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Data-Based Development of an Agent-Based Simulation to Support the Design of Bicycle-Sharing Systems

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Abstract: Bicycle-Sharing Systems are emerging as alternative modes of transportation, successfully combining product and service aspects similar to those of other Product-Service Systems. Since such systems are influenced by a number of factors during their operation, identifying ways to manage the dynamic complexity during the operational phase is desirable. In this paper, we present an approach using agent-based modeling in combination with data analytics of system usage data to analyze the impact system architecture changes would have on overall system behavior.

Keywords: Product-service systems, bicycle sharing, agent-based modeling

1 Introduction

With the expected increase in the use of autonomous vehicles in the near future, major shifts in urban mobility and infrastructure are already challenging traditional forms of transportation, with sharing models in particular gaining a larger influence. Similar to heavily marketed car-sharing services, bicycle-Sharing Systems (BSSs) have rapidly increased in recent years, typically providing short-term rental of bikes (Büttner et al 2011, p. 10). These systems offer numerous benefits, including reduced emissions and congestion, improved overall health, and extended public transportation for what is known as the “last mile” (Shaheen et al 2010).

Such integrated Product-Service Systems (PSS) require complex design processes, thereby increasing the number of involved disciplines (Schenkl et al 2013). More specifically, multiple design aspects must be considered, including bike design, access management, legal regulations, revenue streams, and ongoing maintenance. Each design decision in setting up a BSS has a significant impact on the user experience, associated costs, and sustainability. Further, many of these choices affect one another, thus increasing the complexity and creating a highly intricate system. In brief, decision support is required for stakeholders developing and operating such complex systems (Rouse 2007).

Given the above, our objective in this paper is twofold. First, we present a formalized methodology for managing the complexity of designing a bicycle-sharing operating model with the help of approaches for managing structural and dynamic complexity. Second, based on the structural elements of the BSS architecture, we present a comprehensive agent-based model (ABM) to analyze and improve aspects of our model. We developed the methodology described in this paper primarily for a hybrid (combining station-based and free-floating) BSS in Germany; however, our model is applicable to other systems.

2 Research context and methodology

The research results that we present in this paper stem from a joint research project with a Munich-based BSS operator. The focus of this project was to develop a new BSS targeted at physically impaired users. A core aspect of our research addresses the operating model of said system, including an analysis of the existing BSS operating model.

We rely on the design research methodology defined by Blessing and Chakrabarti (2009) as a foundation for our present research. The *Research Clarification* was conducted in cooperation with an industry partner and based on an initial literature review. Within the *Descriptive Study I*, we investigated the current system and planning practices of the industry partner. Further, we performed a literature review on existing approaches for modeling, analyzing, and designing BSSs. Within the *Prescriptive Study*, our methodology was iteratively developed, applied, and improved upon within the research project context. We collected regular feedback from our industry partner (support evaluation) and a concluding evaluation workshop was held during the *Descriptive Study II*.

3 Background and related work

The approach that we propose in Section 4 below is based on a variety of concepts in complexity management and simulation modeling, which we summarize in the subsections that follow.

3.1 Modeling structural and dynamic complexity

To model system architectures, we can turn to either Domain-Specific Languages or universal languages (e.g., SysML) (Kerzhner & Paredis 2009). Both, graphs or matrices can be used to represent structures of complex systems; both representations are equivalent and transferrable to one another (via adjacency matrices) (Tittmann 2003). Matrix-based representations are, for example, Multiple-Domain-Matrices (MDM) that consist of Design Structure Matrices (DSMs) and Domain Mapping Matrices (DMMs), which represent intra-domain and inter-domain dependencies, respectively (Lindemann et al 2009).

Simulation models can be used to model dynamic complexity, in particular by recreating the behavior of real-world processes or systems over time (Banks et al 2005, p. 3). To model complex real-world systems, Borshchev (2013, p. 37) describes three modeling paradigms, primarily differentiated by their degree of abstraction; these are Discrete Event Modeling, System Dynamics, and ABM.

We selected ABM as the foundation for capturing the temporal behavior of the investigated BSS. Our approach here is based on the bottom-up modeling of the behavior and interactions of individual agents, such as individuals or vehicles. Therefore, it allows observing emergent behavior (Macal & North 2010, p. 1), which often arises in complex systems composed of autonomous subsystems with different objectives (Rouse 2007). This is realized by modeling individual behavior rules (e.g., using State Charts) (Bonabeau 2002, p. 1).

3.2 Existing approaches and research gaps

To identify existing approaches for modeling and analyzing BSSs, we investigated the prevalence of the following aspects in the literature:

- **BSS operating model and description** are defined as the architecture of the BSS during the operational phase, containing all consciously induced and controlled organizational and physical boundary conditions to achieve the system objectives (cf. e.g., Lathia et al 2012, Büttner et al 2011).
- **Data analysis and demand forecasting** are described in detail in Fishman (2016), which provides a review of current approaches regarding BSS and data analysis.
- **Redistribution and user incentives of free-floating systems** are minimally covered in the literature, with only one identified publication that investigates a free-floating system, cf. Reiss & Bogenberger (2016).
- **Station and system planning** primarily addresses the expected long-term demand and corresponding placement and sizing of stations. No literature has been identified that addresses the planning of free-floating systems, e.g., the definition of the business area.
- **The use of pedal electric cycling (pedelecs) in a BSS** is a trend in BSS design, but no publications could be identified that describe the use or long-term system behavior in comparison to regular bikes.
- **Costs and cost structures in BSSs**, often described as optimization targets (e.g., Hu & Liu 2014), were rarely addressed explicitly.
- **Additional approaches for modeling and simulation of a BSS** address only singular aspects but cover the modeling paradigms presented in Section 3.1 above.

While an extensive reproduction of the current state-of-the-art is not the focus of our present paper, based on our literature review, we have identified a lack of research regarding the analysis of hybrid and free-floating BSSs using data- and simulation-based methods. Most literature focuses on station-based systems in which bikes can only be rented and returned at fixed stations. Further, there is no known approach for capturing the overall system architecture with a suitable simulation. Therefore, our work addresses the following four objectives:

- Provide an extensive analysis of a hybrid BSS, including pedelecs
- Define an extensive BSS architecture for the corresponding operating phase
- Show a systematic alignment of problems that may arise during the operations phase with components of the system architecture
- Develop an ABM for evaluating BSS architecture changes

4 Methodology for data-driven development of the ABM

To enable the creation and extensive analysis of a BSS using ABM, we developed a corresponding procedure. In this section, we first provide an overview of this methodology, then we illustrate the individual steps using the particular BSS from our research project. The procedure developed within our work, depicted in Figure 1, is adapted from the methodology described by Hollauer et al (2015). Our approach further adapts the Knowledge Discovery in Databases process formulated by Fayyad et al (1996) to integrate usage data of the BSS into the model-building process. Within our methodology, we build structural models of the system architecture and investigate the model using matrix-based approaches that are later used as a basis for developing the dynamic ABM. Therefore, methods of complexity management (cf. Section 3.1) are integrated within the problem-field analysis step (3) shown in the figure.

As indicated in Fig. 1, our methodology first analyzes existing data related to the usage of the investigated BSS, the results of such analyses being used to describe system behavior and identify the impact of various influencing factors, e.g., weather (1). In parallel, the BSS architecture elements that are relevant to its operational phase are identified and described (2). To support this activity, we developed a general framework for the operational BSS architecture. Next, a problem-field analysis is conducted in which existing everyday operational problems are matched to corresponding system architecture elements in a DMM (3). Based on the knowledge acquired from both the problem-field analysis and the usage data analysis, recommendations for action are then discursively derived; these actions are focused on improving the everyday operations of the BSS (4). Finally, the information acquired from the usage data analysis is used to develop an agent-based simulation of the BSS, which then allows for testing how the recommendations affect overall system performance (5).

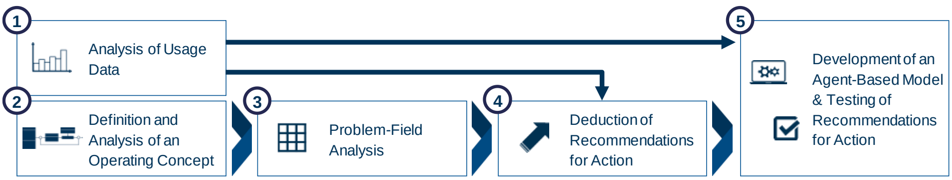

Fig. 1: Basis and developed approach for constructing an ABM of a BSS

4.1 Analysis of usage data for ABM development (step 1)

Within the modeling process, data is initially used to gain a better understanding of the behavior of the real system, then later used during the creation of the model to define individual parameters within the model based on concrete data. Fig. 2 illustrates the procedure that we followed to integrate the data within the modeling process.

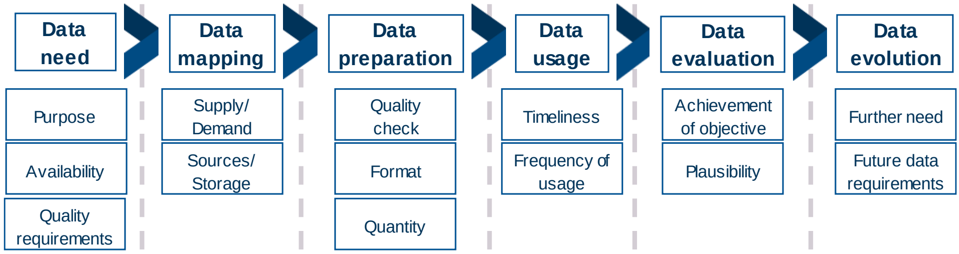

Fig. 2: Our seven-stage procedure for data integration during the modeling process

First, the *data need* for creating the model is determined, after which the sources and storage of the data is *mapped*. Subsequently, the data is *prepared* for analysis and eventually *used* within the modeling process (i.e., analyzed and insights derived, e.g., the median rental rate of a station per each hour of the day). Next, the data is *evaluated* for suitability and possible *needs for further data* are identified.

For our analysis, we used the *Tableau* software to analyze a database containing 621,579 data points describing individual bike rentals ranging from October 2015 to June 2017. Each data point contained, inter alia, data regarding the time and location of the start and end of each trip, the respective bike used, specific customer ID, the price tier of the customer, and the calculated price of the trip. We focused our analysis on the following aspects:

- Rental frequency per bike and per day
- Distribution of rentals per day, with working and weekend days noted
- Distribution of rentals per station within a single day
- Distribution between free-floating and station-based rentals (i.e., pick-up and return mode)
- Development of the number of stations and overall parking spaces over time
- Geographical heat map of rental distribution per postal code area
- Geographical heat map of rental distribution compared with selected price tier
- Ratio of pick-ups and returns per postal code area
- Distribution of trip duration per day
- Distribution of trip distance per day
- Average trip duration per day and per month
- Share of round trips per year and per month
- Average trip duration and distance per price tier
- Number of booked packages per month
- Number of customer service requests per month
- Number of repairs per month
- Number of offline hours of stations per month
- Number of active customers and number of rentals
- Growth of customer base per month
- Correlation between weather influences (e.g., mean temperature, average amount of sunshine, average of cloud cover, average rainfall, mean wind speed, average snowfall, etc.) and number of rentals aggregated per month and per day

As an example, we determined that trips beginning and ending with a free-floating bike position were the dominant trip type, with 47–66% over the investigated period of time. Data regarding the overall and hourly rental distributions and ratios between pick-ups and returns were subsequently used to define the rental parameters for the individual station agents of the ABM. Further, the influence of weather parameters on system usage were calculated and augmented with historical weather data. Note that the analysis we conducted allowed for only tentative insights into correlations between weather conditions and system behavior. Correlation values regarding weather influences on system behavior contained high variances, in particular during the winter months.

4.2 Definition and analysis of architectural elements of the operational phase (step 2)

To manage the architectural complexity of the BSS and derive the inherent dependencies, we created a general framework for structuring the BSS architecture relevant to its operational phase; this construction was based on our previous work and is illustrated in Fig. 3. The resulting model includes all factors that the operator can directly influence, as well as external influences, unforeseeable effects, and so on. The depicted structure follows the logic of a control feedback loop (Lunze 2010). On the left, the *System Input* defines the desired system states and intended usage, which can be divided into *Strategic Management* and *Infrastructure*. In day-to-day use, the system can shift to undesired states, e.g., a malfunction or theft of one or more bikes. Therefore, *Corrective Measures* are required to lead to the desired system state, which contains the item *Service*. The last block, *Usage*, contains the elements *Perturbation* and *System Utilization*. While the latter describes normal and intended usage by customers, *Perturbation* contains all possibly unexpected influences on the system outside of the control of the operator. Note that the structure does not include exogenous factors, such as legislation, the availability of external transportation modes, or traffic route infrastructure.

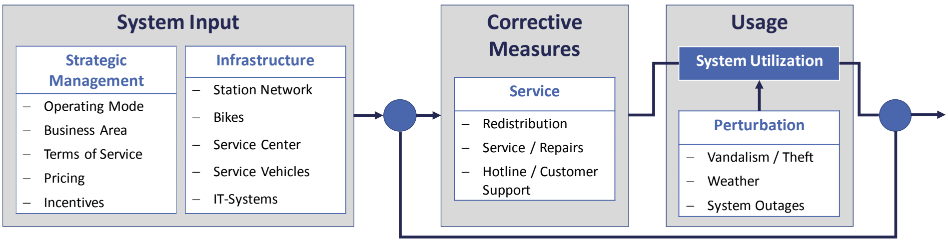

Fig. 3: Generic framework to support modeling the system architecture during the operational phase and identified system architecture elements

4.3 Problem-field analysis (step 3) and deduction of recommended actions (step 4)

The problem-field analysis depicted in Fig. 4 maps identified problems in the BSS operational phase onto BSS architecture elements via a DMM. Here, the DMM can then be converted into a DSM via matrix multiplication to identify connected problem clusters via common architecture elements.

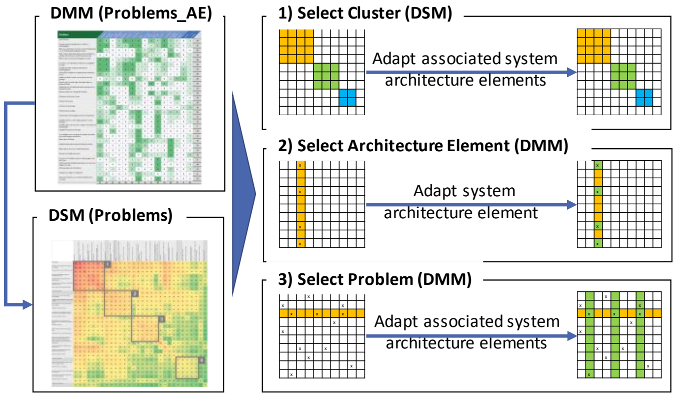

Fig. 4: Structure-based problem-field analysis and derivation of recommended actions (note that we did not intend to have the matrices on the left be readable)

Recommended actions can then be deduced via the three following strategies: (1) selecting a problem cluster to be addressed; (2) selecting an individual architecture element and subsequently analyzing the impact architecture changes have on associated problems; or (3) selecting a problem, then subsequently varying the associated architecture elements and analyzing the impact the change has on all associated problems. Within our specific application, we manually identified four key problem clusters: (1) station fulfillment and redistribution, (2) returning of bikes, (3) overall state of bike maintenance, and (4) the user app used for bike rentals.

4.4 Development of the ABM and testing of architectural changes (5)

The system architecture (step 2) and analysis results (step 1) are used to define the architectural elements required to realistically represent the BSS in an ABM, which we implemented using the *AnyLogic* software. As the BSS architecture indicates, the number of elements is quite high, thus not all elements can be implemented simultaneously. In Fig. 5, we illustrate how various elements of the BSS architecture were implemented in our simulation prototype. While some elements could be implemented in the form of agents, others had to be implemented via system or behavioral parameters. For example, the *Operating Mode* element describes how bikes can be rented and returned, but this element cannot be implemented via an agent; instead, it must be implemented as a behavioral parameter of another agent, i.e., the user.

BSS element	Implementation in the Simulation	Agents
Strategic Management		
Operating Mode	Station Based, Free-Float and Hybrid	
Business Area	Business Area of BSS	
Terms of Service	Partial Replication of the Terms of Service of BSS	
Pricing	Not Implemented	
Incentives	Not Implemented	
Infrastructure		
Station Network	Real Station Network of BSS	*Station*
Bikes	Current Number of Bikes at BSS as well as planned Expansion Number	Bike
Service Center	Implemented at the current location of the service center of BSS	Servicecenter
Service Vehicle	Current Number and Capacity of BSS Service Vehicles	Servicetruck
IT-Systems	Not Implemented	
Service		
...distribution	Implemented (incl. variabl...	

Fig. 5: Implementation of BSS architecture elements in the ABM (excerpt)

Fig. 6 illustrates the basic functional logic of our simulation and the interactions of the agents. The main agent represents the environment within which all other agents act. It contains a map as well as the boundaries of the BSS operating area divided by postal code areas. Interacting agents are the users, bikes, stations, service center, and service trucks. To measure system performance, we introduced Key Performance Indicators into the main agent. As one example, each successful bike rental results in an increase of user satisfaction points, whereas each unsuccessful trip results in negative points. We used the ratio between these positive and negative points as a measure of user satisfaction.

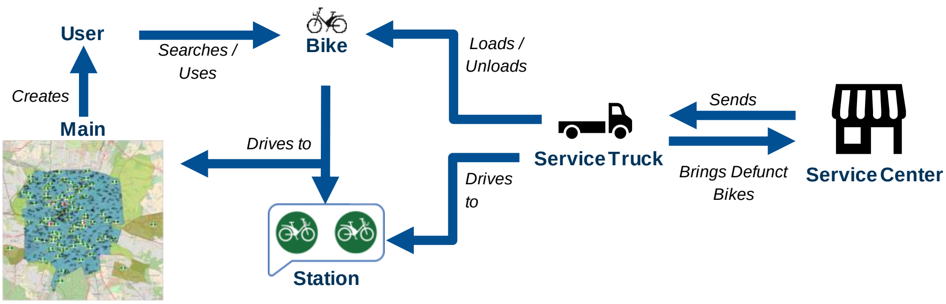

Fig. 6: Functional logic of the ABM, showing the relationships between agent classes

We used the ABM to run tests with a variety of input parameters. The ABM was used to test four specific scenarios for the following recommended actions and their impact on the respective performance metrics (step 3):

1. A reduction of the system to a purely station-based system with nine additional stations derived from real future extension plans
2. A reduction of the free-floating operating area to 10 central postal code areas with a purely station-based system outside this area

3. An increase of 100% in the number of bikes
4. An increase in bike robustness

To test the derived architectural changes, we simulated a one-week period from April 1 to April 8. Longer simulation runs were not possible due to performance constraints. Scenario 1 from above resulted in a dramatic loss of user satisfaction due to the incomplete station network that cannot compensate for the loss of free-floating bikes. Conversely, scenario 2 resulted in very high user satisfaction since users looked for bikes close to well-known stations and the central area was well-saturated with bikes. Conversely, the increased usage and high degree of full stations overloaded the repair cycle, thereby resulting in an increase in damaged bikes since repair trucks were only allowed to re-integrate bikes into the system via stations. Scenario 3 similarly resulted in high initial user satisfaction (97%) followed by a subsequent drop to 88.5% due to the increase in the number of damaged bikes. This increase occurred because the damage model within the simulation calculates the probability of a defect in relation to the number of rentals per bike. The high number of defects eventually overloads the repair cycle, which has not been adapted to the increase in bikes. Finally, Scenario 4 produced increased user satisfaction while simultaneously reducing the repair effort within the simulated period.

5 Interview-based evaluation and discussion

To evaluate the applicability and usefulness of the methodology and ABM, 10 employees of the BSS operator (i.e., the department for strategic planning) and contracted companies were presented with a demo of the approach and asked to fill out a questionnaire based on a five-step Likert scale. Results of this evaluation were generally positive, indicating that our methodology allowed for a structured approach for capturing the current state of the system and systematically searching for measures that can both improve system performance and support planning of future system expansion. From Section 4 above, the application indicated that combining the framework, analysis of usage data, problem-field analysis, and ABM can together help increase the understanding of the current system architecture and systematically deduce potential avenues for improvement. Success and influencing factors on different levels (e.g., customer satisfaction, service performance, profits) can thereby be subject to targeted analyses. In particular, the possibility of analyzing and comparing different architecture configurations should be viewed as a strength that stresses the principal usefulness of the ABM for the design of BSSs and PSSs in general.

Nonetheless, the complexity and effort involved in creating and maintaining the ABM are considerable. Our presented ABM is incomplete in regards to the modeling of external influencing factors, such as alternative modes of transportation, competition, integration within the BSS, as well as such influences as legislature or long-term climate changes. In addition, the interviewed employees noted that our methodology focuses more on the improvement of existing systems and not necessarily the design of new system architectures. The level of detail of the BSS architecture elements varied substantially, and the traceability of the overall process could have been higher.´Therefore, the ABM could only be used to validate limited architectural changes since the results strongly depend on the underlying logic and assumptions of the model (e.g., in regards to the damage model). Further, only a limited time period could be simulated; therefore, long-term effects could not be observed in our simulation as of yet.

6 Summary and future work

In this paper, we presented an approach for modeling and analyzing the dynamic complexity of a PSS applied on a real-life BSS. Our approach utilizes usage data and methods for modeling and analyzing the structural complexity. We applied our approach within a development project focused on the advancement of the current BSS. Our approach was positively evaluated via concluding expert interviews, highlighting the potential for increased system understanding. Conversely, the complexity involved in creating the ABM was considerable, and the potential to validate design decisions is still rather limited. One key area of improvement is extending support to improve the handling of this complexity during the modeling process. One way to address this is to automatically transform structural models into ABM simulations via code generation. Configurable ABMs could further reduce the modeling efforts required since they could easily be adapted, e.g., to different geographical boundary conditions. Further, the ABM could be extended to cover a simulation of a business model by investigating cost and revenue mechanisms more closely, thereby optimizing profits. As design support has only been applied to a single case study, further evaluation of a number of case studies is required to refine our proposed design support.

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