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Designing and Optimizing Autonomous Delivery Systems through MBSE and Discrete-Event Simulation

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Abstract

This paper proposes a hybrid methodology that integrates Model-Based Systems Engineering (MBSE), discrete-event simulation, and simulation-based optimization to support the design and analysis of complex systems. Grounded in the Arcadia method and documented through UML diagrams, the approach offers a structured framework to define operational needs, mission objectives, and architectural alternatives before implementation. To validate the methodology, it is applied to a last-mile delivery system involving autonomous aerial and ground vehicles operating in a gated residential environment. The case study progresses through operational modeling, logical architecture, simulation, and optimization phases. A discrete-event simulation model is developed in Python using SimPy, incorporating a non-homogeneous Poisson process to capture realistic demand patterns. Key performance indicators, such as delivery delay and energy consumption, are measured and used to compare dispatching strategies. In the final phase, a Simulated Annealing algorithm is used to explore optimal fleet compositions. Results demonstrate that the proposed approach can reduce average wait time by over 99% and energy consumption by 12.6% when compared to a baseline configuration. The methodology ensures traceability between stakeholder needs, design models, and performance outcomes, supporting informed decision-making in early design stages. The proposed framework is generalizable and can be extended to other domains characterized by operational uncertainty and complex architectural trade-offs. It contributes to bridging the gap between high-level system architecture and quantitative performance evaluation through a unified, model-driven workflow.

Keywords

Model-Based Systems Engineering, Simulation-based Optimization, Arcadia, System Architecture Trade-Offs, Autonomous Delivery.

1. Introduction

The design and operation of complex systems increasingly demand structured approaches to ensure consistency, traceability, and adaptability. Traditional document-based engineering often fails to handle such complexity, particularly under real-time decision-making and operational uncertainty. As a response, Model-Based Systems

Engineering (MBSE) has emerged as a viable alternative by formalizing the development process through models that can be iteratively analyzed, simulated, and refined (INCOSE 2020, Di Maio et al. 2021; Baron et al. 2023).

While MBSE offers a formal and structured foundation for system modeling (Di Maio et al. 2021), its integration with simulation and optimization techniques has emerged as a promising direction to enhance early-stage analysis and decision-making (Timperley et al. 2024). By combining architecture modeling with operational performance evaluation, it becomes possible to assess dynamic behavior, explore trade-offs, and refine design alternatives based on quantitative insights (Scholz et al. 2025, Mao et al. 2024; Galisson et al. 2022).

To address this opportunity, this paper proposes a hybrid methodology that integrates MBSE, discrete-event simulation, and simulation-based optimization. The approach adopts the Arcadia method (Voirin 2017; Roques 2017) to support a structured derivation of stakeholder needs, operational scenarios, and system and logical architecture. The use of standardized modeling tools, such as UML (Rumbaugh et al. 2004), enhances model clarity and traceability, facilitating architecture assessment through simulation (Mao et al. 2024; Galisson et al. 2022). In addition, a metaheuristic optimization layer supports design space exploration and operational decision-making under resource and performance constraints (Timperley et al. 2024; Gosavi 2015).

Accordingly, this work aims to implement and validate the proposed methodology by applying it to a case study involving an autonomous last-mile delivery system composed of aerial and ground vehicles operating in a gated environment. This controlled yet realistic setting — representative of university campuses, residential condominiums, or industrial complexes — is increasingly studied for sustainable logistics (Gnoni et al. 2025; Shuaibu et al. 2025, Alverhed et al. 2024; Lemardelé et al. 2023). It presents high operational variability due to stochastic demand, limited energy capacity, and spatial constraints. The case study follows three phases: architecture modeling using Arcadia, discrete-event simulation (SimPy), and simulation-based optimization via Simulated Annealing. Results demonstrate substantial reductions in delivery wait time and energy consumption, highlighting the potential of this integrated methodology to inform early-stage design and decision-making.

2. Literature Review

Model-Based Systems Engineering (MBSE) has gained prominence as a response to the increasing complexity of systems. The INCOSE Vision 2035 strongly emphasizes MBSE as a cornerstone of future systems engineering practice, citing its potential to improve stakeholder communication, reduce errors, and accelerate development through continuous refinement. By formalizing system structure, behavior, and requirements through models, MBSE enhances traceability, supports early validation, and promotes cross-domain integration (Timperley et al. 2024; INCOSE 2020). Among MBSE methodologies, Arcadia stands out for its structured, multi-viewpoint approach to architecture development (Baron et al. 2023; Galisson et al. 2022; Di Maio and Lindvall 2021). Recent applications in industrial sustainability, manufacturing and defense illustrate its potential, especially when coupled with simulation for performance evaluation (Scholz et al. 2025; Baron et al. 2023; Mao et al. 2024).

In parallel, significant advances have been made in last-mile delivery through the deployment of autonomous systems—especially drones and ground robots—designed to improve efficiency, sustainability, and flexibility in urban logistics (Gnoni et al. 2025, Shuaibu et al. 2025). These technologies have demonstrated potential to reduce delivery time, operational costs, and carbon emissions, even when operating under constraints such as limited payload, battery endurance, and regulatory compliance (Eskandaripour and Boldsaikhan 2023; Lemardelé et al. 2023; Alverhed et al. 2024). While drones have been extensively studied in terms of routing, recharging, and hybrid integration with ground fleets (Swanson 2019; Eskandaripour and Boldsaikhan 2023, Garg et al. 2023), ADRs are increasingly considered viable for pedestrian-friendly contexts such as campuses and gated residential areas (Alverhed et al. 2024, Engesser et al. 2023, Shuaibu et al. 2025).

Simulation has played a central role in evaluating the behavior and performance of these autonomous delivery systems under realistic operational conditions. Techniques such as discrete-event simulation, agent-based modeling, and Monte Carlo methods have been employed to represent demand stochasticity, spatial constraints, and coordination of heterogeneous fleets (Swanson 2019; Chen and Chankov 2017; Perboli et al. 2018; Gnoni et al. 2025). Comparative studies have examined alternative configurations—including drones, ground robots, electric vans, and conventional vehicles—assessing their impact on energy use, service times, and environmental footprint (Gnoni et al. 2025, Engesser et al. 2023; Lemardelé et al. 2023). Life-cycle analysis and sustainability assessments have reinforced the strategic role of simulation in supporting the development of smart and resilient urban logistics systems (Lemardelé et al. 2023, Gnoni et al. 2025).

To support decision-making and balance trade-offs in design and operation, simulation is increasingly integrated with optimization methods. Metaheuristics have proven effective in tackling challenges in fleet sizing, routing, vehicle coordination, and energy management under uncertainty (Ratnagiri et al. 2022; Shuaibu et al. 2025). These simulation-based optimization (SBO) frameworks allow for design space exploration and performance benchmarking in complex systems where analytical solutions are not feasible (Gosavi 2015; Perboli et al., 2018). Some implementations have also demonstrated experimental validation via scaled robotic platforms, bridging the gap between computational models and real-world deployment (Ratnagiri et al. 2022).

However, despite these methodological advances, most simulation and optimization approaches remain decoupled from formal systems engineering frameworks. This disconnection limits traceability between architectural design and operational behavior, reducing the potential for early validation and coherent system integration (Scholz et al. 2025; Baron and Grenier 2023). Recent literature highlights the need for integrated approaches that combine architecture modeling, simulation, and sustainability-driven optimization (Engesser et al., 2023; Shuaibu et al., 2025), yet few studies offer a unified methodology that operationalizes this integration in a traceable and iterative way.

This study contributes to bridging this gap by proposing a hybrid methodology that integrates MBSE, discrete-event simulation, and simulation-based optimization to support the design and analysis of autonomous delivery systems. By linking architectural models to system performance metrics, the approach supports traceable, simulation-informed decision-making throughout early development phases.

3. Methodology

This study adopts a hybrid methodology that integrates Model-Based Systems Engineering (MBSE), discrete-event simulation, and simulation-based optimization to support the design and analysis of autonomous delivery systems operating under dynamic and resource-constrained conditions. The methodology was constructed iteratively, inspired by recent works that combine architecture modeling and performance evaluation (Scholz et al. 2025; Gnoni et al. 2025, Mao et al. 2024; Galisson et al. 2022; Timperley et al. 2024), and is composed of three interconnected phases: (1) system modeling, (2) operational simulation, and (3) design space optimization.

In the first phase, the problem space is structured using the Arcadia method (Voirin 2017; Roques 2017), which emphasizes stakeholder needs and system functions through a set of interrelated viewpoints. The Operational Analysis defines actors, operational entities, capabilities, and activities. Subsequently, the System Analysis creates a high-level representation of missions and interactions within the delivery context, from which system-level requirements are derived. This process leads to the Solution phase, where a Logical Architecture is designed to describe the system structure and behavior without committing to specific technical implementations.

Although Arcadia is commonly implemented via specialized tools such as Capella, this study employs Unified Modeling Language (UML) diagrams rendered with PlantUML (Rumbaugh et al. 2004; Roques 2021) to document operational, system, and logical models. This tool-agnostic approach supports traceability between system architecture and simulation elements, while reinforcing the methodological applicability of Arcadia independently of specific platforms (Mao et al. 2024).

The second phase involves developing a discrete-event simulation model using the SimPy library (SimPy 2025) in Python. The simulated environment represents a two-dimensional map with a central gate and predefined delivery locations, simulating a gated residential or campus-like setting. Delivery requests are generated by a non-homogeneous Poisson process to reflect temporal variations in demand (Swanson 2019). The model includes two types of autonomous vehicles—drones and ground robots—each characterized by distinct speed, payload capacity, energy autonomy, and recharge mechanisms. Vehicle operations encompass dispatching, travel, delivery, return to base, and battery swapping, all governed by operational constraints.

The simulation tracks key performance indicators such as delivery time, energy consumption, and buffer occupancy. These metrics provide a quantitative basis for evaluating different delivery strategies and system configurations. The case study serves as a controlled yet representative setting for validating the proposed methodology in support of early-stage decision-making in autonomous logistics planning.In the third phase, the simulation model is embedded within a simulation-based optimization (SBO) loop to explore alternative fleet compositions. The optimization problem considers trade-offs between minimizing delivery wait time and energy usage, subject to fleet availability and infrastructure limitations. Simulated Annealing (Kirkpatrick et al. 1983; Gosavi 2015) was selected as the optimization engine due to its robustness in navigating large, discrete, and stochastic search spaces—characteristics commonly associated with autonomous fleet allocation problems under uncertainty. Unlike deterministic heuristics or gradient-based algorithms, Simulated Annealing can escape local optima, and unlike populational metaheuristics, requires minimal parameter tuning, making it well-suited for iterative simulation-driven evaluations.

Each candidate fleet configuration is evaluated through simulation, and the resulting performance metrics are used to construct a Pareto front. This enables decision-makers to analyze trade-offs across competing objectives and select configurations that best align with both operational goals and architectural constraints defined during the modeling phase. This study did not include a formal sensitivity analysis. Future work should investigate how variations in key parameters—such as fleet size limits, recharge duration, or delivery density—impact performance metrics and optimization robustness.

4. Case Study: Autonomous Delivery in a Gated Environment

This section presents a case study used to validate the proposed methodology. It is organized into three parts: the system modeling based on Arcadia, the discrete-event simulation setup and performance analysis, and the results of a simulation-based fleet optimization. Together, these components demonstrate how MBSE artifacts can inform simulation design and support system-level decisions. The study focuses on a gated residential environment, a typical setting for last-mile logistics. Traditional delivery methods using trucks or motorcycle couriers face limitations related to accessibility, labor dependency, and maneuverability. Autonomous vehicles, such as drones and ground robots, offer promising alternatives by improving access to constrained areas, reducing costs, and enabling contactless operations (Garg 2023; Engesser 2023; Shaibu 2025).

4.1 System Modeling using Arcadia

This subsection describes how the Arcadia methodology was applied to structure the design process, from operational modeling to logical architecture. The modeling supported the subsequent simulation phase and guided the definition of delivery behavior, vehicle roles, and system logic.

Operational Analysis. The operational analysis identifies key stakeholders (e.g., delivery coordinator, gate system, customer) and operational capabilities such as dispatching, transportation, tracking, and recharging. Although Capella was not used, the same conceptual structure was implemented using Unified Modeling Language (UML) with PlantUML. This decision ensures consistency with the Arcadia viewpoint framework while maintaining flexibility in tooling.

Figure 1 presents the Operational Entity Breakdown Diagram (OEBD), which defines the main entities involved in the delivery system and their relationships. These include the gate system as the central dispatching and recharging point, the delivery points as final destinations, the autonomous vehicles (drones and ground robots), and the customer who initiates and receives delivery requests.

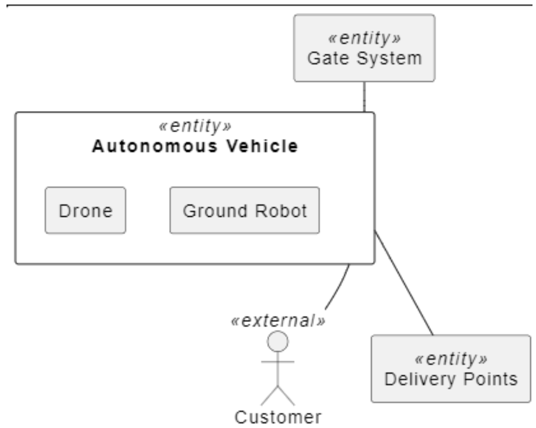

Figure 1. Operational Entity Breakdown Diagram (OEBD) showing stakeholders (operational entities and actors).

Figure 2 presents the Operational Architecture Diagram, mapping each entity to its allocated capabilities. This diagram clarifies how different actors contribute to the system through functions such as dispatching, transportation, recharging, and order confirmation. The architecture ensures traceability between roles and responsibilities, forming the foundation for system analysis.

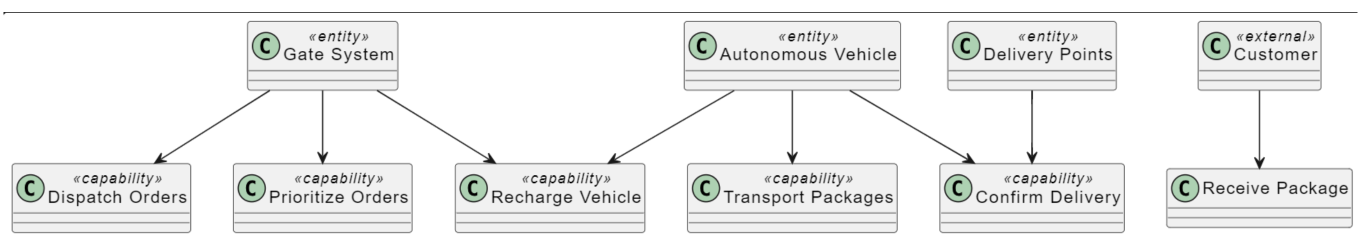

Figure 2. Operational Architecture Diagram mapping stakeholders to capabilities.

System Analysis. The system analysis defines the Delivery Coordination System, responsible for orchestrating deliveries using autonomous vehicles. Its mission includes optimizing delivery time, energy usage, and responsiveness to dynamic demand.

Figures 3 and 4 illustrate this layer: the first shows system-level capabilities, including fleet management, dispatch logic, and energy monitoring; the second presents the external interfaces, showing how the system exchanges information with users, vehicles, and infrastructure. .

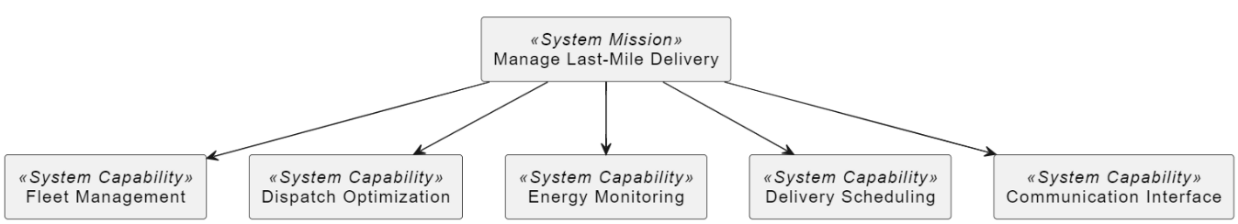

Figure 3. Delivery Coordination System mission and capabilities.

Figure 5 provides a dynamic perspective of the delivery process via a UML sequence diagram, from order creation to package receipt. This model illustrates how the system coordinates autonomous deliveries in response to demand while respecting operational constraints

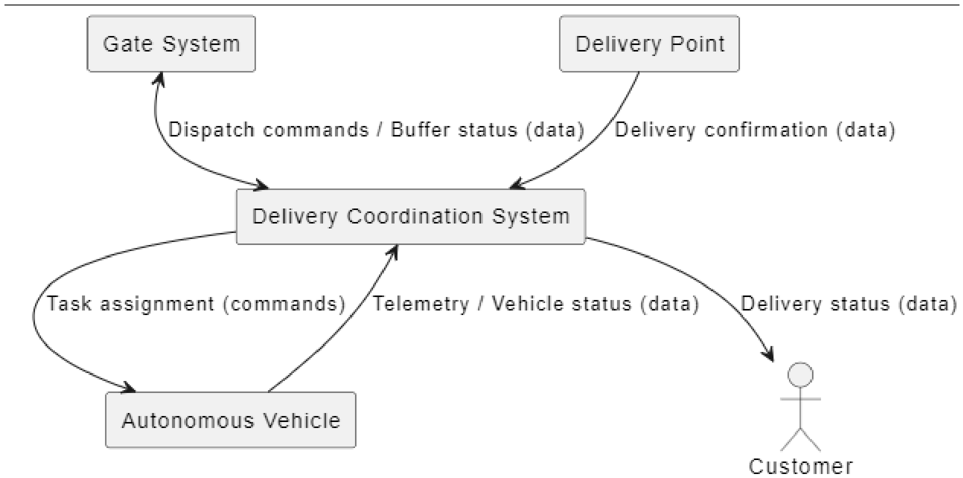

Figure 4. System context illustrating external interfaces.

Based on the above models, functional and non-functional requirements were derived to provide the basis for the system's logical architecture. Also, these requirements guide simulation and evaluation. Table 1 presents representative examples that directly support the simulation and optimization phases.

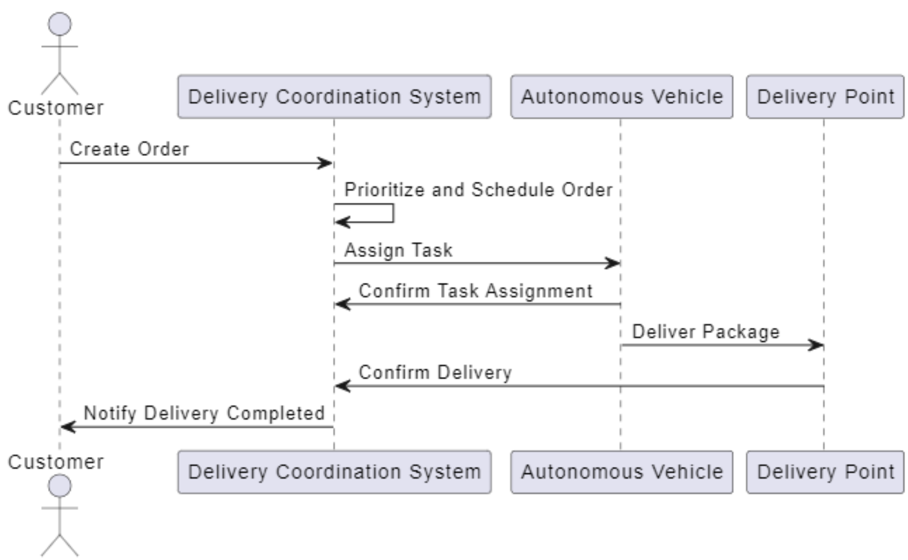

Figure 5. Sequence diagram illustrating the process from order creation to package delivery

Table 1. Examples of Functional and Non-Functional Requirements

Type	**Requirement Description**
Functional	[F-001] - The system shall assign delivery tasks to autonomous vehicles based on delivery time and energy usage.
Functional	[F-002] - The system shall monitor the state of charge (SoC) of each vehicle and schedule recharging when necessary.
Non-Functional	[NF-001] - The average delivery time shall not exceed 10 minutes under nominal demand.
Non-Functional	[NF-002] - The system shall ensure that energy consumption remains under a defined threshold in optimized configurations.

Logical Architecture. The logical architecture describes internal system components, interactions, and behavior. For example, Figure 6 presents a state-machine diagram describing vehicle logic: a delivery is initiated only if the battery level allows for mission completion; otherwise, recharging is prioritized. Figure 7 presents the UML class diagram.

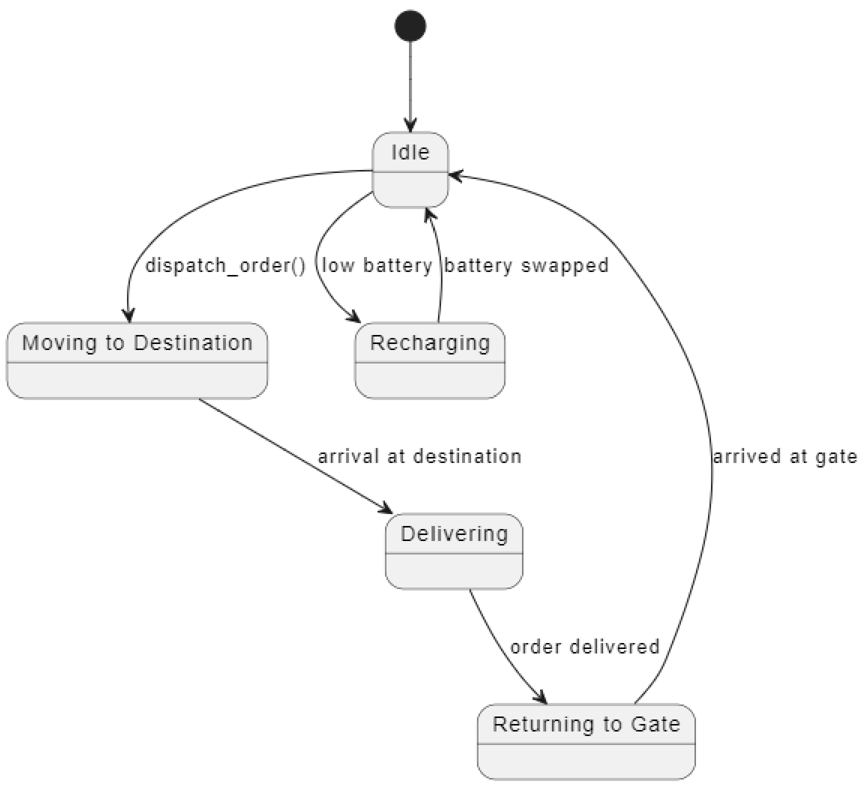

Figure 6. State-machine diagram of a vehicle representing the system behavior.

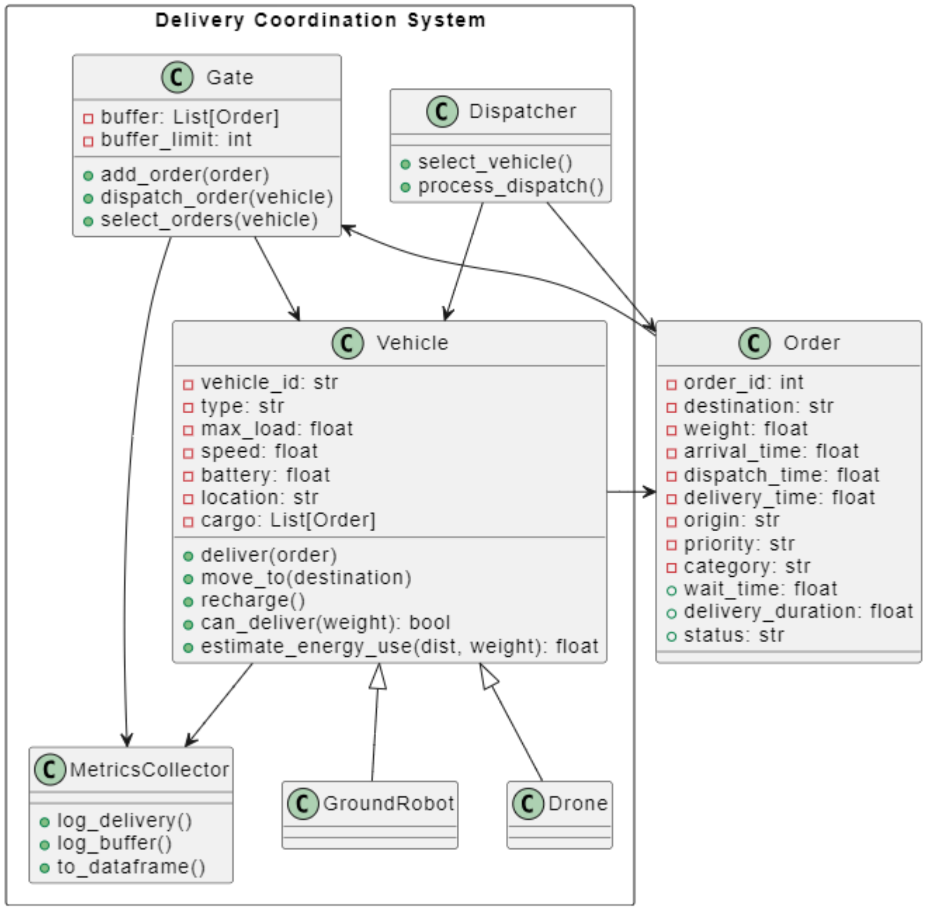

Figure 7. Logical class diagram of the Delivery Coordination System.

The class diagram describes the structure associated to behavior and includes the following classes:

- **Order**: delivery request with destination, weight, and status;
- **Gate**: manages the dispatch buffer and order queue;
- **Vehicle**: superclass for mobile agents, with *Drone* and *GroundRobot* subclasses;
- **Dispatcher**: implements dispatch policies;
- **MetricsCollector**: records KPIs such as time and energy.

This logical model serves as a blueprint for the simulation phase and enabled early exploration of trade-offs between drone and ground robot operations under stochastic demand conditions.

4.2 Scenario Description

The case study simulates a gated residential environment to evaluate the behavior and performance of the autonomous delivery system under realistic, controlled, operational conditions. Although the spatial layout is simplified to enhance model transparency and ensure experimental reproducibility, the model can be extended to more complex settings with additional constraints or operational rules.

The environment is modeled as a two-dimensional grid consisting of one central gate and four delivery points, forming a cross-shaped layout. The gate serves simultaneously as the dispatch center, battery swap station, and buffer for pending delivery orders. All delivery operations begin and end at this central hub. Figure 8 illustrates the spatial configuration adopted in the simulation.

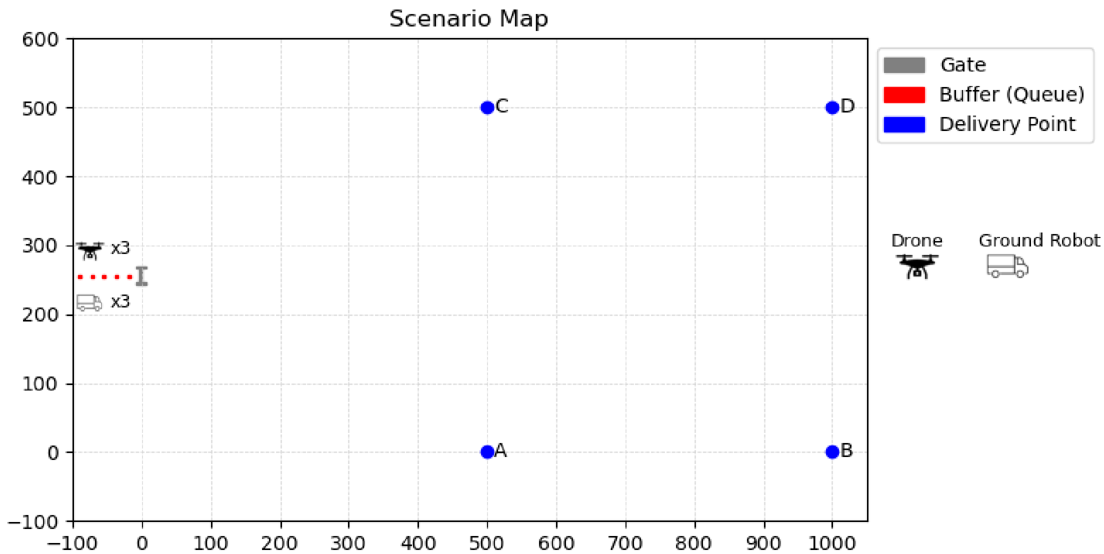

Figure 8. Simplified map of the delivery scenario with one gate and four delivery points.

Two types of autonomous vehicles are simulated: drones and ground robots. Table 2 summarizes their operational characteristics, including maximum payload, autonomy (in seconds), average speed, recharge time (battery swap duration), and the linear energy penalty per kilogram transported. These parameters were defined to reflect realistic operational trade-offs, such as speed versus capacity and energy consumption versus load.

Table 2. Autonomous Vehicle Specifications

Vehicle Type	**Max Load (kg)**	**Autonomy (s)**	**Speed (m/s)**	**Recharge (s)**	**Energy Penalty (/kg)**
Drone	5	2700	15	300	0.10
Ground Robot	30	5400	3	300	0.05

Delivery requests are generated using a non-homogeneous Poisson process to reflect time-varying demand throughout the day. This approach better captures real-world dynamics compared to uniform distributions, allowing for realistic peaks—such as during lunch hours—when delivery activity typically increases. The complete time-dependent arrival rate schedule (λ) is shown in Figure 9.

To prevent artificial blocking during high-demand periods and support stress-testing scenarios, a buffer capacity of 10,000 pending orders was defined. This configuration ensures that the system's operational limits are tested under controlled overload conditions without prematurely halting the simulation.

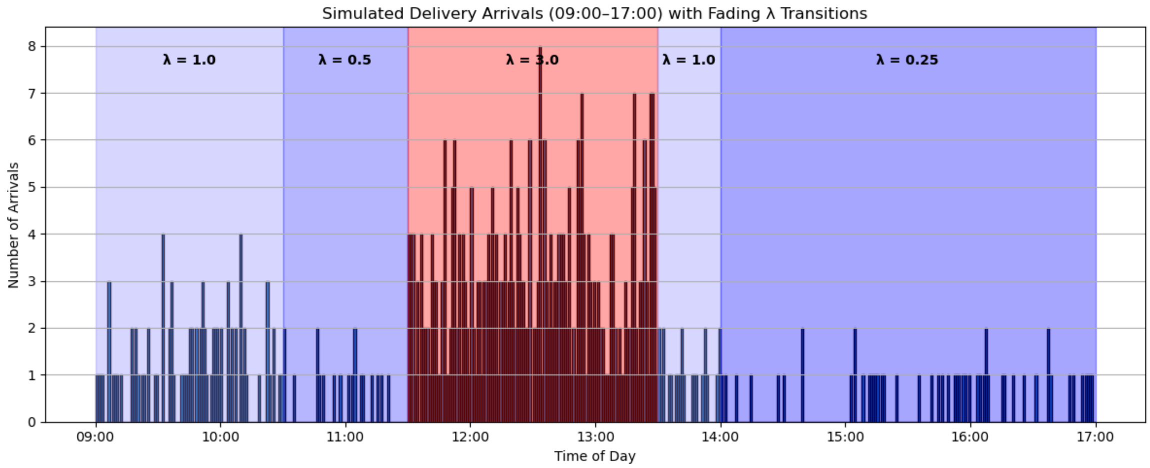

Figure 9. Time-varying $\boldsymbol{\lambda}$ values for delivery request generation. This illustrates how a non-homogeneous Poisson process better captures real-world demand dynamics.

Although the simulation environment abstracts away some real-world complexities, the modular structure of the models facilitates integration with logistics information systems and allows adaptation to specific regulatory or operational constraints.

4.3 Simulation Results

To establish a performance baseline, a fleet composed of three drones and three ground robots was simulated using the *first_available* dispatch policy. This policy assigns tasks to the next available vehicle, regardless of efficiency or type. Although simple, it serves as a reference for comparing more strategic alternatives.

Four dispatching policies were tested using the same fleet configuration:

- **first_available**: assigns the next free vehicle.
- **fastest**: selects the vehicle with the shortest estimateddelivery time.
- **efficient**: prioritizes the vehicle with the lowest projected energy cost.
- **balanced**: uses a weighted score combining delivery time and energy consumption.

Table 3 summarizes how different dispatching policies influence system performance using a baseline fleet configuration. These values directly support the subsequent optimization stage. The *first_available* policy yielded the shortest wait time but the highest energy consumption. In contrast, the *efficient* policy reduced energy use at the cost of longer delays. The *balanced* strategy offered the best compromise.

Table 3. Autonomous Vehicle Specifications

Policy	Mean Wait Time (s)	Total Energy Used
first_available	3,891.91	514,515.69
fastest	4,578.96	508,024.83
efficient	4,626.57	478,108.11
balanced	3,991.24	471,085.06

The simulation highlighted trade-offs between delivery time and energy. Ground robots were more efficient for heavier packages due to their larger capacity and batch capability, while drones achieved faster response for lightweight or urgent orders. These findings support the need for simulation-based optimization to fine-tune fleet composition and dispatch strategies, as discussed next.

4.3 Optimization Results

To further enhance system performance, a simulation-based optimization was conducted using the *balanced dispatch* policy, which previously showed the most favorable trade-offs. The objective was to minimize a composite score that integrates both delivery responsiveness and energy efficiency, defined as:

$$Score = \alpha \cdot Mean\,Wait\,Time + \beta\,.\,Total\,Energy\,Used$$

With weighting coefficients α = 1.0 and β =0.001, adjusting for the magnitude difference between the metrics to reflect equal importance of both performance dimensions.Simulated Annealing was selected as the optimization engine due to its suitability for exploring large, stochastic, and discrete search spaces. The algorithm was initialized with 3 drones and 3 ground robots, a temperature of 1000, a cooling rate of 0.95, and a maximum of 1000 iterations or 300 seconds of runtime. The number of drones and ground robots were the decision variables.

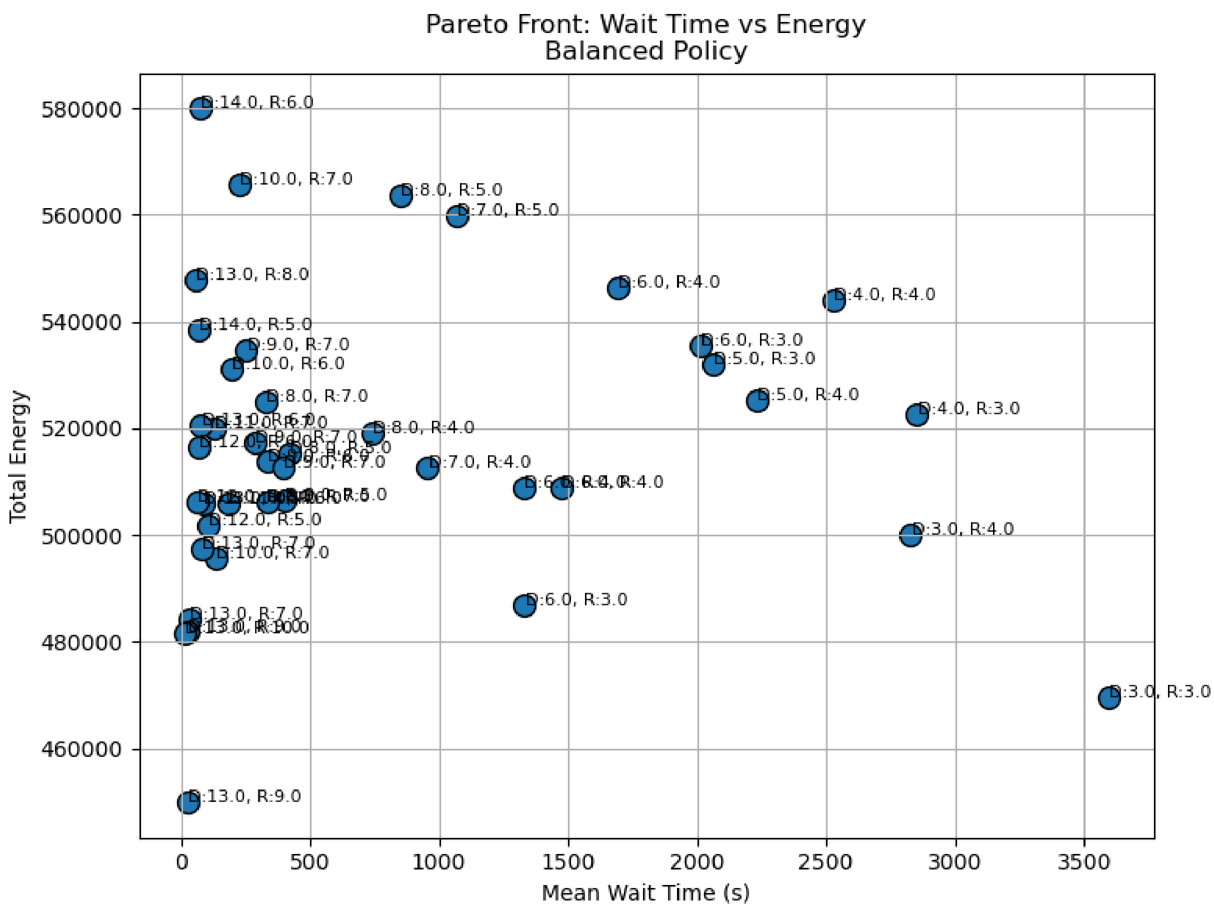

Figure 10. Pareto frontier of fleet compositions using the *balanced* dispatch policy. Labels indicate the number of drones (D) and ground robots (R).

Figure 10 shows the Pareto frontier of tested configurations. Each point reflects a specific combination of drones (D) and ground robots (R), highlighting trade-offs between wait time and energy use. The best result included 13 drones and 9 ground robots, achieving a mean wait time of 26.47 seconds and total energy usage of 449,819 units, corresponding to a composite score of 476.29.

Compared to the baseline (3D+3R, *first_available* policy), which resulted in 3891.91 seconds of delay and 514,515 energy units, the optimized fleet achieved a **99.3% reduction** in wait time and **12.6% less energy usage**. These results confirm the value of simulation-based optimization in identifying high-performance configurations early in the design process.

These findings demonstrate that the proposed methodology effectively supports early-stage system design by integrating architectural modeling, simulation, and optimization in a coherent workflow. The use of Arcadia artifacts ensured traceability between system needs and implementation logic, while simulation-based optimization enabled the identification of fleet configurations that would be difficult to obtain through heuristic or isolated analysis. This approach not only improved performance metrics but also enhanced design confidence by allowing decision-makers to explore trade-offs grounded in operational behavior and architectural structure.

6. Conclusions

This study proposed a hybrid methodology that integrates Model-Based Systems Engineering, discrete-event simulation, and simulation-based optimization to support the design of autonomous last-mile delivery systems. By applying the Arcadia method and documenting models with UML, the approach ensures traceability from stakeholder needs to architectural design and performance evaluation.

A case study in a gated environment validated the methodology. The simulation phase enabled quantitative assessment of delivery strategies and fleet configurations under dynamic demand and energy constraints. The comparison of dispatching policies revealed key trade-offs between responsiveness and energy usage. Furthermore, the use of Simulated Annealing allowed for the exploration of a large, discrete solution space and identified fleet configurations that substantially outperformed the baseline scenario, reducing average wait time by 99.3% and energy consumption by 12.6%. Beyond these quantitative improvements, the study contributes a replicable methodology that links MBSE artifacts to simulation and optimization layers, offering a systematic way to explore operational impacts of architectural decisions. This connection is particularly relevant for early-stage projects involving autonomous systems, where design errors are costly and operational constraints are complex.

Future work may expand this framework in several directions. First, a broader comparison with other metaheuristic optimization methods (e.g., Genetic Algorithms, Particle Swarm Optimization) could offer further insights into solution quality and convergence behavior. Second, sensitivity analyses can help quantify how changes in key parameters, such as vehicle autonomy, dispatch rules, or demand profiles, affect performance and robustness. Third, the methodology could be extended to more complex topologies (e.g., multi-gate or multi-hub systems) and real-time dispatching scenarios. Finally, exploring integration paths with existing logistics management platforms may facilitate the transition from simulation to deployment, enabling digital continuity in real-world implementations.

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Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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Biographies

Leonan Entringer Falqueto is an officer in the Brazilian Air Force with background in military aviation, remote sensing, and operational research. He completed his military pilot training at the Brazilian Air Force Academy from 2005 to 2008, graduating through the Officer Training Course for Aviators (CFOAV). From 2009 to 2016, he served on active duty in maritime patrol aviation, conducting search & rescue and surveillance missions over strategic areas of the South Atlantic. He holds a master's degree in Remote Sensing and Maritime Surveillance from the Graduate Program in Space Science and Technology (PG-CTE), a joint initiative of ITA, IEAv and IAE. His research focused on Automatic Target Recognition (ATR) using Synthetic Aperture Radar (SAR) imagery. Between 2019 and 2022, he was assigned to the Institute of Operational Applications (IAOp), under the Air Force's Operational Command (COMPREP), where he developed expertise in simulation, operational research, and systems engineering. Since 2023, he has been a Ph.D. candidate at the Instituto Tecnológico de Aeronáutica (ITA), with research interests in model-based systems engineering (MBSE), simulation, and optimization techniques applied to complex defense, surveillance and logistics scenarios.

Dr. Christopher Shneider Cerqueira received a B.Sc. in Computer Engineering from the Federal University of Itajubá (UNIFEI) in 2010, and an M.Sc. in Space Engineering and Technology from the National Institute for Space Research (INPE) in 2014. In 2018, he completed his Ph.D. at INPE, concentrating on integrating Tangible User Interfaces with Model-Based Systems Engineering (MBSE) for complex space missions. He has more than 15 years of experience in digital engineering, systems-of-systems analysis, and aerospace systems design. Dr. Cerqueira has collaborated with major international institutions, including NASA, through the SPORT mission, and has led multiple funded research projects sponsored by Brazilian space and defense agencies. He is currently a Tenured Assistant Professor in the Aerospace Engineering Department at the Instituto Tecnológico de Aeronáutica (ITA), where he coordinates a national research network on MBSE for critical systems. He has published extensively in peer-reviewed journals and international conferences on systems architecture, digital transformation, and engineering education, and has advised over 30 graduate and undergraduate theses. His research interests include AI-assisted systems engineering, formal methods for safety-critical systems, and integrated digital frameworks for certification and operational readiness.