Towards an approach on location data analysis for reusable small-load carriers

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Abstract

This paper describes a new approach to collect and extrapolate location data for small load carriers (SLCs) as a basis for the simulation of multi-site SLC cycles. The approach enables realistic multi-site SLC cycle simulation studies, which can lead to better decisions on cycle parameters, which in turn leads to cost reductions and makes the use of reusable SLCs more attractive. It is based on 3 sub-studies with different location technologies to test them for use in SLC cycles. We compare the technologies concerning real-world requirements and use the results of two of these sub-studies to develop our approach for extrapolating data. According to our research, such an approach has not yet been applied to multi-site SLC cycles. Our research contributes to SLC management research and location intelligence research.

Keywords: reusable container, small load carrier, indoor/outdoor localization, multi-site SLC cycle, simulation

1. Introduction

The use of innovative technologies to analyze and control material and information flows is a crucial logistics trend. A significant challenge is integrating both internal location data and external supply chain data (Lieberoth-Leden et al., 2017). Analyzing resource use, inventory counts, and time data is crucial for supply chain optimization (Bauernhansl et al., 2014), offering ecological (inventory minimization) and economic (cost-saving) benefits (Hofmann et al., 2020). Given these advantages, reusable packaging systems, particularly reusable small load carriers (SLCs), are essential for sustainable supply chains. SLCs, such as standardized boxes or trays (Figure 1), provide environmental and economic benefits over single-use systems (Coelho et al., 2020). These plastic, stackable carriers, commonly used in production logistics, are smaller than standard pallets, making them advantageous in many situations (Ziegler et al., 2023).

Figure 1. SLCs - cover, inlay, box.

For logistics service providers responsible for the management of SLC cycles and all cycle partners, it is important to configure the SLC cycle in the best possible way. Previous studies have shown that simulation studies are a powerful tool to do that (Giubilato et al., 2019). Using simulations to plan, monitor, and control closed-loop supply chains can identify uncertainties and weaknesses, allowing for early interventions through forecasting. For instance, monitoring return information can help dynamically monitor flows and provide reliable estimates of volumes and optimized container inventories (Yang et al., 2018). Alqahtani and Gupta (2018) demonstrate another optimization method by identifying the right time for reprocessing containers, which avoids disposal and maximizes profit. Elbert and Lehner (2020) developed a simulation system for pallet exchange, identifying optimization potentials and cost savings based on analyzed throughput times, monitored bottlenecks, and optimized batch sizes. The critical step in developing a simulation model is defining key performance indicators and data evaluation possibilities.

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Regarding evaluating the simulation study, using a small sample size inherently limits precision. This preliminary study aims to demonstrate principles for future research with more comprehensive data to ensure higher-quality analysis. Additionally, legal aspects such as data transparency via intelligent contracts (Henke et al., 2020) must be considered to address privacy and security concerns.

In contrast to deterministic models, stochastic simulation approaches consider random factors like transport delays, inventory and demand fluctuations, and return times and quantities (Vidal, 2023). Collecting proximate process data enables real-time tracking of SLCs through the entire supply chain, enhancing productivity by identifying waiting times (Pinkston et al., 2017). This data facilitates the calculation of expected costs, optimization of inventory levels, and other metrics (Rajeswari et al., 2021). Partners in SLC cycles often lack or hesitate to share data; thus, location intelligence can address this issue by precisely tracking and identifying process inefficiencies (Ellsworth-Krebs et al., 202, Pinkston et al., 2017). Numerous studies have shown the benefits of such location intelligence in improving operational efficiency and reducing costs (Sarkar et al., 2024, Bazarah & Li, 2024).

Smart logistics objects with corresponding location sensors are one way to obtain location data from SLCs. However, although there are a variety of concepts for intelligent logistics objects, there still needs to be more transparency, especially for cycles with SLCs (Goldmann et al., 2020). Several issues hinder the widespread use of intelligent SLCs in these cycles:

- The high number of variants and the large amount (e.g. 100k in one of our project partner's container depots) of SLCs used exacerbates this problem.
- Competitive fears are often a challenge for the exchange of time data.
- SLCs are used in both production and cleaning, unlike large containers.
- Limited space and existing labels on SLCs restrict tag placement.
- High SLC density requires indoor and outdoor positioning (IPS/OPS).

Current challenges prevent logistics service providers and manufacturers from effectively utilizing smart SLCs for multi-site cycles. This hampers data collection for simulation analysis, reducing the lack of concrete case studies and corporate data in scientific publications (Coelho et al., 2020). Our research addresses these issues by using location technology on a small sample of SLCs and extrapolating the data. This approach enhances SLC cycle transparency without additional infrastructure or APIs, making it suitable for volatile networks. Furthermore, it can support the profitable use of reusable containers, boosting supply chain sustainability. Therefore, this paper addresses the following research question:

How can sensor data for multi-site SLC cycles be collected considering requirements from practice and how can small sensor-based data samples be prepared for simulation of the entire cycles?

Our research, part of the DIBCO project on reusable SLC management funded by Bavaria, involved a logistics service provider, system provider, and software provider. This paper primarily examines the logistics service provider's perspective, filling a gap for new concepts that Pick & Sarkar (2024) identified. Existing issues deter logistics service providers and manufacturers from adopting smart SLCs in multi-site cycles. Challenges include the complexity of data collection due to a lack of structured guidelines and the necessity of deep process understanding (Baruffaldi et al., 2019), as well as the need for enhanced process and data analysis capabilities to effectively evaluate key metrics (Svensson et al., 2018). Our research aims to resolve these challenges by utilizing location technology on a small sample of SLCs and extrapolating the data. This approach simplifies data collection and enhances SLC cycle transparency without requiring additional infrastructure or APIs, making it suitable even for volatile networks. Additionally, it could support the profitable use of reusable SLC, thus boosting supply chain sustainability.

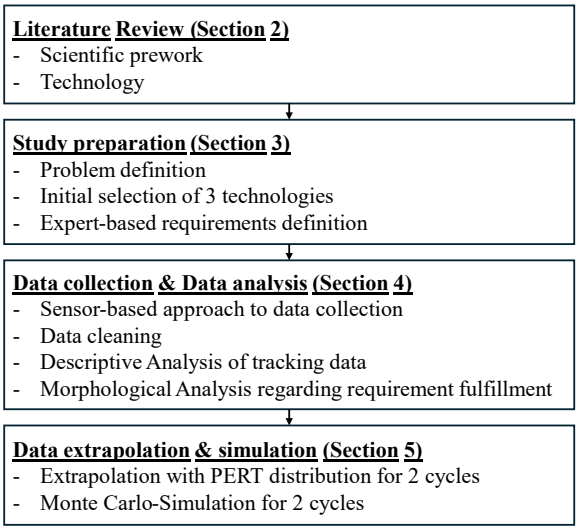

Figure 2. Methodological Overview.

The objectives of this paper are therefore:

- to compare suitable location technologies available on the market for SLC,
- to conduct an explorative study with a small sample and 3 different technologies,
- to propose an approach to use the given datasets for SLC cycle simulation.

To achieve our goals, we use a mixed methods approach combining elements from CRISP-DM (Wirth & Hipp, 2000) and simulation techniques (Law & McComas, 1991). The paper is structured accordingly: after a brief literature review, we present a study with three parts. Section 3 covers study preparation, including problem definition and technology selection through expert workshops. Section 4 details data collection using various localization sensors, data cleaning, and analysis via descriptive statistics and morphological analysis (Zwicky, 1967). Section 5 discusses data extrapolation using PERT distribution and provides an overview of our Monte Carlo simulation before presenting the results.

2. State of the Art

Amin et al. (2020) and Glock (2017) have conducted literature reviews on closed-loop supply chain models and decision support models for the management of returnable transportation items (RTI). While Amin does not mention a container type, Glock explicitly refers to specific containers, which include small load carriers. He categorizes the research into 4 groups according to their application: Alternative Packaging System Decisions, Predicting Returns RTIs, Managing Container Systems in General, and Sourcing New RTIs. In total, he found 33 papers, of which 8 papers used simulation approaches. However, none of them explicitly address how sensor data can be used as a basis for this or explicitly refer to the extraction of sensor data. Glock (2017) concludes from the literature review that there is a lack of practical cases and simulation models, which could be due to a lack of data.

Giubilato et al. (2019) present the results of a simulation study on the implementation of RFID in reusable container management and its impact on supply chain performance. It remains unclear what the basis of their study is. Tsao et al. (2017) discuss RFID implementation for the design of a multi-site supply chain. They use a continuous approach and use numerical examples based on a case study. However, the corresponding case study data does not include behavioral data but inventory data. The data source remains unclear.

Fan et al. (2019a, 2019b) introduce an inventory model in a container cycle to calculate the optimal stock level of containers. They do not consider sensors or sensor data in their research. The same applies to Yangyang et al. (2016), who developed a game-theoretical model for the coordination of containers between port areas. Gerrits et al. (2020) describe the results of an investigation of a container terminal with mixed traffic. Elbert & Lehner (2020) present the results of an analysis of a pallet exchange platform. Both Gerrits et al. (2020) and Elbert & Lehner (2020) use simulations as a method. While Gerrits et al. (2020) use company data, Elbert & Lehner (2020) create a more theoretical case study for an exchange platform. Furthermore, Gerrits' (2020) analysis only refers to two nodes in a container cycle.

A more general look at the introduction of tracking in container cycles is provided by the work of Ellsworth-Krebs et al. (2021) and Yangyang et al. (2016). Ellsworth-Krebs et al. (2021) developed an open data standard for the tracking of reusable packaging. They used expert-based methods for this. However, even if the sensor data is available, it is questionable whether the data is shared between the cycle partners. Yangyang et al. (2016) discuss this problem from a game-theoretical perspective. The parameters for a game-theoretic simulation were determined based on experts knowledge but without the use of sensor data.

Our brief overview of scientific studies on reusable container research shows the following results on SLC research:

- It is not always clear which work refers to which type of container. In particular, theoretical works do not distinguish between large packaging (e.g. pallets) and SLCs. The term RTI is often used, which includes both (e.g. Elbert & Lehner (2020).
- Most of the work focuses on the introduction and description of new analytical models to optimize certain performance indicators (e.g. inventory) of the cycles.
- We found only 3 papers that explicitly address the use of sensors in multi-site container cycles, 2 of them from an economic perspective (Giubilato et al., 2019, Tsao et al., 2017), 1 of them considers data exchange (Ellsworth-Krebs et al., 2021).
- The literature review on reusable transportation items emphasizes the lack of practical use cases and the lack of simulation analyzes (Glock, 2017).

One reason for the lack of simulation studies is the availability of realistic data for an entire SLC cycle. Due to the characteristics of SLCs (high number, low cost of SLCs), these problems appear even stronger. To close these gaps and to take advantage of the availability of behavioral data for an SLC cycle, we present an approach to use the data from small samples as input for a simulation analysis based on SLC localization data

Since both indoor and outdoor localization systems are relevant and since we excluded the installation of additional hardware at the participating cycle partners for cost reasons, we consider the following technologies in our study: Global Positioning System (GPS), Global System for mobile communication (GSM), Bluetooth Low Energy (BLE) and with some limitations WiFi Sniffing.

GPS is the most widely used technology for localizing objects. Technically, it is a satellite navigation system that is available worldwide (Liu & Yao, 2017). It enables the determination of geographical position. Although GPS tags enable cost-effective localizing with a long runtime and an accuracy of a few meters, this is only usable as OPS. An increase in accuracy can be achieved by using an Assisted Global Positioning System (A-GPS), in which the satellite network is combined with wireless mobile technology (Van Heeswijk et al., 2019).

In the Global System for mobile communication GSM, localization is achieved using triangulation methods in which the tag identifies the signal strength of the nearest mobile phone masts and generates radii around the masts and thus intersections that determine its position (Maurya et al., 2012).

BLE uses a low bandwidth, which results in lower energy consumption. The problem here is that BLE applications, like the technologies mentioned above, are usually limited to an IPS-only solution. Receivers (so-called beacons or gateways) are attached to strategic points, and then various options are used to locate the objects. With beacon technology, battery-powered transmitters are attached that emit Bluetooth signals at regular intervals, which can be received by other Bluetooth-enabled devices (Furmans et al., 2019). In this way, it is possible to measure distances and then use receiver positions to create intersections for locating the beacon. For the case that existing mobile devices such as smartphones and tablets can be used as receivers, no additional infrastructure is necessary.

The last technology presented is known as wireless fidelity sniffing or WiFi sniffing. Transmitters and receivers are placed in a way that triangulation can be implemented. Signal strength can be measured, and distances can be defined to pinpoint the location of the objects to the nearest meter (Franklin, 2019). As WiFi networks can be found almost everywhere, no additional infrastructure is required. The WiFi routers act as gateways and create zones (Satish et al., 2020).

Ultra-wideband (UWB) and RFID were excluded due to cost and the need to implement additional infrastructure at the sites.

3. Study preparation

Our study, conducted with our project partners, aims to find an approach for sensor-based simulation analysis in multi-site SLC cycles. We define required technological attributes and select suitable technologies, initially excluding UWB and RFID due to the need for additional hardware. In workshops with our project partners, we identified the relevant attributes: the technology must enable indoor and outdoor localization, be weatherproof, have precise transmission, and include long-lasting batteries to avoid frequent recharging. Additional hardware should be minimal unless it enhances accuracy. Data should be accessible via APIs and ETL. Financial aspects consider rental or purchase fees relative to total costs, including ongoing software costs. The current setup with a tracker (price: €150) is viable only for sample data collection. However, our simulation technique shows that even small sample sizes can provide helpful insights into the system without deploying numerous trackers.

According to Zwicky (1967), morphological boxes are utilized for attribute comparison. Each box includes attributes and 2 to 3 specifications for requirements (Table 1). Specifications are then marked for each technology (Tables 2 to 4).

Requirements	Specifications		
Indoor/Outdoor	Yes	No	Partial
Battery	Few weeks	Weeks to months	App. 1 year
Precision	cm	1-10 m	10 m+
Hardware	Tags	Routers/Anchors &Tags	
Size	<10 cm	>10 cm	
Purchasing	€	€€	€€€
Running Costs	€	€€	€€€
Data Access	Via API	Via GUI	
Upgrade	Not possible	More receivers	Additional Technology

Table 1. Localization technology attributes.

Our study consists of three sub-studies. Sub-study 1 uses GSM tags (Kizy K-2), sub-study 2 uses Apple AirTags with BLE, GSM, and GPS, and sub-study 3 collects data via industrial A-GPS tags (SLOC STR300+).

For sub-study 1 (GSM), we provided sensors for localization and extracted data via cloud-based portal. We attached six tags to various SLCs in watertight tubes to protect them from weather and minimize sensor loss. Our initial test confirmed their functionality. The data was provided in a standard format, including position and time information. We chose cycles where data transparency was lacking, or container losses had been reported. To ensure reliability, we transmitted two SLCs during the same cycle.

In sub-study 2 (BLE, GSM, GPS), shorter test SLC cycles were employed over two weeks. Four sensors were distributed to subjects traveling different distances, passing through multiple nodes with only starting and target nodes overlapping. The process ran daily,

with the control center acting like a warehouse within a container cycle.

Sub-study 3 (A-GPS) was a collaborative effort to test industrial suitability using a combination of IPS and OPS. We worked closely with another logistics company, and the setup involved buildings equipped with WiFi routers at starting and target nodes. The tag switched from GPS to WiFi sniffing when reaching the node. Tags were assigned to company vehicles for shuttle routes, enabling a seamless transition from OPS to IPS. A wheel loader was tracked exclusively for IPS and another vehicle for the OPS use case to generate comparable route data. This two-week study aimed to validate the tags' functionality.

4. Data collection and data analysis

Sub-study 1: GSM. During sub-study 1 (GSM) implementation, which lasted more than four months, six tags were fixed at SLCs and sent through a SLC cycle. Three tags completed the cycle and generated data, two failed due to battery expiration. One tag was still in the cycle at the end of the test period and was partially considered. The tags emitted a signal with each position change, maintained by set rhythms (24 hours, 3 hours). This variation was used across three test cycles to create different data structures. The data export template included timestamps, longitude, latitude, and parent IoT data source. Transportation and waiting times were calculated based on this data. After exporting the datasets, they were sorted by sensor and cleaned. Position data outside the test period and data collected on weekends and holidays were removed, leaving only the first and last positions of each day and changes in location. All locations, routes, cycles, and storage times were determined. Individual routes and resulting cycles, consisting of three locations, were identified for analysis. Concerning the relevant technological attributes (Table 2), several problems were encountered. The indoor positioning failed, making it challenging to locate SLCs for recharging. Data generation rhythms could have been more precise due to the lack of clear event triggering. Although the installation and mounting of tags were acceptable, the sub-study failed to meet most technical requirements due to low precision, short battery life, and lack of indoor positioning options. Financial requirements were met due to favorable conditions and acceptable operating costs, but the potential to improve accuracy through further investment was not feasible. Access via REST API and the data format for analysis met the required data attributes.

Requirements Sub-study 1: *GSM*			
Indoor/Outdoor	Yes	**No**	Partial
Battery	**Few weeks**	Weeks to months	App. 1 year
Precision	cm	1-10 m	**10 m+**
Hardware	**Tags**		Routers/Anchors &Tags
Size	**<10 cm**		>10 cm
Purchasing	€	**€€**	€€€
Running Costs	**€**	€€	€€€
Data Access	**Via API**		Via GUI
Upgrade	Not possible	More receivers	**Additional Technology**

Table 2. Technology attributes in sub-study 1

Requirements Sub-study 2: *GPS, GSM, BLE*			
Indoor/Outdoor	Yes	No	**Partial**
Battery	Few weeks	Weeks to months	**App. 1 year**
Precision	cm	**1-10 m**	10 m+
Hardware	**Tags**		Routers/Anchors &Tags
Size	**<10 cm**		>10 cm
Purchasing	**€**	€€	€€€
Running Costs	**€**	€€	€€€
Data Access	**Via API**		Via GUI
Upgrade	**Not possible**	More receivers	Additional Technology

Table 3. Technology attributes in sub-study 2

Sub-study 2: BLE, GSM, GPS. Apple AirTags were used in sub-study 2 (BLE, GSM, GPS). As AirTags are typically for private use, a software solution was developed to create a data history for each route. Cycles were repeated up to 3 times weekly and analyzed over two to four weeks. Inaccuracies arose due to minimal GPS position changes affecting address data in the Apple Maps application, which were manually corrected. Data was cleaned and prepared similarly to sub-study 1. The lack of motion-dependent data transmission led to inaccuracies, as the polling rhythm could create gaps. Additionally, an Apple PC was required to query the JSON file, limiting industrial suitability, and for IPS, querying UWB data required a frequency of <1s, which was not technically feasible due to resource constraints and data volume. Financially, the costs were

acceptable, as in sub-study 1. Table 3 provides an overview of the technological attributes in sub-study 2.

Sub-study 3: A-GPS. A REST API was used for data export in sub-study 3 (A-GPS). The data was cleaned similarly to previous sub-studies. Individual routes were monitored over two to four weeks, with up to 5 routes per week. Concerning the technological attributes (Table 4), the feasibility of an IPS in sub-study 3 fails due to financial constraints. Although sensors can localize inside buildings via BLE or WiFi sniffing, this requires additional programming and new infrastructure. Mounting and installation were complicated due to the size of the tags. Financial requirements were met, except for the increased accuracy cost. The tags' variability eliminates the need for accuracy improvements through expensive tags. Data access, format, and network outage requirements were easily met.

Requirements Sub-study 3: *A-GPS*			
Indoor/Outdoor	Yes	No	**Partial**
Battery	Few weeks	**Weeks to months**	App. 1 year
Precision	cm	**1-10 m**	10 m+
Hardware	Tags		**Routers/Anchors &Tags**
Size	<10 cm		**>10 cm**
Purchasing	€	**€€**	€€€
Running Costs	€	**€€**	€€€
Data Access	**Via API**		Via GUI
Upgrade	Not possible	**More receivers**	Additional Technology

Table 4. Technology attributes in sub-study 3

Quantitative results. To obtain a quantitative overview of the sub-studies, we use the following descriptive indicators:

- *Number of tags:* for each technology we used a certain number of tags.
- *Number of cycles (mean):* Each tag goes through several cycles. Since there is more than 1 tag per technology, we report the mean value
- *Runs per tag (mean):* Since some cycles were run repeatedly, this number is greater than the number of cycles. Again, we report the average of the number of runs for each tag.
- *Routes per tag (mean):* A cycle consists of multiple routes connecting locations. Since there is more than 1 tag per technology with a different number of cycles, we report the average.
- *Locations per tag (mean):* Each tag runs through some locations. This indicator shows the average number of locations per tag.

As Table 5 shows, we used more tags in sub-study 1 than in the other sub-studies. This was necessary as there was only 1 run per cycle. One reason for this is the long cycle times in sub-study 1. The average number of routes per cycle varies between 4 in sub-study 3 and 7.75 in sub-study 1, while the average number of locations per cycle is similar in all studies. The cycle time is defined as the time it takes for an SLC to return to the starting node of the cycle after it has passed through all relevant node of the cycle. While the runs in cycle 1 lasted several weeks and led to some problems, we selected shorter cycles of a few days for sub-studies 2 and 3.

Sub-study	*No. of tags*	*No. of cycles per tag (mean)*	*Runs per cycle (mean)*	*Routes per tags (mean)*	*Locations per tag (mean)*
1	6	1	1	5.5	5
2	4	4.7	3.92	7.75	4.75
3	3	3.25	2.83	4	5.3

Table 5. Characteristics for each sub-study

In summary, the tags of sub-study 2 (BLE, GSM, GPS) appear to be superior in terms of precision, size, price, and battery consumption, while the tags of sub-study 3 (A-GPS) are preferred in terms of data availability and suitability for industrial use.

5. Data extrapolation and simulation

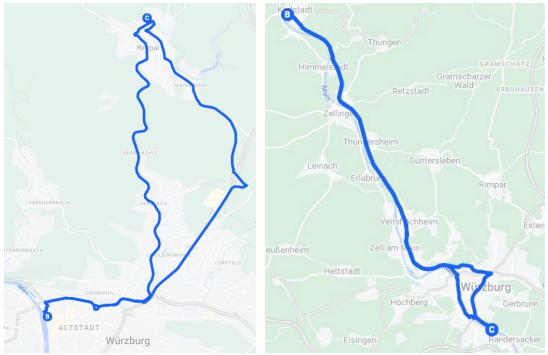

Figure 3. Relevant cycles of sub-study 2 (left) and sub-study 3 (right). (Google My Maps)

In the following, we describe the data extrapolation and simulation for one specific cycle each from sub-studies 2 and 3 (Figure 3). The two cycles consist of the elements in Table 6. Our simulation study aims to demonstrate data extrapolation applicability and identify routes with insufficient performance. It also forms a

basis for future analyses considering incoming and outgoing SLCs and the logistics service provider's inventory to simulate the entire cycle. The data quality of substudy 1 was too low for extrapolation and simulation. For the two selected cycles, we calculated the average transportation time and the average time at a location for a run, as shown in Table 7, to assess performance.

Cycle Substudy: Technology	Runs	Routes	Locations
Cycle 2: BLE, GSM, GPS	10	4	4
Cycle 3: A-GPS	8	2	2

Table 6. Characteristics of selected cycles

Cycle Substudy: Technology	Transportation Time per Run *Mean (Std)*	Time at Location per Run *Mean (Std)*	Total *Mean (Std)*
Cycle 2: BLE, GSM, GPS	45 min (5 min)	1133 min (228 min)	1178 min (225 min)
Cycle 3: A-GPS	115 min (25 min)	965 min (52 min)	1080 min (60 min)

Table 7. Times for selected cycles

To prepare the data for the simulation and get some insights into the performance on each cycle, we combined the sensor data with the transportation values for the cycles on Google Maps and Apple Maps. Based on these values and the sensor values, the minimum (fastest throughput time), maximum (slowest throughput time), and the mode (most probable throughput time) were calculated. The mode of the distribution as the most-likely case is determined as the average of the two different navigation times from Google Maps and Apple Maps, as these account for all factors such as traffic, driving behavior, and weather conditions, and apply in most cases. The minimum and maximum were determined based on sensor data. The three values allow us to use the "Program Evaluation and Review Technique" distribution (PERT) for the simulation. This was preferred over a triangular distribution for the present case. The reason for choosing a PERT distribution is that, unlike a triangular distribution, it does not include the mean value as a third statistical variable in the calculation. This is replaced by the mode, which represents the most frequently occurring, i.e. the most probable value of a sample. This smoothes the area at the top of the triangle and thus increases the frequency of values in this area. Similarly, the extreme values, which are given constant weight in a triangular distribution, are neglected or given less weight in the PERT distribution. In addition, unlike the triangular distribution, PERT does not assign the same importance to the extreme values, which is correct as these normally occur less frequently than the most probable case. Therefore, a triangular distribution can be negatively influenced by the small amount of data in the underlying sample and the associated high frequency of extreme values and thus lose significance, which is avoided by using the PERT distribution. For a meaningful evaluation of the data, we carry out 10,000 runs for each technology based on a simulation. Concerning the probability of occurrence, the data sets were therefore calculated proportionally for each route in a Monte Carlo simulation. The open-source Excel add-in pyscripter/XLRisk (available on GitHub) and a proprietary python program was used for this. If the analysis relates to more than just one cycle of a tag, the probabilities for the occurrence of a particular route can be calculated as a basis for further analyses. It also enables the investigation of pairwise dependencies between 2 routes or 2 cycles.

To evaluate the time data, various evaluation cases were defined in the next step so that individual routes can be classified independently of a detailed individual analysis.

- Case 1: "Over Performance" - in this case, the times of the simulated data were well below the mode and indicate potential for capacity optimization instead.
- Case 2: "Under Performance" - this indicates that the majority of the simulated runs took significantly more time than planned so there is a need for optimization.
- Case 3: "Normal performance" - here the expected values and the actual simulated data were almost identical so that a kind of normal distribution occurred within the data, which may represent a realistic performance.

Cycle Substudy: Technology	Overperformance	Normal Performance	Underperformance
Cycle 2: BLE, GSM, GPS	11.97%	51.85%	36.18%
Cycle 3: A-GPS	72.82%	16.56%	10.62%

Table 8. Performance for selected cycles

The results in Table 8 show that the times in cycle 2 looks as expected but most of the runs in cycle 3 took more time than planned. As a result of our simulation study, it is possible to:

- identify the cycles and routes with systematic underperformance and inefficient routes themselves like cycle 3.
- take the cycle times for item-customer-master data in the SLC management software as a fundament for the planning. For cycle 3, we have to increase the time, if the reason for it could be cleared.

- carry out future simulation analyses that extend the above to include incoming and outgoing SLCs, the annual demand rate, and stocks at the logistics service provider and thus simulate the stock throughout the entire cycle using only data from the logistics service provider and the sensors.

6. Discussion and Outlook

This paper addresses the implementation of sensor-based data utilization for simulation in multi-site SLC cycles, considering practical requirements. Our approach is to overcome the deficit of behavioral data for simulation analyses in reusable SLC cycles, improve efficiency, and make these cycles more attractive for supply chains using single-use packaging. The relevance of our study is reinforced by the lack of thorough market research regarding various technologies in combination with software, as highlighted by Abdel-Basset et al. (2018) and Ellsworth-Krebs et al. (2021).

The first part of our research focused on acquiring sensor data in multi-site cycles. We compared three technologies based on financial, technological, and data attributes, demonstrating that the combined use of BLE, GPS, and GSM (sub-study 2) is a promising approach due to its cost-effectiveness and compactness. This addresses a gap noted in prior works, which applied one technology, such as RFID, without justifying the choice or comparing multiple sensors (Abdel-Basset et al., 2018, Satish et al., 2020). However, challenges such as data extraction and data privacy require further investigation. Our findings align with and extend those of previous studies, particularly in cross-company data collection, emphasizing the necessity of practical improvements, as Giubilato et al. (2019) stated.

The second part of our research involved the extrapolation of data for simulation. We utilized data from two navigation applications in conjunction with sensor data and a PERT distribution to generate input for a Monte Carlo simulation. This method, executed with 10,000 runs per tag, allowed us to identify cycle routes, determine delays, and inform decision-making processes. Similar simulation techniques have been used in the literature, such as by Cobb and Li (2022), although their focus was on inventory cycles, whereas we concentrated on routes and throughput times.

Our approach process is easier to implement and less time-consuming as traditional approaches which rely on precise system data of all cycle partners (Delpla et al., 2022, Iassinovskaia et al., 2017). By employing simulations, comprehensive analyses can be derived from relatively small yet significant samples without encountering the risks and the costs associated with extensive sensor deployment.

We have presented an initial solution to the issue of missing real-time data in SLC cycles using sensors, backed by similar efforts in the literature (Giubilato et al., 2019, Goldmann et al., 2020, Bauernhansl et al., 2014). Notably, our approach relies on something other than the cycle partners' systems for data recording. For this approach, we assume that the behavior of SLCs is similar for all SLCs of one type in one cycle within a certain timespan. We further assume, that a set of possible and relevant locations, such as warehouses and production sites, are known, and that the signal emission rhythm covers all relevant location changes. For the data generation we assume, that the behavior of the SLCs overall matches a PERT distribution. While new data on SLC cycles were generated, they were limited to isolated data sets in sub-study 1, needing long-term data generation. This is similar to the challenges in comprehensive, cross-company data collection noted by Yang et al. (2018).

Despite these limitations, we improved data analysis as Bauernhansl et al. (2014) sought in sub-studies 2 and 3. We consistently considered the logistics service provider's perspective, although the small sample size hindered our ability to identify seasonal patterns. Additionally, while we designed our test cycles to be realistic, actual implementation may reveal unforeseen challenges. Boschert et al. (2016) similarly observed this and recommended setting up parallel data analysis to draw real-time system conclusions and maintain process improvement post-implementation.

Our paper provides evidence of the potential of sensor-based data collection and simulation to enhance the efficiency of multi-site SLC cycles. It also underscores the importance of ongoing research to address practical and technological constraints. (Vinod and Sudhi, 2019, Elbert and Lehner, 2020, Rabe et al., 2008)

Our study has several limitations. Firstly, the exclusion of location data without a relevant node simplifies the model but may miss complexities, such as random position queries in traffic. The use of IPS was impractical in sub-study 3 due to unexpected infrastructure requirements at cycle partner locations. BLE and WiFi sniffing can enable indoor object localization but require additional costs, programming, and hardware, making cost-effective indoor positioning challenging. Technological constraints were significant. Active RFID requires costly gateways, GPS has indoor signal loss, mobile networks have short battery lives and positional imprecision, and UWB, while precise, is expensive. BLE is typically only feasible indoors, and WiFi-sniffing needs dense infrastructure. These issues necessitate further research to balance accuracy, cost, and applicability for SLC cycles. Simulation inaccuracies also arose due to GPS data processing limitations, causing location er-

ror. The reliance on Apple-specific hardware limits industry applicability, and the lack of movement-sensitive data transmission may introduce timing inaccuracies. Effective IPS visualization software is also complex and costly to implement. Legal considerations, such as using smart contracts for data transparency, must be addressed to ensure privacy and security compliance, and ethical aspects of the field invites researchers to contribute to its development. In addition, the static nature of SLC cycles reduces dependency concerns. Existing SLC cycle maps can be stored as screenshots or modeled manually, requiring updates only for changes or new constructions. Simple schematic zoning (e.g., warehouse areas) is usually sufficient for tracking.

Although these limitations exist, the results demonstrate that our approach can provide valuable insights into multi-site SLC cycles. Unlike most other studies (e.g., Yang et al. (2018)), we consider more than just two sites and incorporate multiple technologies, thus offering a viable way to increase transparency and efficiency in multi-site SLC cycles. This approach could encourage more companies to adopt reusable SLCs. Future research should address the following areas:

- From a technological perspective, further investigation is needed to analyze the industrial possibilities of location technology for multi-site SLC cycles with throughput times of a few weeks. In particular, the trade-off between accuracy and costs of the relevant technology within and outside buildings needs to be improved to allow studies such as ours to be carried out efficiently.
- Further research on data extrapolation should cover seasonal and specific effects, e.g. expiring contracts. It should also refer to the definition of an adequate sample size for SLC cycles.
- For the simulation of SLC cycles with multiple locations, we recommend combining the sensor data with additional context data, such as the daily delivery rate, annual demand, size of pallets, or loss of boxes. All this data is available from logistics service providers who are responsible for SLC management.
- Furthermore, it should be examined how additional transparency in the SLC cycle affects the efficiency and proliferation of reusable SLCs. This could demonstrate the impact of our research on the sustainability of supply chains.

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