects the benefits of IP67 enclosure. The cost for the parts for the TBLMU sensor is 161.85 usd. Further, the expertise and work for tailored electronics requires skillful resources.

Another smart bin sensor node for fullness monitoring was built on specifically designed circuit board (Mustapha et al., 2021). The module is based on a PIC18F2550 microcontroller and deploys ultrasonic, temperature/humidity, and GPS sensors. It uses GSM/GPRS for wireless communications and is enclosed in a plastic enclosure. The battery life is not evaluated, but it is mentioned that solar panels could be used in the future. The used HC-SR04 ultrasonic distance sensor is popular among hobbyists, but as the sensor itself if not waterproof, it is not suitable for real world outdoor applications.

Further, a smart bin sensor node for fullness monitoring with a tailored design was proposed (Addabbo et al., 2019). The sensor node is based on ATMega328 P microcontroller and deploys ultrasonic, temperature, and tilt sensors. The wireless connections are enabled by a Libelium SX1272 LoRa module. The complete electronic circuitry is enclosed inside an IP65 ABS plastic enclosure with a hole for the ultrasonic sensor. The theoretical battery life of the sensor was estimated to be up to 500 days with a measuring frequency of 1 h. The system was successfully tested with four sensors for about three months.

In conclusion, the literature review shows the lack of viable sensors for long-term data collection. The four most prominent sensor modules are yet considered expensive, or are not waterproof, or not flexible, i.e., require somewhat complicated electronic circuit design and higher-level embedded system programming. These can be insurmountable obstacles for researchers with limited resources. The number of Arduino-based sensors in the research indicates the easiness and affordability of the tools. Correct tools can bolster the research where the actual novelty comes from the collected data or system development, not from the development of tools such as electronics. I.e., to allow researchers to focus on research and scholarship rather than on the development of tools (Lee et al., 2018). This need for effective development and testing of new IoT solutions has been pointed out in several scientific publications and (Lee et al., 2018; Martikkala et al., 2021a, 2021b). From that perspective, the question is more about the usability of the tools. Therefore, the development and testing of a feasible sensor is proposed to provide results for research gaps (ii) and (iii).

The remainder of the paper is organized as follows. Section 3 provides the research methodology and background for system development and route optimization analysis. Section 4 presents the results obtained from the work and discusses the implications and proposes future improvements. Section 5 concludes the paper and summarizes the results.

3. Material and methods

This work adopts the DIKW (Data, Information, Knowledge, and Wisdom) pyramid. In the DIKW pyramid, each level is defined in terms of the level below it, eventually leading to wisdom. The idea of three cornerstones as models, tools, and techniques is adopted (Lobov, 2018). These are defined in Fig. 1. The tools are the base for building the solution. Further, the techniques are used as instructions towards a solution, such as which tools to use to create the models. Finally, leading to a solution using low-cost data collection, analysis, and simulations resulting a comparison that shows the benefits of smart textile collection.

The DIKW methodology is in line with the research gaps: (i) what is the reduction in costs by using IoT/route optimization approach for the textile collection, (ii) real-world data is rarely used in research regarding the optimization of solid waste collection, (iii) the viability of flexible, low-cost tools needs to be proven/improved. These gaps are illustrated in Fig. 2, followed by methods to fill the gaps. The hypothesis that a lack of suitable sensors for data collection results the lack of real-world data implementations in optimization of solid waste collection is an interim result to fill the gap. This hypothesis is supported with evidence from a literature review.

According to research gap (ii) real-world pilots are requested to complement research in smart waste management. However, a full real-world pilot implementation is outside the scope of this work. The benefits of smart bins with route optimization are evaluated with simulations based on the real world. Further, this work qualifies a set of viable tools for long-term data collection for future research on the topic. I.e., the proposed system could be extended beyond proof-of-concept with more extensive installations.

As described, the methodology includes a two-step approach. *First,* a smart bin IoT system is developed, which consists of fullness sensors, databases, and visualizations to offer a better test setting. Using such tools also supports the envisioned wider potential of affordable IoT by developing the system utilizing low-cost and open-source IoT hardware and software. *Secondly*, the benefits of the smart bins with route optimization are investigated with a simulated case study that is based on the collected real-world data. The results will present and discuss the environmental and economic sustainability potential.

3.1. *The smart bin IoT system*

Following the outlined methodology, the smart IoT system is developed. The system is based on low-cost and open-source tools. It covers the sensor development, as well as tools for interoperability between the different parts of IoT system architecture. Communication is the most crucial part in IoT (Atzori et al., 2010). Therefore, the sensor development is started from defining a suitable hardware platform from the perspective of wireless data transfers. Consequently, the sensors are based on low-cost Heltec CubeCell development boards with LoRa communication capabilities, shown in Fig. 4. The detailed bill of materials for the sensor and the costs are shown later in Table 1. The CubeCell boards can be easily programmed with Arduino IDE and used with a large variety of compatible sensors. Finally, the power consumption (~12 μW) in hibernation is low, which makes them especially suitable for the case.

The distance sensors drain power only when measuring as they are powered via controllable Vext pins of the CubeCell. The selected laser sensor is adopting I2C bus for communications, whereas the ultrasonic sensor can be connected to any digital I/O pin to calculate the distance based on the time between the trigger and echoed signal. Further, the electronics are installed inside a waterproof enclosure with sealed holes for the waterproof sensors.

The architecture of the smart bin monitoring system is shown in Fig. 3. The local low-cost InfluxDB database on RP may not be reliable enough to store data for long periods; therefore, a Google Firestore cloud database is used as a backup. Further, the collected data is presented in real-time with an open-source Grafana visualization tool run on RP. The data collection is done with the Heltec CubeCell based sensors connected to a nationwide LoRaWAN network provided by a Finnish transmission network operator Digita. However, it is possible to set up a LoRaWAN

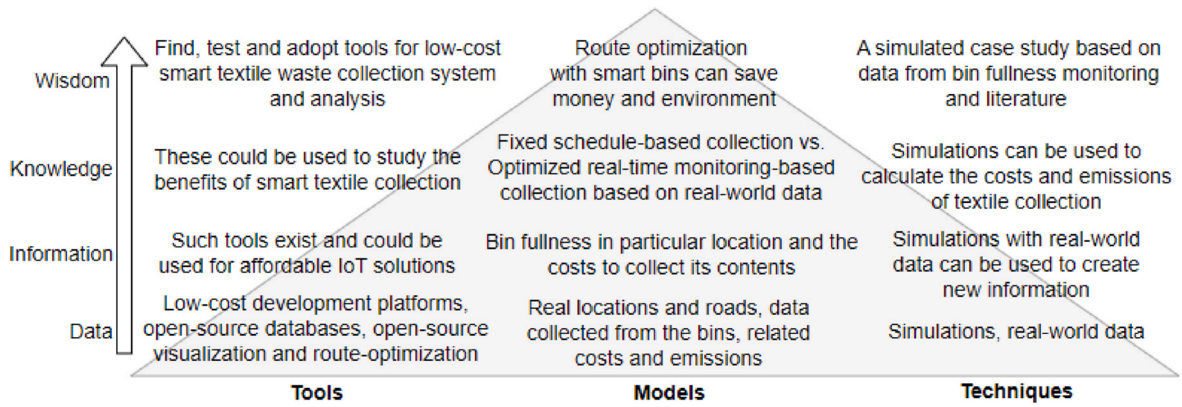

Fig. 1. DIKW pyramid in three cornerstones.

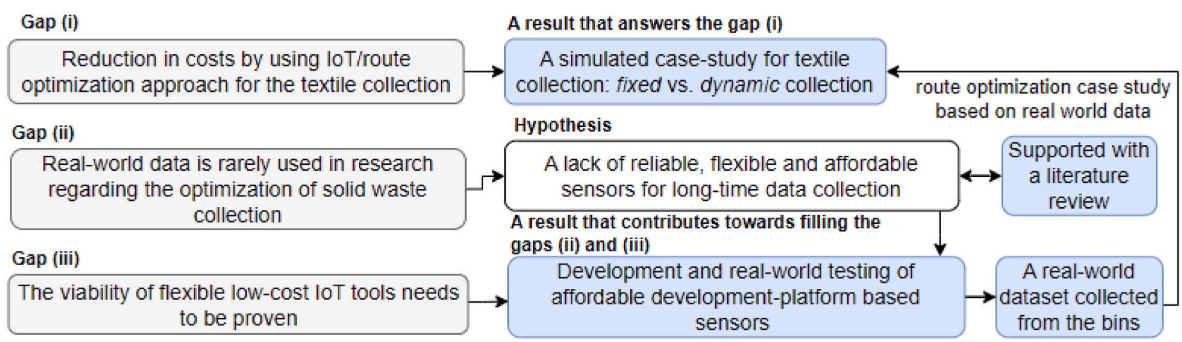

Fig. 2. Research gaps to results.

Table 1
The cost of single sensor module.

Item	Cost [eur]
Heltec CubeCell LoRa development board	10
Laser sensor - TOF200F VL53L0X	11
Battery holder for 2 AA batteries	0.81
Enclosure, IP67	7
Total cost [eur]	28.81

network with own gateways by adopting The Things Network, a crowdsourced, open, and decentralized LoRaWAN network. The LoRaWAN network provider Digita uses ThingPark platform for managing the sensors and the sensor data destinations. The data from the system is sent in a specific JSON format that is not supported by InfluxDB or Google Firestore. Therefore, a middleware (Martikkala et al., 2021a, 2021b) is adopted to parse the data and support the APIs of InfluxDB and Firestore. In the future, a real-time route optimization could be connected to the system by adopting either one of the databases.

3.2. Case study with ODL software

The benefits of route optimization are estimated by a case study based on the real locations of the bins and generated data. The case study compares two different collection schemes named as *fixed* and *dynamic*. In the fixed scheme, the textile bins are emptied with fixed scheduled trips, whereas in the dynamic scheme, the collection is done based on the fullness of the bins.

Route optimization can improve the collection by reducing operating time and fuel consumption, resulting more cost-effective and environmentally friendly routes (Expósito-Márquez et al., 2019). The two schemes are compared using open-source Open Door Logistics (ODL) software. It adopts Graphopper routing library and uses contraction hierarchies to optimize routes. Inputs such as geocode location, waste quantity in each bin, service time, capacity/time constraint are used. The results will show the optimized collection, including travel time, service time, distance, and cumulative waste quantity in each case. The costs are calculated separately by adopting the exported results from ODL. The following formulas are used for the calculations.

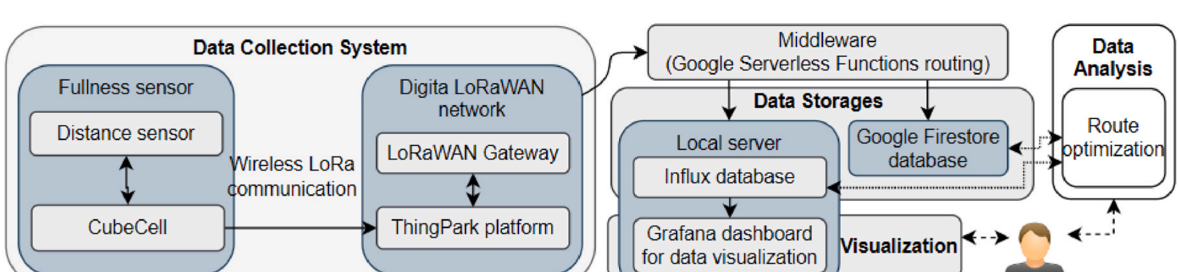

Fig. 3. Technical architecture of the smart bin monitoring system.

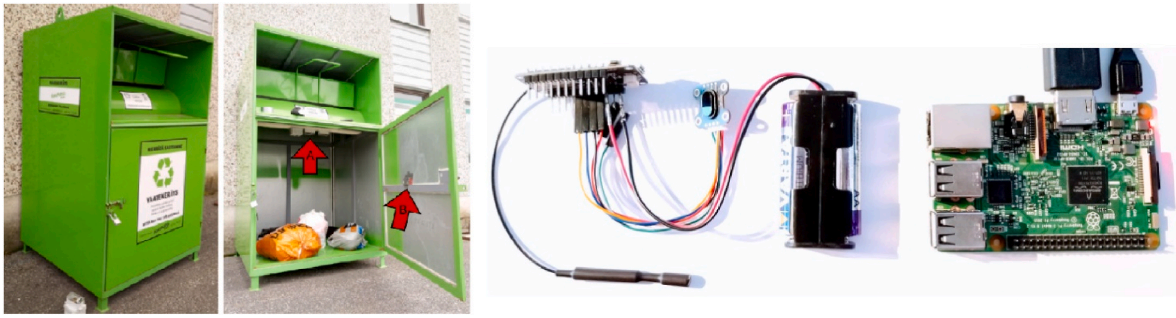

Fig. 4. The clothes collection bin with vertical and horizontal sensors installed, the CubeCell based laser distance sensor, and a Raspberry Pi based local server.

3.2.1. Amount of waste transported per km

The collection times are fixed for the conventional scheme, whereas the dynamic scheme may have more or fewer trips depending on the filling rate of the bins. This situation could lead to different amounts of waste being collected within the timeframe. Therefore, the amount of waste transported per km (m_{km}) is used to compare efficiency between these two collection schemes as shown by equation (1). Where m_{tot} and d_{tot} are total waste collected (kg) and distance (km) traveled within the period of observation, respectively.

$$m_{km} = \frac{m_{tot}}{d_{tot}} \tag{1}$$

In addition to m_{km}, physical parameters as waste overflow, total time, and average filling rate are compared between these two collection schemes. Waste overflow (kg) indicates the total excess waste the bin cannot contain on the collection day. The reusability or recyclability of textile waste depends on its quality. Moisture and mold can occur in textile waste even when it is stored inside a metal container. Total time (hours) shows the time required to collect and transport textile waste, whereas average filling rate refers to the average occupancy of the bins on the collection day.

3.2.2. Collection cost in total

The collection cost is used as an economic parameter to compare conventional and dynamic collection schemes. For a fair comparison, the economic implication per kg waste (C_{kg}) is used, as shown by equation (2).

$$C_{kg} = \frac{Vehicle_{cost} + Labour_{cost} + Sensor_{cost} + Fuel_{cost}}{m_{tot}} + \frac{Bin_{cost}}{UR} \tag{2}$$

Where m_{tot} and UR are total waste (kg) and total usage rate of bin (kg) within 4 weeks period, respectively. The total costs consist of different components as vehicle cost, bin cost, fuel cost, labor cost, and sensor cost (when applicable).

3.2.3. Vehicle cost

Vehicle cost consists of capital costs, insurance, and maintenance costs. The insurance and maintenance costs are defined as 7% and 1.4% of capital cost, respectively (Martinez-Sanchez et al., 2015). Equation (3) calculates the annualized capital cost (A).

$$A = \frac{P}{\left(\frac{(1+r)^l - 1}{r.\ (1+r)^l}\right)} \tag{3}$$

Where P, r, and l refer to the vehicle purchase cost, interest rate, and a vehicle's lifetime, respectively (Sørensen et al., 2004). The annualized amount is converted for a 4-week observation period.

3.2.4. Bin cost

Bin cost is estimated by calculating the investment cost of purchasing a textile waste metal container. Equation (4) is used to calculate bin cost (Bin_{cost}). Here C_{bin}, Ls_{bin}, and n_{bin} represent the price of a bin, bins' lifespan, and the number of bins, respectively.

$$Bin_{cost} = \frac{C_{bin}}{Ls_{bin}} .\ n_{bin} \tag{4}$$

3.2.5. Fuel cost

Fuel consumption cost consists of idle and travel fuel. The former occurs when the vehicle stops to empty the bin or to transfer the textile waste at the transfer station. The latter is caused by the collection and transportation of the textile waste. To estimate the cost of fuel consumption, equation (5) is used.

$$Fuel_{cost} = (FC_{idle} .\ idle\ time + FC_{travel} .travel\ distance).\ C_{diesel} \tag{5}$$

Where FC_{idle} and FC_{travel} are fuel consumption while the truck is idle (liter/hour) and traveling (liter/km), respectively. Whereas *idle time*, *travel distance*, and C_{diesel} indicate the time when the truck idling (hour), the distance when the truck travels (km), and the price of diesel (€/liter), respectively.

3.2.6. Labor cost

The average of labor wage is estimated to be 25 €/hour, with two workers in charge whenever the waste is collected. Equation (6) shows how to calculate labor cost where *wage*, *time*, and *n* represent the driver's wage (€/hour), the total time spent (hours), and the number of workers, respectively.

$$Labour_{cos\ t} = Wage\ .\ time_{tot} .n \tag{6}$$

3.2.7. Sensor cost

Sensor costs consist of the investment cost, installation cost and maintenance cost. It is assumed that annual maintenance cost is 7% of capital cost and installation time is 20 min, and labor cost for installation is 25 €/hour. Equation (7) shows the estimation of sensor cost ($Sensor_{cost}$). Here C_{sensor} is the sum of capital and installation costs and total maintenance costs. Ls_{sensor} and n are the sensor lifespan and number of bins, respectively.

$$Sensor_{cost} = \frac{C_{sensor}}{Ls_{sensor}} .\ n \tag{7}$$

3.2.8. Sensitivity analysis

Perturbation analysis is applied to investigate the effect of modifying the inputs with regards to the results. Cost-related input parameters are tested by adjusting their value by 10% one at a time while maintaining all other parameters the same as the baseline values. These parameters include vehicle cost, labor cost, bin cost, fuel cost, and sensor cost. The results obtained from perturbation analysis are applied to calculate the sensitivity ratio (SR) using equation (8). SR indicates the ratio of two relative changes involving the relative change in the input parameter and results (Bisinella et al., 2016).

$$SR_i^j = \frac{\left(\frac{\Delta result}{initial\ result}\right)^j}{\left(\frac{\Delta parameter}{initial\ parameter}\right)_j} \approx \frac{\partial z_j}{\partial x_i}\frac{x_i}{z_j} \tag{8}$$

4. Results and discussion

First, a novel system for textile collection bin monitoring and data collection is developed. The system is based on low-cost and open-source tools, is relatively easy to implement, has suitable wireless connections, and is maintenance-free without mains power. The development of suitable sensors for long-term data collection often requires too many resources and therefore becomes impractical for most researchers. Further, the available commercial sensors are usually designed to be used with some specific system and are sold as a service with a complete IoT platform. Such tools do not support research projects where flexible case-specific tools are needed.

Secondly, the economic assessment of route optimization between conventional and dynamic collection of textile waste is presented by a case study. Conventional collection implements a fixed schedule of the collecting fleet, whereas dynamic collection employs level sensors to provide real-time information regarding bins' filling rate to adjust the collection schedule. The case study aims to provide information regarding the potential of using smart bin sensors and route optimization from an economic and environmental perspective.

4.1. Development and utilization of open IoT to monitor waste collection

Three different types of sensors shown in Fig. 4 were tested on the field: 1) a vertical ultrasonic sensor, 2) a vertical laser sensor, and 3) a horizontal single-limit laser sensor. The vertical sensors are attached over the textile waste to measure the height of the pile. Correspondingly, the horizontal laser sensor on the door is used to verify the results of the vertical sensors. The tests showed that the ultrasonic sensor was unreliable with soft textiles inside the bin. However, the vertical laser sensor was found to be viable. Consequently, vertical laser sensors were installed inside four textile collection bins to collect fullness data. These four bins are located in Seinäjoki (a city in western Finland), where one is a movable collection bin, and rest three are bigger stationary bins.

The bin monitoring relied on the low-cost CubeCell based laser sensors and the RP server shown in Fig. 4. Nonetheless, the data was successfully collected during a six-month test period from January to July. However, the continued tests showed that the sensors can run without a battery change for over twelve months. The sensor inside the movable bin also collected data for six months, but the bin was not used during the collection period. All in all, during the test period, valuable data was collected with three sensors for six months.

The collected data was transformed into fullness percentages and turned into a cumulative format by considering the increments in the bin fullness. The variations under 5% (corresponds 6 cm in distance) were dismissed from the data as measuring errors. The described manipulation was conducted on the successfully collected data from the collection bins. Fig. 5 presents the resulted cumulative accumulation of the textile from three bins from January to July. In the cumulative format, 1 unit (as 100% fullness) represents a full bin. Therefore, a simple calculation from the six-month period with a cumulation of 25 units suggests that the bin should be emptied at least 50 times per year.

The fact that sensors have been running continuously with two AA batteries for so long is convincing as they were used in outdoor conditions during the Finnish summer temperatures of +30 °C as well as in the cold winter temperatures below −20 °C. This supports the findings that the trends indicate that open hardware manufacturers are putting more emphasis on reliability and even on industrial use (Martikkala et al., 2021a, 2021b). The results undoubtedly increase confidence in the low-cost and open-source solutions based on affordable development platforms. Heltec CubeCell with low-cost sensors has been proven to be quite a reliable combination for long-range wireless IoT data collection implementations. The system can be considered affordable as the software tools used are open source or free, whereas the hardware cost of Raspberry Pi is around 50 eur, and the cost of a single sensor is under 29eur. The detailed costs of the sensor module are presented in Table 1.

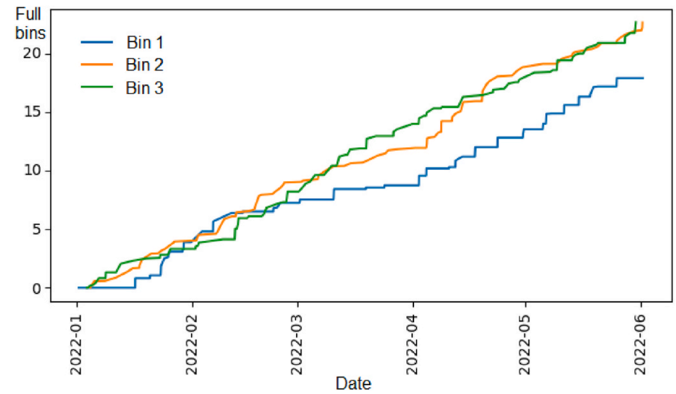

Fig. 5. Cumulative accumulation of textiles derived from the collected sensor data.

In conclusion, firstly, this result offers a solution for the interim research gap, i.e., a lack of viable tools for data collection, as well as makes its part in showing the usability/reliability of low-cost IoT devices. Most of the developed sensors according to the literature review in scientific publications are not viable. I.e., cannot run without mains power for several months or they lack long-range wireless connectivity or are too expensive, etc. This paper proposed a system that overcomes the limitations.

The collected fullness data is converted into textile weight by considering the size of the collection bin and the weight of the textile. However, the textiles are piling and are not packed tightly inside the waste bin. Further, as the textiles are dropped from one side of the bin, the total free volume of the bin cannot be assumed to be fully utilized. Consequently, we use the textile density of used clothes 133.5kg/m3 and the volume of 0.24m3, which is the same as standard wastebin (Environmental Protection Agency, 2006, 2016). This corresponds to the effective volume in practice. Hereby 1 unit (full bin) in the bin fullness corresponds to 32 kg of textiles. Further, according to the data, the average filling rate from the bin is 4,3 kg of textile per day. This means that on average, it will take 7.4 days for the bin to get full.

4.2. Route optimization for enhanced economic and environmental performance

Route optimization is used to demonstrate the potential of using IoT for collection bins. The performance of dynamic and conventional collection is evaluated based on physical and economic indicators in relation to the deployment made in Seinäjoki area in Finland. The goal is to calculate the reduction in cost by using IoT/route optimization approach for the textile collection. It considers all the costs related to the textile collection as well as the costs of the smart bin system.

4.3. Cost calculation

4.3.1. Case study: Seinäjoki smart textile collection

This research simulates dynamic and conventional textile waste collection in a case study to illustrate the potential differences that occurred due to using waste bin fullness sensors. The illustrative case is from Seinäjoki, a city with a population of 64,000 and land area of 1432 km^2 located in Southern Ostrobothnia province. The real locations of ten textile collection bins are used. Six of the bins are located around the city center, and the other four are in the outskirt area. Each bin has a capacity of 240 L (0,24m3), which equals 32 kg.

According to the collected real-world data the filling rates seem to be quite linear. Further, it was calculated that on average, it takes 7.4 days for the bin to get full. Hence, this study assumed that the conventional collection would collect the textile waste once a week. The filling rate of the bins is estimated twice a day for total 28 days by generating random number that follows the pattern of the data shown by the sensor. Since the variability was found among the three sample bins and in each bin from month to month, we replicated it in our case study by differing the filling rate pattern of the bins. Six bins that are located around the city center were assumed to be fully occupied or even overflow by the end of day seven, whereas the other four bins will be filled for about half of the total capacity.

In the conventional scheme, the truck will collect the textile waste from each bin by the end of day seven, regardless of the bin occupancy (some may be overflow or underutilized). For the dynamic collection, it was assumed that the actual filling rate is reported twice a day, in the morning and evening. At the evening report, the bins with a filling rate of around 90% will be marked for the next morning collection. The collection route will be determined in the morning before collection by additionally considering other bins that reach at least 80% filling rate to make the route more efficient. Service times in each bin and transfer station were ten and 20 min, respectively. The illustrative case was simulated for four weeks in both conventional and dynamic collections.

4.3.2. Route optimization

The findings showed that the conventional scheme resulted a longer collection distance compared to the dynamic scheme. The conventional scheme had four trips during the observation period and used the same routes for each trip. It resulted 40 stops at the bins and four stops at the transfer station. The dynamic scheme resulted six trips shown in Fig. 6, where each trip collected textile from different bins. Within this scheme, there were 31 stops at bins and six stops at the transfer station. Since each trip emptied different bins, the routes became dynamic and were optimized each time the collection was performed.

Moreover, dynamic collection resulted improved loading rate of the collection truck compared to conventional. It also increased the waste transported per distance from 1.47 kg/km to 1.65 kg/km for the conventional and dynamic schemes, respectively. Operating time, including the travel time and service time was similarly decreased in the dynamic scheme. The conventional scheme's service and travel time were around 8 h and 10.8 h, respectively. In dynamic collection, there were six trips within the four weeks where each collection involved different bins. The number of bins emptied in each trip of dynamic collection was ranging between 2 and 4 bins. It resulted a service time around 7.2 h and a travel time for about 9 h.

Table 2 displays the summary of route optimization in both conventional and dynamic collection within four weeks. The percentual change from conventional collection to dynamic collection is calculated. However, these two schemes are not fully comparable as different quantities of textiles were collected in each scheme. Therefore, the difference percentages for the number of trips, distance, time, and fuel consumption are normalized with respect to the weight of the textile collected.

The average filling rate was calculated using the filling rate of the bins when the collection occurs. Whenever the bin is overflowed, the average filling rate is assumed to be 100% since it should not exceed the maximum occupancy of the bin. Conventional scheme showed lower occupancy rate since we assumed that some bins have slower filling rates

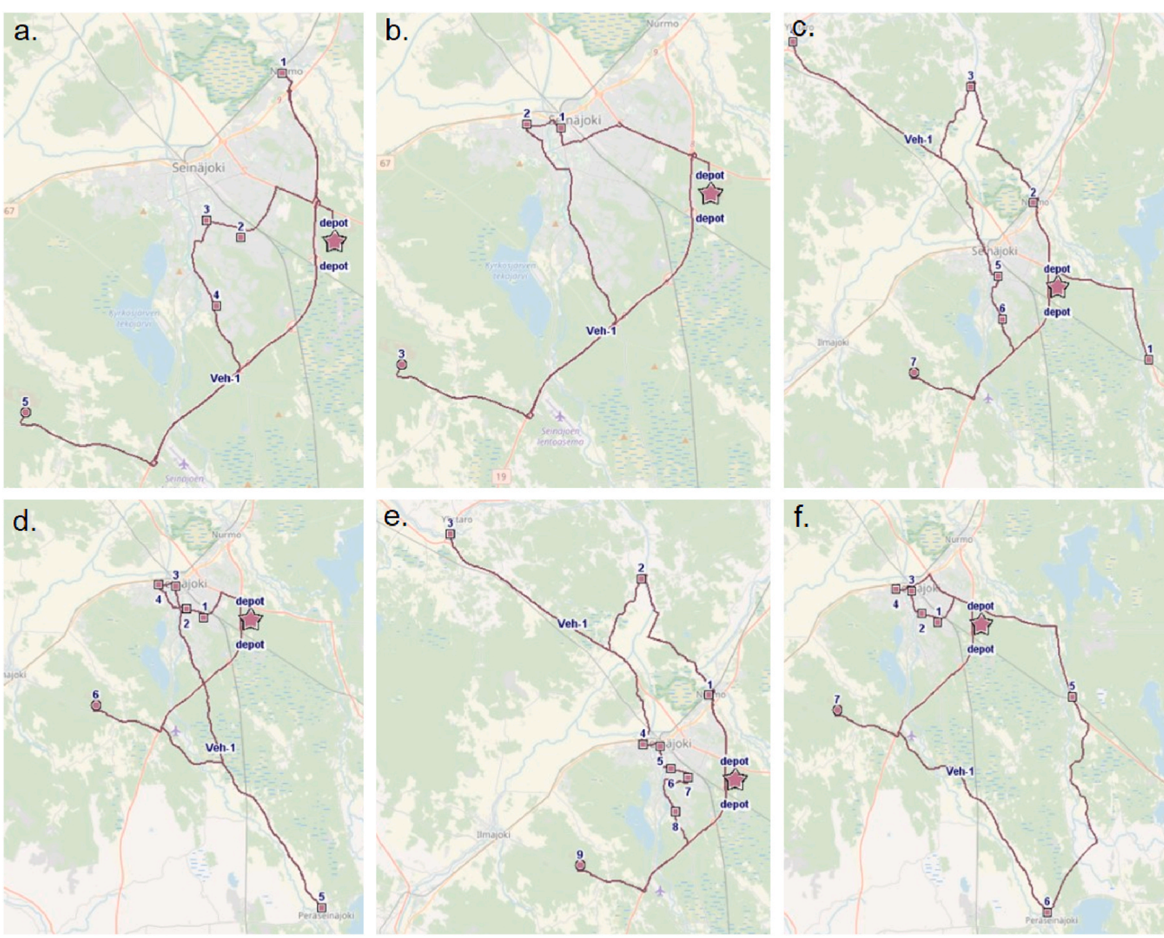

Fig. 6. Optimized route of dynamic collection: a. Trip 1, b. Trip 2, c. Trip 3, d. Trip 4, e. Trip 5, f. Trip 6.

Table 2
Summary of results of conventional and dynamic collection.

Item	Unit	Conventional	Dynamic	Difference %
Number of trips		4	6	+61.32% *
Total distance	Km	675.2	557.5	−11.20% *
Total time	Hours	18.8	16.2	−7.33% *
Fuel consumption	Liter	268.3	224	−10.21% *
Waste quantity	Kg	989.4	920	−7%
Waste transported per distance	Kg/km	1.47	1.65	+12%
Waste overflow	Kg	10.6	2.3	−78%
Average filling rate of the bin	%	75	92	+22.67%

* The difference per kilogram of textile collected.

and conventional scheme will still collect the textile regardless the bin occupancy. Whereas dynamic scheme had a threshold value for bin occupancy so that the collection would target the bins that were almost full. As a side effect, this was also found to reduce the bin overflow. Further, the decrease in fuel consumption is directly related to the decrease in CO2 emissions (Ghahramani and Pilla, 2021). Consequently, the decrease in CO2 emissions is shown to be 10.2%.

4.3.3. Cost analysis

The total collection costs within four weeks for conventional and dynamic collection were around 1575.5 € and 1361 €, respectively. These values were translated into 1.61 €/kg and 1.51 €/kg for conventional and dynamic collection, respectively. Fig. 7 shows the cost items of both collection schemes. Both schemes showed that labor wage contributed highest to the total cost for about 59%, followed by fuel cost and vehicle cost around 22% and 17%, respectively. For the dynamic collection, adding sensor and its software did not increase the cost significantly, where its contribution to the total cost was around 1.1%. In conclusion, with smart bins and route-optimization the cost of collected textile waste per kg is reduced by 7.4%.

4.3.4. Sensitivity analysis

The most sensitive parameters were investigated by calculating sensitivity ratio (SR). Each parameter was increased by 10% while holding the rest constant. If SR shows value of 2.5, it implies that a 10% increase in a particular parameter will increase the cost by 25%. Fig. 7 shows SR of five parameters against the collection cost.

There was only a slight difference between dynamic and conventional collection as seen in Fig. 7. Moreover, the patterns obtained in both collection schemes were comparable. The SRs for both schemes were ranging around 0.01–0.59. The most sensitive parameter was labor cost where a 10% of it will result around 5.9% increase in the total cost in conventional and dynamic collection. For conventional scheme, the least sensitive parameter was bin cost in which a 10% increase of bin cost would drive up the cost for about 0.2%. Meanwhile, sensor cost was found to be the least sensitive parameter in dynamic collection, where the increase in its price would make the total cost increase around 0.1%. Conducting an assessment of the most critical parameters is important to deal with uncertainties caused by price fluctuation of different items.

4.3.5. Comparison with previous studies

The comparison of previous work in Table 3 shows quite a lot of variation in the results. For a comparison, a decrease of 15% in costs (Fujdiak et al., 2016) and 47.77% decrease in fuel costs (Akhtar et al., 2017a, 2017b) were calculated. However, a shown decrease only in fuel cost does not include the other costs as sensors and labor. The decrease of 7.5% in cost according to this study is substantially less than in the referenced studies. Nonetheless, the other studies were showing the benefits of route optimization in the collection of municipal waste rather than textile waste.

Moreover, the decrease in cost is affected by the use case, i.e., the number of bins, topography/roads, and the rate of waste accumulation, etc. This means that the results in the literature of different methods used for the optimization of waste collection are not directly comparable. Ideally, one could compare mentioned route optimization methods by taking each method and applying it in different setups tried by the other methods. However, the value and contribution of this paper is not in direct comparison of methods but highlighting the possibilities and performance for route optimization with smart bins. The thorough comparison between different approaches can be a research topic itself and a part of a future work.

5. Conclusions

Following outlined methodology (Fig. 1) and research gaps (Fig. 2), the paper presented an IoT solution (Fig. 3) deployed to the curbside textile collection bins. For this, corresponding tools, models, and techniques were developed and integrated to support the target application of smart collection for textile. Waste collection is typically based on a fixed schedule to collect waste from the bins. Such practice has drawbacks as the waste generation is irregular and difficult to predict. This study investigated the benefits of a smart bin IoT system combined with a dynamic collection scheme for textile waste collection. Real-world data and long-term real-world implementations are rarely present in research regarding the optimization of solid waste collection. It was found that Arduino and Raspberry Pi are largely used for data collection due to their low-entry barrier, flexibility, and low cost. However, the majority of the developed sensors are not suitable for long-term bin fullness monitoring, which could be the reason behind the gap.

Therefore, flexible low-cost tools were used to develop a viable monitoring system. The developed sensors are based on Arduino-compatible Heltec CubeCell development boards and laser distance sensors inside an IP67 enclosure. Here the total cost of one sensor stayed under 29eur. The reliability and power consumption of the sensors were convincing as the sensors stayed operational for over a year and survived through the cold winter and warm summer temperatures in Finland. The result strengthens the credibility and possibilities of low-cost and open-

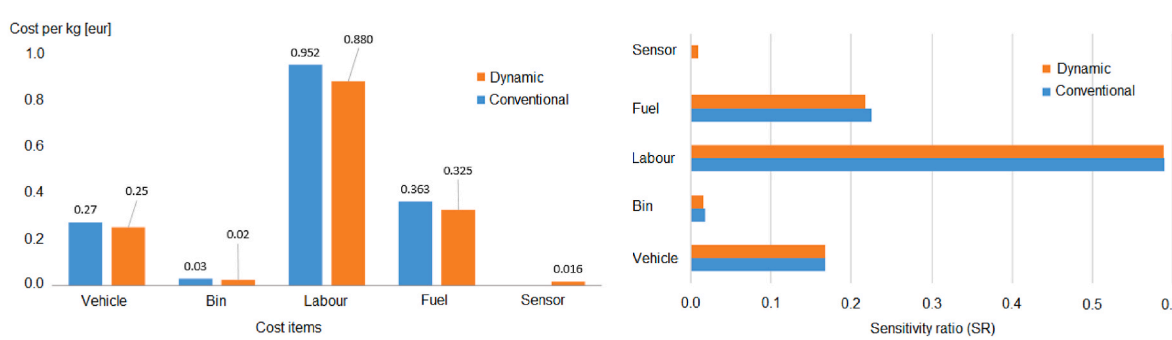

Fig. 7. Cost items for conventional and dynamic scheme and Sensitivity ratio of input parameters to the costs.

Table 3
Comparison of results with previous studies.

Authors	Distance	Time	Fuel	Emissions	Costs	Overall efficiency
Bakhshi and Ahmed (2018)	up to −26%	up to −18%	up to −46%			−18 to −63.4%
Amal et al. (2018)	−8%	−28%	−3%			
Fujdiak et al. (2016)					−15%	
(Akhtar et al., 2017a, 2017b)	−36.8%		−50%	−44.68%	−47.77% (fuel)	on average −36.78%
Castillo et al. (2021)	−11.49% to −25.9%	−17.60% to −29.41%				
Our work	−11.2%	−7.33%	−10.2%	−10.2%	−7.4%	

source tools in data collection and IoT system development. The collected data showed the textile generation with the bins to be quite linear. Further, according to the data, the average filling rate from the bin is 4,3 kg of textile per day. This equals to that on average it will take 7.4 days for the bin to get full.

The economic and environmental feasibility of the level sensor implementation is demonstrated through a case study with real textile bin locations and data generated based on real-world sensor data. Two different collection schemes, named conventional and dynamic were simulated, and the results were compared. Most of the studies in the area are focusing on the reduction in operating hours, distance, and fuel consumption. For better decision-making, such physical indicators must be converted into monetary indicators. This work showed that dynamic collection had shorter travel distances and fewer stops, which translated into reduced operating time, fuel consumption, and cost. Most importantly, the four-week observation showed that the collection cost per kg of waste for the dynamic scheme was around 7.4% lower than for the conventional one. Similarly, the CO2 emissions were observed to be reduced by 10.2%.

According to the results, the monetary benefits of dynamic route optimization for textile recycling businesses are clear. In a fully operational smart waste collection system, the additional costs of level sensors are insignificant compared to the other costs related to the textile collection. Moreover, there is an indirect benefit as the overflow of the bins is less likely to occur. Further, improved efficiency in the textile collection makes it more profitable and can increase the share of textiles being recycled. It is known that the convenience of recycling affects the behavior of people. With smart waste collection, the utilization of a larger number of bins could be profitable, which would also bring the collection closer to people. Future research could investigate if the dynamic collection makes it possible to increase the number of bins and get even more benefit from the optimization. I.e., what would be the optimal number of bins with conventional and dynamic waste collection.

Further, for future work, a more extensive installation of sensors is proposed. A comparative study adopting a fully operational smart waste collection system with real-time route optimization would confirm the results of the simulations. The employment of such a system for research would now be easier as the affordable tools proposed in this paper were proven to be reliable. Also, for deeper understanding, the different approaches for route optimization should be tested in various environments. Moreover, the proposed IoT system for data collection could be effortlessly applied to other use cases, possibly with other types of sensors attached. Such work would strengthen the results of the reliability of the flexible low-cost tools for IoT.

Credit author statement

Antti Martikkala: Conceptualization, Methodology, Writing- Original draft preparation, Investigation (The IoT system development), Writing - Review & Editing. **Bening Mayanti:** Formal analysis (Route optimization case study), Writing- Original draft preparation. **Petri Helo:** Supervision, Funding acquisition, Conceptualization. **Andrei Lobov:** Conceptualization, Supervision, Funding acquisition, Writing - Review & Editing. **Iñigo Flores Ituarte:** Conceptualization, Supervision, Funding acquisition, Writing - Review & Editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Antti Martikkala reports financial support and article publishing charges were provided by Tampere University. Bening Mayanti reports financial support was provided by University of Vaasa. Petri Helo reports financial support was provided by University of Vaasa. Andrei Lobov reports financial support was provided by Norwegian University of Science and Technology. Inigo Flores Ituarte reports financial support was provided by Tampere University.

Data availability

Data will be made available on request.

Acknowledgements

This research has received support from European commission structural fund project Kiertodigi.

Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.117548.

References

Addabbo, T., Fort, A., Mecocci, A., Mugnaini, M., Parrino, S., Pozzebon, A., Vignoli, V., 2019. A LoRa-based IoT Sensor Node for Waste Management Based on a Customized Ultrasonic Transceiver SAS 2019 - 2019 IEEE Sensors Applications Symposium. Conf. Proc. https://doi.org/10.1109/SAS.2019.8705980.

Akhtar, M., Hannan, M.A., Begum, R.A., Basri, H., Scavino, E., 2017a. Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization. Waste Manag. 61, 117–128. https://doi.org/10.1016/J.WASMAN.2017.01.022.

Akhtar, S., Baig, S.F., Saif, S., Mahmood, A., Ahmad, S.R., 2017b. Five year carbon footprint of a textile industry: a podium to incorporate sustainability. Nat. Environ. Pollut. Technol. 16 (1), 125–132.

Amal, L., Son, L.H., Chabchoub, H., 2018. SGA: spatial GIS-based genetic algorithm for route optimization of municipal solid waste collection. Environ. Sci. Pollut. Control Ser. 25 (27), 27569–27582. https://doi.org/10.1007/S11356-018-2826-0/TABLES/12.

Arebey, M., Hannan, M.A., Begum, R.A., Basri, H., 2012. Solid waste bin level detection using gray level co-occurrence matrix feature extraction approach. J. Environ. Manag. 104, 9–18. https://doi.org/10.1016/J.JENVMAN.2012.03.035.

Atzori, L., Iera, A., Morabito, G., 2010. The internet of things: a survey. Comput. Network. 54 (15), 2787–2805. https://doi.org/10.1016/j.comnet.2010.05.010.

Bakhshi, T., Ahmed, M., 2018. IoT-enabled smart city waste management using machine learning analytics. In: ICECE 2018 - 2018 2nd international conference on energy conservation and efficiency, Proceedings, pp. 66–71. https://doi.org/10.1109/ECE.2018.8554985.

Ben-Daya, M., Hassini, E., Bahroun, Z., 2019. Internet of things and supply chain management: a literature review. Int. J. Prod. Res. 57 (15–16), 4719–4742. https://doi.org/10.1080/00207543.2017.1402140.

Bisinella, V., Conradsen, K., Christensen, T.H., Astrup, T.F., 2016. A global approach for sparse representation of uncertainty in life cycle assessments of waste management systems. Int. J. Life Cycle Assess. 21 (3), 378–394. https://doi.org/10.1007/s11367-015-1014-4.

Calzolari, T., Genovese, A., Brint, A., 2022. Circular Economy indicators for supply chains: a systematic literature review. Environ. Sustain. Indicat. 13, 100160 https://doi.org/10.1016/J.INDIC.2021.100160.

Castillo, L.V., Chirinos, D.G., Trujillo, E.H., 2021. Progressive application for route optimization and monitoring processes in solid waste pick-up, based on smart collection points using IoT sensors and the OR-tools algorithm. In: Proceedings of the 2021 IEEE Sciences and Humanities International Research Conference, *SHIRCON 2021*. https://doi.org/10.1109/SHIRCON53068.2021.9652206.

Chavan, S., Patil, U., Koshy, S.S., Srikanth, S.V., 2021. Garbage Zero (Garb0): an IoT framework for effective garbage management in smart cities. In: Proceedings - International Conference on Artificial Intelligence and Smart Systems, ICAIS 2021, pp. 1336–1342. https://doi.org/10.1109/ICAIS50930.2021.9395970.

Concari, A., Kok, G., Martens, P., 2022. Recycling behaviour: mapping knowledge domain through bibliometrics and text mining. J. Environ. Manag. 303, 114160 https://doi.org/10.1016/J.JENVMAN.2021.114160.

Environmental Protection Agency, 2006. Standard Volume-To-Weight Conversion Factors. United States Environmental Protection Agency *(EPA)*. https://archive.epa.gov/epawaste/conserve/smm/wastewise/web/pdf/conversions.pdf.

Environmental Protection Agency, 2016. Volume-to-weight Conversion Factors. United States Environmental Protection Agency *(EPA)*. https://www.epa.gov/sites/default/files/2016-04/documents/volume_to_weight_conversion_factors_memorandum_04192016_508fnl.pdf.

Expósito-Márquez, A., Expósito-Izquierdo, C., Brito-Santana, J., Moreno-Pérez, J.A., 2019. Greedy randomized adaptive search procedure to design waste collection routes in La Palma. Comput. Ind. Eng. 137 https://doi.org/10.1016/j.cie.2019.106047.

Ferreira, J.A., Figueiredo, M.C., Oliveir, J.A., 2017. Household packaging waste management. Lect. Notes Comput. Sci. 10405, 611–620. https://doi.org/10.1007/978-3-319-62395-5_42.

Fujdiak, R., Masek, P., Mlynek, P., Misurec, J., Olshannikova, E., 2016. Using genetic algorithm for advanced municipal waste collection in Smart City. In: 2016 10th International Symposium on Communication Systems, Networks and Digital Signal Processing, CSNDSP 2016. https://doi.org/10.1109/CSNDSP.2016.7574016.

Ghahramani, M., Pilla, F., 2021. Analysis of carbon dioxide emissions from road transport using taxi trips. IEEE Access 9, 98573–98580. https://doi.org/10.1109/ACCESS.2021.3096279.

Goutam Mukherjee, A., Ramesh Wanjari, U., Chakraborty, R., Renu, K., Vellingiri, B., George, A., C, R.S., Valsala Gopalakrishnan, A., 2021. A review on modern and smart technologies for efficient waste disposal and management. J. Environ. Manag. 297 https://doi.org/10.1016/J.JENVMAN.2021.113347.

Hannan, M.A., Akhtar, M., Begum, R.A., Basri, H., Hussain, A., Scavino, E., 2018. Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm. Waste Manag. 71, 31–41. https://doi.org/10.1016/j.wasman.2017.10.019.

Koch, K., Domina, T., 1999. Consumer textile recycling as a means of solid waste reduction. Fam. Consum. Sci. Res. J. 28 (1), 3–17. https://doi.org/10.1177/1077727X99281001.

Koot, M., Mes, M.R.K., Iacob, M.E., 2021. A systematic literature review of supply chain decision making supported by the Internet of Things and Big Data Analytics. Comput. Ind. Eng. 154 (December 2020), 107076 https://doi.org/10.1016/j.cie.2020.107076.

Lee, K.P., Kuhl, S.J., Bockholt, H.J., Rogers, B.P., Reed, D.A., 2018. A cloud-based scientific gateway for internet of things data analytics. In: ACM International Conference Proceeding Series, p. 7. https://doi.org/10.1145/3219104.3219123.

Li, J., Dai, J., Issakhov, A., Almojil, S.F., Souri, A., 2021. Towards decision support systems for energy management in the smart industry and Internet of Things. Comput. Ind. Eng. 161, 107671 https://doi.org/10.1016/J.CIE.2021.107671.

Lobov, A., 2018. Smart manufacturing systems: climbing the DIKW pyramid. In: Proceedings: IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society, pp. 4730–4735. https://doi.org/10.1109/IECON.2018.8591221.

Lounais-Suomen Jätehuolto Oy, 2020. National collection of end-of-life textiles in Finland. *The telaketju network*. https://telaketju.turkuamk.fi/uploads/2020/08/0c08d295-national-collection-of-end-of-life-textiles-in-finland_lsjh.pdf.

Martikkala, A., David, J., Lobov, A., Lanz, M., Ituarte, I.F., 2021a. Trends for low-cost and open-source IoT solutions development for industry 4.0. Procedia Manuf. 55 (2021), 298–305. https://doi.org/10.1016/j.promfg.2021.10.042.

Martikkala, A., Lobov, A., Lanz, M., Flores, I., 2021b. Towards the interoperability of IoT platforms : a case study for data collection and data storage. In: Proceedings of the 17th IFAC Symposium on Information Control Problems in Manufacturing Budapest, Hungary, June 7-9, 2021.

Martinez-Sanchez, V., Kromann, M.A., Astrup, T.F., 2015. Life cycle costing of waste management systems: overview, calculation principles and case studies. Waste Manag. 36, 343–355. https://doi.org/10.1016/J.WASMAN.2014.10.033.

Montecinos, J., Ouhimmou, M., Chauhan, S., Paquet, M., 2018. Forecasting multiple waste collecting sites for the agro-food industry. J. Clean. Prod. 187, 932–939. https://doi.org/10.1016/J.JCLEPRO.2018.03.127.

Mustapha, A., Bousmina, Z., Keskas, I., Guettatfi, Z., Hentout, A., Mansoul, A., 2021. Practical IoT-enabled monitoring platform for solid waste collection: a case study for the municipality of baba hassen, algiers, Algeria. In: 2021 IEEE International IOT, Electronics and Mechatronics Conference, *IEMTRONICS 2021 - Proceedings*. https://doi.org/10.1109/IEMTRONICS52119.2021.9422640.

Nencková, L., Pecáková, I., Šauer, P., 2020. Disposal behaviour of Czech consumers towards textile products. Waste Manag. 106, 71–76. https://doi.org/10.1016/J.WASMAN.2020.03.001.

Nirde, K., Mulay, P.S., Chaskar, U.M., 2017. IoT based solid waste management system for smart city. In: Proceedings of the 2017 International Conference on Intelligent Computing and Control Systems, ICICCS 2017, 2018-Janua, pp. 666–669. https://doi.org/10.1109/ICCONS.2017.8250546.

Ramayah, T., Lee, J.W.C., Lim, S., 2012. Sustaining the environment through recycling: an empirical study. J. Environ. Manag. 102, 141–147. https://doi.org/10.1016/j.jenvman.2012.02.025.

Ramson, S.R.J., S, V., Kirubaraj, A., Anagnostopoulos, T., Abu-Mahfouz, A.M., 2021. A LoRaWAN IoT enabled trash bin level monitoring system. IEEE Trans. Ind. Inf. 3203 (c), 1. https://doi.org/10.1109/tii.2021.3078556, 1.

Seifert, A.M., Messing, K., 2006. Cleaning up after globalization: an ergonomic analysis of work activity of hotel cleaners. In: The Dirty Work of Neoliberalism: Cleaners in the Global Economy, pp. 129–149. https://doi.org/10.1002/9781444397406.ch8.

Sosunova, I., Porras, J., 2022. IoT-enabled smart waste management systems for smart cities: a systematic review. IEEE Access 10, 73326–73363. https://doi.org/10.1109/ACCESS.2022.3188308.

Sørensen, M., Jordal-Jørgensen, J., Martens, B., Glenting, C., 2004. The FEASIBLE Model, Version 2, User Manual and Documentation. Ministry of the Environment DANCEE. https://www.oecd.org/env/outreach/36229036.pdf.

Watson, D., Aare, A.K., Trzepacz, S., Petersen, C.D., 2018. Used Textile Collection in European Cities. *Study Commissioned by Rijkswaterstaat Under the European Clothing Action Plan (ECAP)*. http://www.ecap.eu.com/wp-content/uploads/2018/07/ECAP-Textile-collection-in-European-cities_full-report_with-summary.pdf.

Yan, G., 2019. Reverse Logistics in clothing recycling: a case study in chengdu. Int. J. Earth, Energy Environ. Sci. 12 (5) https://doi.org/10.5281/zenodo.2702785.