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Automated Cargo Bikes: Assessment of Application for Goods Delivery

Bicicletas de carga automatizadas: Evaluación de la aplicación para el reparto de mercancías

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Abstract: Freight transport in urban areas faces significant challenges related to efficiency, environmental impact, and city livability. A promising approach to this is the deployment of autonomous or automated delivery vehicles. Existing solutions, however, still confront limitations, with larger automated vehicles, i.e., delivery vans exacerbating traffic congestion, and small delivery robots suffering from limited capacity and speed.

In the Eaasy System (Electric Adaptive Autonomous Smart deliverY System) research project, we develop a delivery system that bridges the gap between automated delivery robots and vans, specifically through developing adaptive automated driving functions for cargo bikes. These functions enable both manual control (e.g., for longer or complex routes) and autonomous operation based on task demands. To validate the system's applicability, we employ a simulation-based planning tool that calculates potential time savings and return on investment for specific delivery routes or urban regions, referencing delivery via conventional cargo bikes. This paper pivots on the development of a comprehensive conceptual model, which meticulously defines objectives, inputs, outputs, and content, laying a foundational step towards the future development of a simulation model. Our work introduces the Eaasy System and provides a systematic depiction of the conceptual modeling process, thereby offering a structured methodology for exploring adaptive automated cargo bike deliveries in diverse urban contexts.

Keywords: (*Last mile delivery; Autonomous delivery; Cargo bike; Conceptual Model, Simulation model*).

Resumen: *El transporte de mercancías en áreas urbanas se enfrenta a desafíos críticos en términos de eficiencia, impacto ambiental y vivibilidad de la ciudad. El Eaasy System (Electric Adaptive Autonomous Smart deliverY System, es decir, Sistema de Entrega Inteligente Autónoma Adaptativa Eléctrica) busca abordar estas cuestiones, proporcionando una solución intermedia entre robots de entrega pequeños y furgonetas de entrega más grandes, mediante el desarrollo de funciones de conducción automatizada adaptativa para bicicletas de carga. Estas funciones permiten tanto el control manual, para rutas largas o complejas, como la operación autónoma, dependiendo de las demandas de la tarea. Para validar la aplicabilidad del sistema, se utiliza una herramienta de planificación basada en simulación que calcula los ahorros de tiempo potenciales y el retorno de inversión para rutas de entrega específicas, comparándolo con bicicletas de carga convencionales. Este artículo introduce el Eaasy System y desarrolla un modelo conceptual que define meticulosamente objetivos, entradas, salidas y contenido, estableciendo un paso fundamental hacia el desarrollo futuro de un modelo de simulación, y proporciona una metodología estructurada para explorar las entregas de bicicletas de carga automatizadas adaptativas en diferentes contextos urbanos.*

Palabras Claves: *(Entrega de última milla; Entrega autónoma; Bicicleta de carga; Modelo conceptual; Modelo de simulación).*

1. Introduction

Due to ongoing urbanization, the global demographic landscape is undergoing a significant transformation with 68% of the world’s population is expected to live in urban areas by 2050 [1]. This urban shift inevitably leads to higher demand for goods deliveries and hence to increased delivery traffic, especially in the context of last mile delivery [2]

However, this increase in delivery traffic results not only from the sheer volume of goods demanded but is also due to the ongoing rise of e-commerce and the related increase in variety and availability of goods [3, 4]. On the one hand, there is a change in goods distribution resulting in deliveries being no longer confined to areas specifically designed for this purpose in terms of urban planning (i.e., shopping centers, supermarkets), but widely spread across the whole city [5, 6], coupled with multiple, often fully integrated online and offline distribution channels [7]. On the other hand, there is a transition in consumer behavior towards an on-demand economy with increasing customer demands for delivery speed, flexibility, and customizability [8, 9]. Additionally, the growth in public's consciousness about sustainability, spanning both social and ecological realms, puts even more pressure on logistics companies to align their operations with societal values [8].

These changes confront logistics service providers with a multitude of challenges which, referencing the Three Pillars of Sustainability, can be mapped to social, economic and ecological challenges [10–13]:

- Socially, congestion, noise, and air pollution associated with increased delivery traffic disrupts safety, well-being and city-livability.
- Economically, there is a persistent need to innovate and provide faster, more personalized services. Resulting schemes like same-day deliveries demand significant logistical resources and often lead to underutilized assets and hence increased costs.
- Ecologically, the increased volume of delivery vehicles raises concerns over emissions and energy consumption. In response to these, authorities are reinforcing measures to control negative impacts (e.g., access restrictions, time-windows), adding another layer of costs and operational complexity for logistics service providers.

Since delivery continues to be a pivotal factor for market differentiation and customer satisfaction [14], this puts delivery services in a challenging spot as they must strike a balance between trimming costs while still meeting intricate demands of modern customers. Given these challenges, providers are keenly focused to adopt novel technologies with automation of delivery processes being one of the most prominent topics [15–18].

Despite the potential advantages of automated delivery systems, including streamlined operations, reduced labor costs, and increased delivery speed [16], there are still many drawbacks. For instance, while smaller, sidewalk-based autonomous vehicles can avoid congestion, they are lacking capacity and are vulnerable to vandalism [9]. Conversely, larger, street-based autonomous vehicles offer greater capacity but exacerbate urban traffic congestion [19]. In addition, both systems suffer from the lack of personal delivery, which is particularly disadvantageous for elderly or handicapped persons [20].

To tackle these issues, as part of the Eaasy System research project, we aim to develop a delivery system that bridges the gap between sidewalk and street-based autonomous vehicles. More specifically, our objective is to develop adaptive automated driving functions for cargo bikes. In this context, the concept of adaptive automation means that the vehicle can be either controlled manually by the delivery person (e.g., for long or complex routes) or operated in automated driving mode.

A crucial aspect for the large-scale implementation of our system is proving its applicability and overall economic viability. Within the Eaasy System research project, we aim to achieve this by implementing a simulation-based planning tool that calculates potential time savings and return on investment for specific delivery routes or urban regions referencing delivery via conventional cargo bikes.

According to Robinson [21], a key prerequisite for developing a simulation model is the design of an underlying conceptual model. Consequently, our primary objective in this paper is to develop a conceptual model for simulating adaptive automated cargo bike deliveries in urban areas, utilizing the framework for simulation conceptual modeling proposed by Robinson [22].

The structure of this paper is outlined as follows: The next section provides a brief description of the adaptive automated delivery system. In section 3 and 4, we describe the methodology for generating the conceptual model and its adoption for our research project, respectively. In section 5, we finally discuss our findings, summarize our work and highlight future research initiatives.

2. Eaasy System Delivery Concept

The delivery concept of Eaasy System builds upon conventional last-mile delivery of packages using cargo bikes and micro hubs. At the start of a delivery tour, the delivery person loads the cargo bike and then manually heads towards the actual delivery area. Upon arrival, they can activate automated driving mode, which we also refer to as come-with-me mode (CWM), through voice commands, enabling hands-free instructions to the vehicle. Depending on the situation, the vehicle is capable of autonomously driving behind or beside the walking delivery person or navigating itself to a safe parking spot. For longer or more complex routes, or for the return journey to the depot, the delivery person can then manually operate the vehicle again. A simplified representation of the delivery process can be found in Figure 1.

Apart from the benefits arising from the general use of cargo bikes, i.e., the balance between flexibility, speed, and capacity, the system offers multiple advantages, especially in dense urban areas. Automated driving functions eliminate inefficiencies like repeated mounting and dismounting or walking back to a parked vehicle, leading to increased route efficiency. This system, therefore, allows for cost savings. At the same time, it keeps the deliverer integrated into the process, ensuring the possibility for complex interactions with consignees or the delivery environment. Another significant advantage comes from its resemblance to conventional cargo bike-based delivery processes, reducing the effort required to incorporate Eaasy System into existing logistics systems.

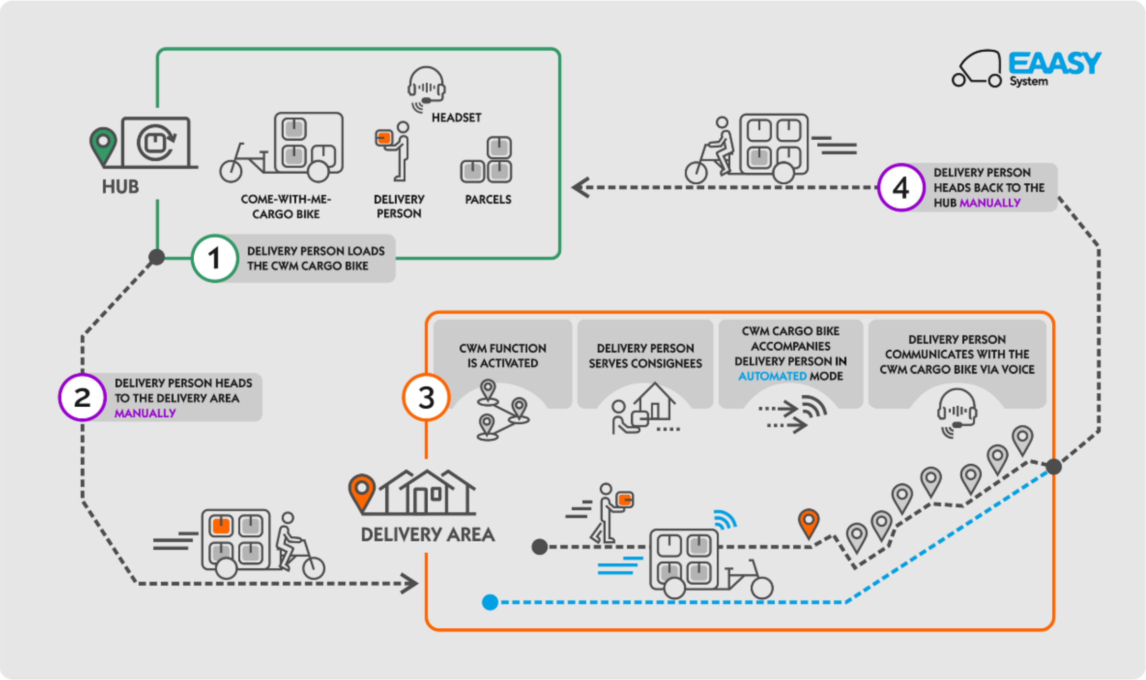

Figure 1. Eaasy System delivery process

3. Methodology

For the generation of our conceptual model, we follow the framework for simulation conceptual modeling provided by Robinson [22], which has been widely recognized and adopted in the field of simulation modeling [23]. We chose Robinson's framework due to its structured approach, which on the one hand ensures a clear and thorough description of the model's objectives, inputs, outputs and content, while on the other hand being flexible enough for the adoption to problem-specific simulation architectures and contexts.

The proposed framework consists of five major steps [22, 24]:

1. Understanding the problem situation: The initial step involves understanding the issue to be simulated, acknowledging that full comprehension may develop over time.
2. Determining objectives: Objectives, categorized into modeling and general project types, need to be defined; the former permeates all modeling process aspects, while the

latter guides the model's design and usage, with a focus on aspects like flexibility, run-speed, visual display, ease-of-use, and user-friendliness.

3. Identifying model outputs (responses): Within the framework, the primary purposes of model outputs are to determine if the modeling objectives have been met and to identify reasons for objectives not being achieved.
4. Identifying model inputs: Concerning inputs, the framework distinguishes between general input, which is essential for the model's realization, and experimental factors, which can be altered to meet the modeling objectives.
5. Determining model content: For determination of the model content, the framework separates model scope and level of detail. Defining the model scope requires the identification of the model's components, including but not limited to, entities, activities, queues, and resources. For this, the framework suggests a three-step approach comprising identification of model boundary, identification of all components in the real-world system laying in the model boundary, and assessment of including or excluding those components to the model. Subsequently, the level of detail for each component has to be defined, utilizing tabular form for clarity and deriving further data requirements.

While the proposed sequence of key activities – specifically, defining model input and output prior to determining model content – might initially seem counterintuitive, Robinson [22, 24] emphasizes the criticality of understanding responses and experimental factors during the design phase of the conceptual model, given that these elements respectively represent the primary outputs and inputs that the model provides and receives.

4. Modeling Results

The following chapter covers the application of Robinson's framework [22, 24] for developing a conceptual model for simulating adaptive automated cargo bike deliveries in urban areas.

4.1 Understanding the Problem Situation

As outlined in chapter 1 and 2, Eaasy System provides a promising solution for tackling the multifaceted challenges caused by the increase in urban last mile delivery activities. However, despite its potential, the large-scale adoption of adaptive automated cargo bikes from a logistics view point is constrained by:

- Knowledge Gap: Due to its novelty, there is a lack of empirical data demonstrating quantified benefits of using adaptive automated cargo bikes in specific urban delivery scenarios.
- Tool Deficiency: As a consequence, logistics industry lacks planning and comparison tools for evaluation the benefits of adaptive automated cargo bike-based delivery systems.

4.2 Determining Objectives

Referencing this problem situation, we based our simulation study on a number of general project and modeling-specific objectives. From a broader perspective, the overall project goal is to introduce adaptive automated cargo bikes as a means for sustainable urban logistics. To this end, we defined the following general project objectives:

- Promotion of Adaptive Automated Cargo Bikes: Provide compelling cases, informed by empirical data derived from conventional cargo bike deliveries, for the adoption of adaptive automated cargo bikes for urban delivery processes.
- Tool Development: Construct a user-friendly, simulation-based tool that aids in logistics planning, leveraging insights from both empirical data and our simulation results.
- Knowledge Dissemination: Generate and share findings on cargo bike-based delivery systems, with a particular emphasis on adaptive automated cargo bikes.

In order to guide the technical aspects of our study and to ensure alignment with our project goals, we further identified the following modeling objectives:

- Sensitivity Analysis and Scenario Testing: Understand how altering shipment structures, consignee, urban, and logistical configurations influence cargo bike deliveries by testing different scenarios.
- Performance Analysis: Measure and compare the efficiency of conventional and adaptive automated cargo bike-based delivery systems across multiple scenarios with varying urban setups.

4.3 Identifying Model Outputs

In alignment with our modeling objectives, we defined the following outputs to assess the applicability and viability of adaptive automated cargo bike deliveries, ensuring they are versatile for various analytical and evaluative purposes in subsequent studies (Table 1).

Table 1. Model outputs

		Category	**Output**	**Description**
Modeling objective	Sensitivity analysis, scenario testing	Delivery efficiency	Average delivery time	Time taken for each delivery tour, considering the number and location of consignees, parcel metrics, and infrastructure
		Configuration efficiency	Hub proximity impact	Change in average delivery time based on the proximity of the nearest hub
			Vehicle utilization rate	Percentage of active delivery time versus idle time for each vehicle, considering the number of vehicles available
			Distance	Covered (idle) distance per delivery tour
		Infrastructure efficiency	Infrastructure delay index	Average delay in minutes caused by missing or inadequate infrastructure
	Performance analysis	Delivery mode comparison	Cost efficiency	Cost per delivery, considering labor, vehicle maintenance, and other overheads
			Emission rate	Carbon emissions per delivery or per kilometer
		Operational efficiency	Downtime percentage	Percentage of time vehicles are idle, i.e. standing during a delivery tour
			Capacity utilization rate	Ratio of used to available cargo space on each delivery tour, considering the number and volume of parcels

4.4 Identifying Model Inputs

Following the identification of our model's outputs, the next step was to determine the necessary inputs to accurately simulate adaptive automated cargo bike deliveries in urban contexts. Aligning Robinson's approach [22, 24], we categorized these inputs: experimental factors and general input data. Table 2 provides a breakdown of our model inputs, including ranges for numerical input data and the respective input methods.

4.5 Determining Model Content

With the inputs defined, we proceeded to determine the model content consisting of scope and level of detail. For the former, Robinson's framework [22, 24] suggests a structured approach, which we slightly adapted for our study.

Table 2. Model inputs

	Input	**Description**	**Input method**
Experimental factors	Delivery metrics	Location of consignees and number, weight, and volume of parcels	Data file (csv), range according to real-world cargo bike delivery observations
	Configuration metrics	Number and location of hubs, number of vehicles	Model based menu (optimized vs. manual input)
	Infrastructure	Overall street network configuration	Model based menu (abstract representation of different types of city districts)
General input data	Task duration distribution	Distribution of the duration for the handling of delivery processes	Model code (results from analysis of real-world cargo bike delivery observations)
	Route	Predefined path between consignees	Model code (provided by routing algorithm based on OSM data)

As a first step we had to define the model's boundary. For our study, this boundary encapsulates the urban delivery environment, excluding upstream processes. Deliveries, in our model, start and end at a hub near the delivery area, with parcels being loaded onto the vehicle at the start. Depending on the number of vehicles and parcels, vehicles return to a depot during the delivery tour to pick up new parcels or return undelivered parcels.

Next, we identified all components within this boundary and assessed whether to include them to our model. While doing so, instead of strictly adhering to Robinson's proposed components, i.e., entities, activities, queues, and resources [22, 24], we adapted them to better represent urban delivery processes. The resulting model components include entities (dynamic components), resources (tools and personnel), activities, locations (static components), and infrastructure (environmental influencers). The identified model components as well as a justification for inclusion to the model is outlined in Table 3.

The visual representation of the model scope roughly corresponds to the schematic representation of the Eaasy System delivery system (Figure 1), where the number and location of the depots, the composition of parcels (flow object), the number of vehicles, the location of the consignees, and the road network connecting the consignees and depots are variable according to the model inputs (Table 2).

Table 3. Model content: Scope

Components		**Include/ Exclude**	**Justification**
Entities	Parcels	Include	Experimental Factor
	Cargo bikes	Include	Experimental Factor
	Light/heavy duty vehicles	Exclude	No consideration of upstream processes
	Street traffic	Exclude	Limited impact on tour duration
	Pedestrians	Exclude	Limited impact on tour duration
Resources	Delivery persons	Exclude	Required for operation of manual processes, however always provide standardized service and cause no significant variation in delivery duration
	Loading aids	Exclude	Assume always available or not needed
Activities	Travelling	Include	Key influence on tour duration, can be further broken down to driving or walking with respect to distance and path type
	Loading/unloading at hub	Include	Assumed to have standardized duration and not causing variation in delivery duration
	Delivery	Include	Key influence on tour duration, can be further broken down into different sub activities
	Charging/Refueling	Exclude	Assume vehicles have a sufficiently high range for a tour
Locations	Consignees	Include	Experimental Factor
	Micro hubs	Include	Experimental Factor
	Central hub	Exclude	No consideration of upstream processes
	Loading zones	Exclude	Assume vehicles can stop near consignee location
Infrastructu	Network	Include	Major impact on tour duration, specifies all possible paths on which vehicles can move
	Intersections	Include	Arise due to network structure, can cause delays

Having established the model’s scope and its components, we next focused on the granularity of our simulation by determining the level of detail for each component. This was made with a dual focus: firstly, to ensure alignment with our previously defined objectives, and secondly, to maintain the model's simplicity, thereby reducing both implementation and computational effort.

As with the model scope, we again deviated from Robinson’s framework [22, 24]. Instead of using the proposed template for level of detail by component type, we tailored our measurements to fit the unique components we had identified for our model. The specifics of the level of detail for each component are presented in Table 4.

Table 4. Model content: Level of detail

Components		**Details**	**Description**
Entities	Parcels	ID	Number for identification
		Destination	Consignee ID
		Dimension	Weight [kg], Volume [m^3]
		Status	Status of delivery
	Cargo bikes	ID	Number for identification
		Capacity	Max. payload [kg] and volume [m^3]
		Load	ID of parcels currently loaded
		Vehicle Route	Sequence and ID of target locations
		Speed	Const. values for driving and walking [km/h]
		Emissions	CO2, NOX and PM10 emissions [t/km]
Activities	Travelling	Mode	Driving or walking
		Start/End	ID from starting and ending point
		Duration	Duration for movement between locations [s], depending on route
	Delivery	Duration	Duration for delivery (random according to previously derived duration distribution) [s]

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Table 4. Model content: Level of detail (continued)

Components		**Details**	**Description**
Locations	Customer	ID	Number for identification
		Location	Lat/lon coordinate
	Micro hub	Location	Lat/lon coordinate
		ID	Number for identification
		Load	ID of parcels currently stored
		Handling time	Time for loading/unloading a parcel to/from cargo bike
Infrastructure	Network	Structure	Structure of road network, including a definition of available road types
		Restrictions	Definition of allowed vehicle types per road type
	Intersections	Delay	Average delay per crossing [s]

Lastly, while defining the model content, Robinson [22, 24] emphasizes the value of documenting assumptions and simplifications made throughout the modeling process, as they are integral to the model's functionality and interpretability, but also inherently introduce certain limitations. In alignment with this, we have detailed the following assumptions incorporated into our model:

- Delivery: The Duration of delivery processes follow a previously determined distribution and are independent of the respective delivery person.
- Emissions: Emissions for electrically assisted vehicles are based on average grid mix unless mentioned otherwise.
- Vehicle Range: Vehicles have sufficient battery/fuel range to complete a tour without needing a recharge or refuel.
- Crossing Delays: The average delay at crossings and intersections is constant regardless of the time of day or number of vehicles present.

Furthermore, we introduce specific simplifications to manage model complexity and facilitate a more streamlined simulation, as follows:

- Customer Presence: If a customer is not available for delivery, the parcel is taken to the subsequent hub.

- No External Disruptions: Factors like weather conditions, or any unexpected events are not considered in the simulation.
- Parcel Dimensions: While weight and volume of parcels are considered, other dimensions like shape or fragility are not.
- Fixed Routes: Vehicles follow a predetermined route without dynamic route optimization during the delivery process.
- Static Infrastructure: While the simulation considers different infrastructure elements, dynamic factors like road maintenance, temporary roadblocks, etc., are not included.
- Uniform Vehicle Performance: All vehicles of a specific type (e.g., all cargo bikes) are assumed to have similar speed, capacity, and emissions, without accounting for differences between makes or models.
- Consistent Loading/Unloading Times: The time taken to load or unload parcels at hubs is averaged out, without considering variations due to parcel size, weight, or the individual efficiency of workers.

5. Conclusions and Future Work

In addressing the multifaceted challenges embedded within urban delivery landscapes, this research illuminates the potential of adaptive automated cargo bikes, presenting a conceptual model meticulously developed to simulate their applicability and viability in varied urban contexts. The introduction of the Eaasy System and the conceptual model, anchored in Robinson's framework [22, 24], emerge as our pivotal contributions, providing not only insights into the deployment of adaptive automated cargo bikes but also establishing a flexible foundation for exploring various cargo bike-based delivery concepts, such as nano-hubs or teleoperated upstream.

However, while providing these insights, our study also underscores the necessity for additional research and acknowledges inherent limitations. One limitation lies in the choice of the framework for implementing the conceptual model. As Robinson [22, 24] points out, there is no universally "correct" conceptual model for a specific problem, as its development is significantly influenced by the modeler (and clients and domain experts), and respective personal preferences. Another constraint arises from the iterative nature of conceptual models. As we proceed with the construction of the simulation model and subsequently gain more insights into the nature of the simulated system, we will need to iteratively refine our model to accommodate those insights.

Therefore, future endeavors will be channeled towards validating the conceptual model, engaging in comprehensive data collection and analysis, and implementing the simulation model, thereby enabling a deeper exploration of adaptive automated cargo bike deliveries in urban areas.

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