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IMPARTING ADAPTIVENESS AND RESILIENCE TO PARCEL DELIVERY NETWORKS: A DIGITAL TWIN CENTRIC SIMULATION BASED APPROACH

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ABSTRACT

Contemporary parcel delivery companies face a significant surge in demand, along with increased customer expectations for flawless and timely delivery. They must meet these expectations within a shrinking window of opportunity in an increasingly competitive world while dealing with various micro and macro level uncertainties. Current industry practice relying on localized analysis to meet these expectations has turned out ineffective. This paper argues that imparting adaptiveness and resilience to parcel delivery network is the key to a pragmatic solution. It presents a holistic approach based on simulatable digital twins and composable agents to enable "in silico" business experimentation wherein a set of what-if scenarios are simulated to help evaluate efficacy of current strategy and identify suitable modifications to the strategy if necessary. The paper illustrates the proposed approach on a case study from the parcel industry and demonstrates its utility and efficacy on a set of real-life scenarios.

1 INTRODUCTION

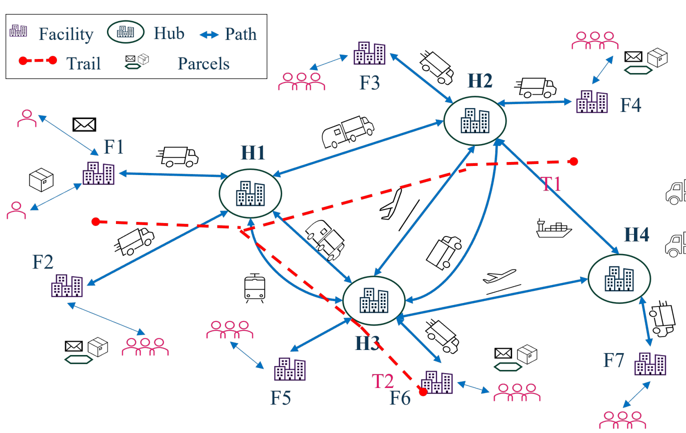
Increasing connectedness of the world is leading to a growing demand for efficient parcel delivery. As a result, the parcel delivery industry valued at USD 486.47 Billion in 2023 is projected to expand at a 4.2% CAGR to reach USD 648.84 Billion by 2030 (Steller Market Research 2024). However, as this growth comes with intensifying competition, the parcel delivery companies are experiencing a rapid narrowing of profit margins while customer expectations for flawless and punctual deliveries continue to rise (Orenstein and Raviv 2022). The uncompromisable commitment to delivering parcels promptly across vast geographic expanses poses a significant challenges for these companies. These challenges are compounded by the need for increasingly shorter delivery windows and the demand for efficient operations using optimal resources. Establishing a delicate balance between meeting customer demands and ensuring profitability in the face of the micro and macro uncertainties of the domain is paramount. At the micro level, parcel delivery companies grapple with challenges such as fluctuating parcel volumes, dynamic resource availability across facilities, and unforeseen disruptions within the network. Concurrently, they must navigate macro-level uncertainties, including evolving consumer preferences and shifting market trends in terms of new services and business models. As a result, adaptation and resilience emerge as two key properties of large parcel delivery companies for effectively managing the complexity and uncertainty.

Adaptation, in this context, refers to the ability of the network to adjust its strategies, operations, infrastructure and resources in response to changing environmental conditions such as fluctuating parcel volumes, evolving customer preferences, and unforeseen disruptions. It involves proactive decision-making for necessary changes to better network performance, enhance efficiency, improve service level commitments, and provide better services. Resilience, on the other hand, pertains to the network's ability to recover from disruptions or disturbances while maintaining its essential functions and services. Resilience involves building robustness into the network's structure and operations to minimize the impact of disruptions and enable swift recovery when disruptions occur. It expects continuous sensing and reactive changes to bounce back from disruptions and continue functioning effectively despite challenges.

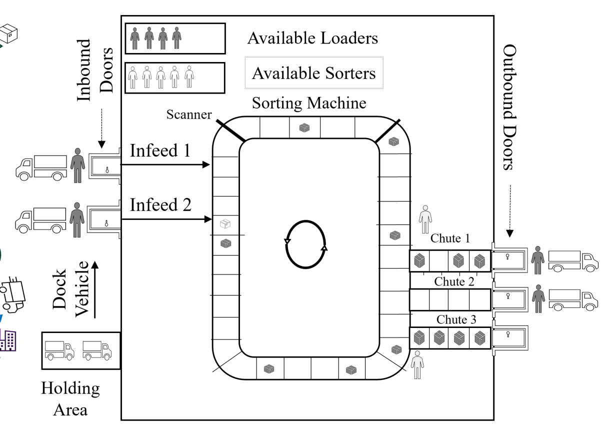
Balancing adaptability and resilience within parcel delivery networks requires consistent focus on two crucial loops: the resilience loop for sensing and recovering from undesired network states by adjusting the existing network, and the adaptation loop for foreseeing and extending the capacity or capability of the network to avoid undesired future conditions. While the resilience loop emphasizes network robustness, the adaptation loop demands extensibility and flexibility. However, achieving this equilibrium is complicated for large parcel delivery networks due to factors such as network size, heterogeneity in terms of nodes (i.e., facilities) and edges (paths connected through fleets), dynamism of the operating environment, and inherent uncertainty. Several trade-offs arise such as: enhancing the capacity of individual nodes versus extending topology of the network, investing in redundant resources for resilience versus optimizing resource utilization for adaptability, and prioritizing short-term efficiency versus long-term adaptability and resilience.

Currently, companies take decisions by focusing on localized context, such as operation within the facility (Ghosh et al. 2021), fleet management for a specific type of vehicle (Lin et al. 2018), and path planning for expected parcel volume. They consider a wide range of optimization techniques, bin packing approach, routing algorithms and so on. However, these locally optimal solutions fail to ensure global robustness and flexibility for the entire network (Govindan et al. 2017). Furthermore, these solutions frequently encounter challenges in scalability for handling large numbers of parcels and generally do not account for the inherent heterogeneity and uncertainty involved. More advanced AI-powered data-centric approaches, such as (Toorajipour et al. 2021), produce ineffective solutions when: (i) the available data is limited, (ii) the context is dynamic (thus posing a question mark on relevancy of data), and (iii) faced with unforeseen scenarios.

Drawing inspiration from the emerging field of digital twins (Grieves and Vickers 2017), wherein virtual replicas of physical systems are created to simulate behaviors in a virtual environment, this paper advocates for a paradigm shift from focusing on localized contexts to the entire parcel network to impart adaptiveness and resilience. At the heart of this holistic approach is the concept of a composite digital twin (Kuruppuarachchi et al. 2022), where digital twin of the network is a composition of constituent digital twins each catering to facilities, fleets, resources and so on. We use an extended form of agent / actor (Agha et al. 1997) formalism to implement constituent digital twins. Each of these digital twins is a set of autonomous interacting agents responding to their events of interest and taking suitable actions aimed at achieving their individual goals. We use the same agent / actor formalism to implement digital twin of the parcel network (i.e., composite digital twin) as a set of autonomous interacting agents where each of these agents represents the corresponding constituent digital twin. For the sake of clarity, we call these agents as composite agents. The simulatable nature of our digital twin facilitates in-silico experiments at various levels, ensuring both local and global properties. This empowers stakeholders to understand the bottlenecks within the existing network, explore alternative future scenarios, devise strategies to reduce bottlenecks, and prevent undesired future situations.



(a) Parcel Delivery Network



(b) Facility

Figure 1: A pictorial representation parcel delivery network and facility.

The rest of the paper is structured as follows: Section 2 introduces the context and correlates the parcel delivery network with the core concepts and properties of network theory. It also discusses the state-of-the-art modeling and analysis techniques, along with their limitations. Section 3 presents our contributions by introducing a simulatable model for representing the parcel delivery network digital twin and the adopted approach for constructing and effectively using it. Section 4 illustrates the proposed approach using a real-life scenario. The paper concludes with limitations and the scope for future work in Section 5.

2 MOTIVATION

2.1 Context

Postal delivery companies handle a significant volume of parcels, often in the magnitude of millions per day, transporting them from senders to receivers across vast geographical expanses. This operation is managed through a sophisticated network, Parcel Delivery Network (*PDN*), comprising strategically positioned facilities like collection centers, distribution centers, sorting terminals, and hubs, interconnected along predefined paths as depicted in Figure 1 (a). In this network, parcels are collected from designated facilities, moved along interconnected paths via various fleets such as trucks, tractors, rail, flights, and ships, and finally delivered to their intended destinations. Conceptually, the PDN is represented as a network with nodes representing facilities (F), and edges representing paths (P) connecting these facilities. Each facility is a unique self-organizing autonomous unit, while the paths have specific modalities like road, air, or water, along with distinct characteristics such as distance and geographical traits. Additionally, the PDN includes fleets or vehicles (V) that traverse dedicated paths, known as trails (T), making PDN a directed and temporal network. Facilities within the PDN are complex units responsible for various activities such as parcel collection, sorting based on parcel characteristics and destinations, and onward delivery by loading sorted parcels onto fleets or containers. Figure 1 (b) provides a visual representation of a typical facility. These facilities have a layout with holding areas, infeeds, scanners, sorting machine, and chutes to manage parcel movements efficiently. Facilities have autonomy to dynamically control operational factors, such as resource allocation including loaders and sorters, sorting machine configuration, and engaging and allocating chutes for specific destinations to optimize key performance indicators (KPIs) including parcel throughput, dwell time within the facility.

The overall performance of the PDN, measured through KPIs like rate of on-time parcel delivery, average delay time, parcel transit time, fleet utilization, and average of facility-specific KPIs, relies heavily on the capacity of facilities, existing paths and their characteristics, trail definitions, and number of fleets and their characteristics. Here, adaptability in a PDN is achieved by adding new facilities (F), paths (P), or fleet (V) types, while resilience is enhanced by rebalancing network by redefining trails, resource adjustments, and reconfigurations of facility related parameters. Adaptations and resilience for facilities can include introducing or changing sorting schedules, destination chute assignment, resource assignments, and infrastructure reconfigurations like recirculation count (Barat et al. 2022). However, deciding effective changes for facility and network level adaptation and resilience presents significant challenges due to the large number of heterogeneous facilities, frequent change of parcel volumes, uncertainties along fleet availability, disruption in the path and resource availability, and various other factors . The remaining part of this section delves into the core concepts and fundamental properties of PDN, and the state-of-the-art techniques considered to achieve desired KPIs alongside their limitations.

2.2 Foundation of Parcel Delivery Network

Conceptually, PDNs can be formed by categorizing facilities into collection centers (C) and distribution centers (D) and connecting them as a *bipartite graph*. While this setup can ensure timely parcel delivery, it is not logistically and economically viable for a company aiming to deliver a high volume of parcels across multiple destinations. A conventional *regular network* where facilities are connected only with their neighbor facilities results in long *characteristic path lengths*, leading to potential delays and operational losses. These networks also lack resilience, making them vulnerable to disruptions in facilities or paths. Adding paths between frequently connected facilities as suggested by the *Watts-Strogatz* (WS) model (Watts and Strogatz 1998) improves adaptability but struggles with sudden parcel influxes, impacting resilience negatively. A *scale-free network* (Barabási and Bonabeau 2003) with a *Core-Periphery* (CP) structure (Borgatti and Everett 2000), conforming to the power law and *small-world* properties of network theory, enhances resilience but may underutilize some hubs, necessitating cost optimization. Similarly, a dense core enhances adaptability but risks fleet underutilization.

For practical reasons, geographically central facilities with multiple transportation options gain strategic importance. Exemplifying the *rich-get-richer* principle in network theory, they form dense clusters with high local *clustering coefficient* and multiple *triadic* relationships. However, multiple such clusters with low inter-cluster connectivity elevate the *betweenness* property of specific facilities in H (bridge facilities between clusters), potentially reducing network resilience and causing bottlenecks. Therefore, balancing and rebalancing the core topology by meticulously evaluating the capability and elasticity of core facilities (H) alongside the parcel load of the entire network is crucial to ensure resilience. Predictions about future parcel loads and potential disturbances across the network must be intricately correlated with different core properties to establish PDN adaptability.

2.3 State-of-the-Art Techniques

The logistic network has been extensively studied in the supply chain literature for over four decades (Hearnshaw and Wilson 2013; Mangiaracina et al. 2015). Two broad aspects are prominent in the literature: distribution network structure and operational policies. The distribution network structure focuses on defining and extending the network and its elements, such as facilities and fleets. Their explorations, which are pertinent to our study, include factors like the number of facilities needed for a distributed network, their optimal locations, demand allocation, and capacity planning. The supply chain literature also delves into echelon definition to align the network structure with different phases of the supply chain, but this aspect is less relevant to our research. In contrast, operational policies and decision-making activities include configuring established networks and facilities. Their key exploration areas are transport routing design, path planning, fleet allocation and planning, fleet loading and packing, and resource allocations. Additionally, they extensively explore inventory-related aspects such as replenishment and optimum inventory levels, which are less relevant to our research focus.

In terms of modeling and analysis techniques, the literature predominantly leans towards mixed-integer programming models (Vidal and Goetschalckx 1997) with various algorithmic formulations, including linear or non-linear and single or multi-objective functions. Other mathematical approaches, such as Ant Colony Optimization (Barcos et al. 2010) and fuzzy goal programming (Selim et al. 2008), are also explored. Simulation is considered in limited contexts (Chan 2006; Barat et al. 2022), primarily to predict the impacts of specific interventions on distribution network performance within localized contexts.

From an analysis objective perspective, the literature prominently focuses on single objective functions. The exploration of multiple objective functions is less explored. There are limited instances of multi-objective models that primarily consider cost as one factor and different service level criteria like timely delivery as another for tradeoff. These models aim to identify the best trade-offs between objectives. For example, Melachrinoudis et al. (2005) proposed a multiple criteria optimization model for minimizing annual operating costs while maximizing customer service. Similarly, Sabri and Beamon (2000) developed a multi-objective model to solve the supply chain planning problem, taking into consideration cost minimization, fill rate maximization, and the maximization of delivery flexibility.

The key limitations of these approaches are manifold. Firstly, many techniques focus on limited contexts, such as individual facilities or fleet management, for context-specific local optimization without considering network-level global factors. Secondly, most of the mathematical approaches are not cognizant of the associated heterogeneities of the elements, such as a wide range of parcel characteristics and fleet types, and the inherent uncertainties of PDN. Lastly, most analyses rarely consider more than two

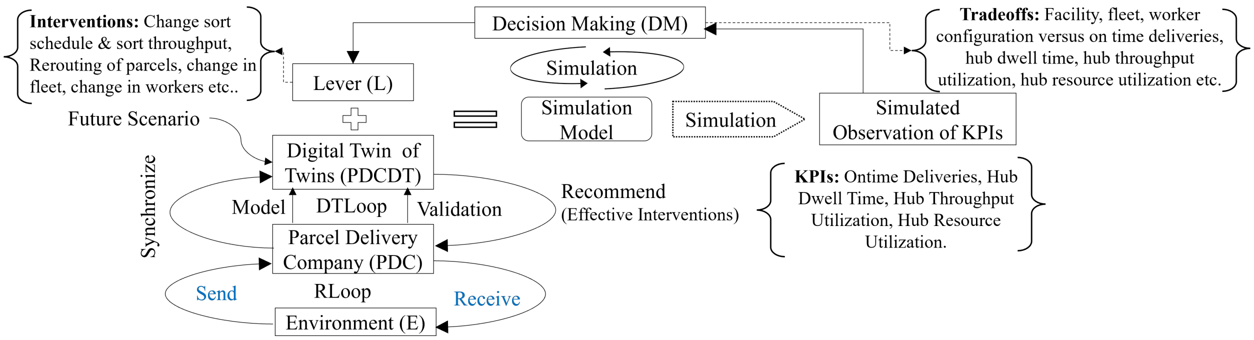


Figure 2: Our Approach - digital twin based exploration.

objective functions and trade-offs, and they struggle to scale beyond certain levels, necessitating the use of approximation techniques. Grossly approximated approaches fail to produce effective solutions for large and complex PDNs.

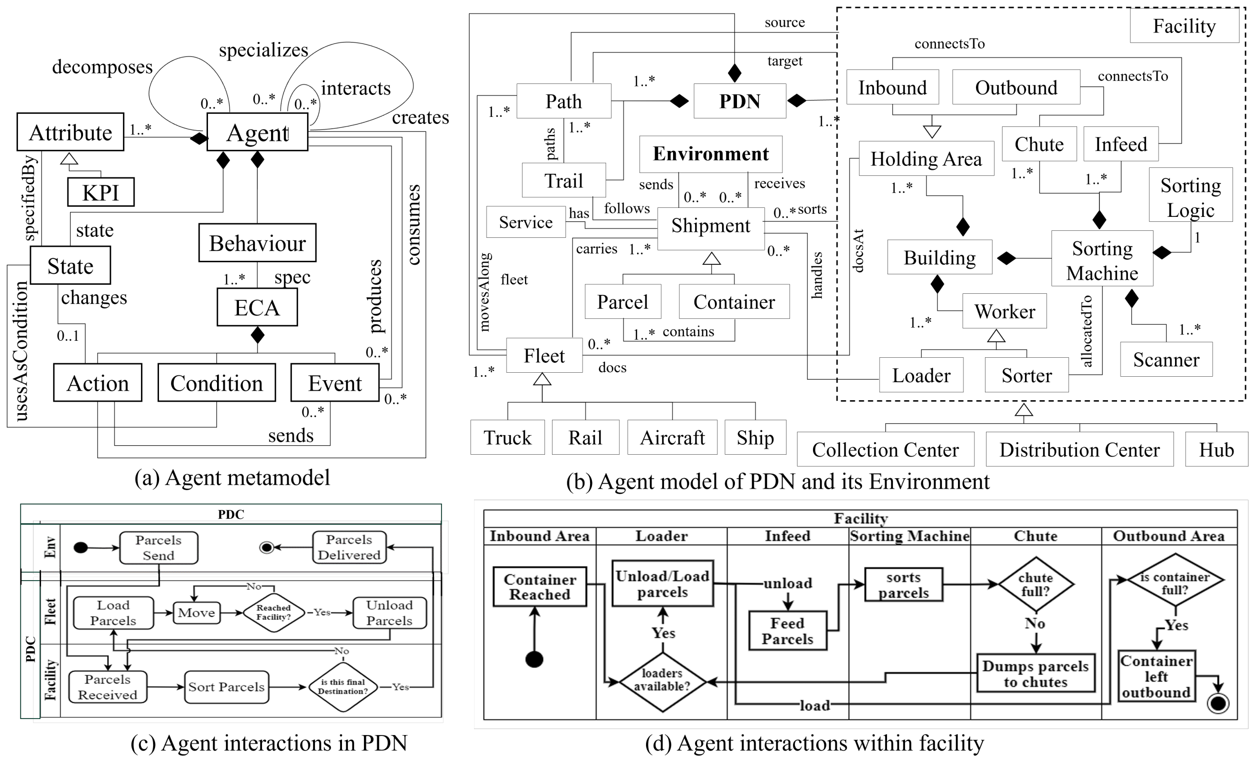
3 PROPOSED APPROACH

Contemporary parcel delivery companies require a comprehensive understanding of their network structure and operational policies. Furthermore, these aspects should be aligned and complementary to each other to achieve the desired adaptability and resilience in the best possible way. While existing techniques play a critical role in comprehending and optimizing specific aspects or properties in a localized context, achieving global optimality and addressing trade-offs remains a challenge. Our aim here is to analyze both network structure and policies within the same framework and evaluate the effectiveness of localized changes pertaining to one or both aspects in a holistic context for justification-based informed decision-making for resilience and adaptation.

We adopt a concept of composite digital-twin-based, an advanced agent-based modeling and simulation technique for quantitative analysis, and in-silico scenario explorations considering the entire network. The proposed approach, depicted in Figure 2, considers two loops: the reality loop (RLoop) and the digital twin loop (DTLoop). RLoop represents the real interactions between the parcel delivery company (PDC) and its environment (E). These interactions include the sending and receiving of parcels by individuals, organizations, and other PDCs. The DTLoop is an in-silico loop for system understanding and exploring what-if scenarios that include comprehending the potential causes for bottlenecks, predicting future trends, and evaluating the efficacies of potential interventions. Our key contributions here are the construction of a digital twin of PDC (termed as PDCDT) and establishing necessary links with RLoop to adequately replicate the PDC, and also leveraging PDCDT effectively towards informed decision-making.

Conforming to our method for applying the digital twin concept in decision-making of socio-techno-economic systems (Barat et al. 2022), we follow a 4-step process to construct and use PDCDT. The method starts with adequately modeling or mimicking the PDC and its environment into a simulatable agent model, which we term as PDCM. We employ a simulatable agent abstraction that extends the canonical form of an agent (Agha et al. 1997). This simulatable form of the specification facilitates scenario explorations. The next step delves into the validation of PDCM, where we use conceptual validity and operational validity as suggested by Robert Sargent (Sargent 2010). Conceptual validity is a qualitative step and is performed by explaining the model elements and their behaviors to domain experts and incorporating their views. Operational validity, on the other hand, is established by setting up the model to the historical state, simulating it with representative real interventions, and comparing simulated KPIs with system KPIs.

Once the PCDM is validated, it is expected to be synchronized with the real system (i.e., data from RLoop). We set up a link to ensure the continued/on-demand synchronization of the digital model with the real system. A validated and synchronized PCDM forms PDCDT. We leverage this PDCDT to enable simulation loop (as shown in Figure 2) to explore different means (referred to as levers) to understand



(a) Agent metamodel

(b) Agent model of PDN and its Environment

(c) Agent interactions in PDN

(d) Agent interactions within facility

Figure 3: Metamodel and models representing parcel delivery company.

the root cause of bottlenecks and explore potential solutions to address them. A wide spectrum of levers can be evaluated by introducing levers (L) to PDCDT and comparing simulated KPIs through multiple simulation runs. After exploring potential levers, the best lever, set of levers, or sequence of levers can be recommended to the PDC. This helps address resilience-related criteria. We use the same simulation loop for adaptation-related explorations, where possible disruptions and future scenarios can be emulated by conceptualizing future scenarios as levers and populating the PDCM with the future state, as shown in Figure 2, to explore effective adaptation-related interventions. The remainder of this section introduces an agent metamodel, derived from our previous work, which we use to represent the digital twin of PDC, the digital model of the PDC, and a realization of the PDC digital twin.

3.1 Agent Metamodel

The agent metamodel of our extended form of agent abstraction is depicted in Figure 3 (a). Our extended agent can hierarchically compose multiple agents or decompose into fine-grained agents at any level to sufficiently represent elements of complex systems, including those exhibiting the system-of-systems notion. An agent can be specialized to represent different types of elements capturing their heterogeneity and variations, such as facilities with different configurations and capacities, types of fleets, and types of parcels and services. These agents interact with each other through sending and receiving events. For example, a fleet can notify its arrival event to the facility where it has arrived, or a facility can send an event to its loaders for parcel pickup.

Internally, an agent encapsulates a set of attributes, its state, and behavior, where the value space of the attributes defines the state. The behavior of an agent is defined using a set of ECA specifications: If an event occurs and a condition on the state space is satisfied, then perform an action. An action can change the state space of the agent, send events to its own or other agents, create new agents, or perform a combination of these possible types of actions. We make an agent probabilistic by associating probability values with the action specification, i.e., perform action a1 with probability x1, a2 with probability x2, and so on. Further, we make the agent specification temporal by considering internal or external events explicit to the agent, for example, the end of a day or hour. In this specification, certain attributes of an agent can represent KPIs of the elements, such as KPIs of facilities, fleets, and PDN. This enhanced notion of agent abstraction allows us to capture the intricacies of the constituent elements of the PDC and its environment. The stochastic behavioural specification is one of the crucial aspects for capturing the inherent uncertainties and randomness of PDN elements, while temporal behaviour allows us to model time-dependent activities, such as parcel delivery times or facility processing rates.

3.2 Parcel Delivery Network Model

A parcel delivery company (PDC) can be effectively represented (PDCM) using three fundamental entities: Environment (E), PDN, and parcels/shipments (S), i.e., $PDCM$ is tuple $< E, PDN, S >$. The environment entity (E), which mimics the PDC's environment (refer to RLoop in Figure 2), is responsible for sending parcels and shipments (S) with distinct characteristics such as weight, size, shape, destination, and delivery service options like normal, priority, or 1-day delivery to the PDC. The PDN orchestrates the delivery process, which further can be defined using three elements: Facilities (F), Paths (P), and Fleets (V), i.e., a tuple $< F, P, V >$. Facilities and fleets are dynamic and autonomous entities, while paths, connected through the movement of fleets, act as directed links between two facilities, represented as $p =< f_i, f_j, v_k >$ where f_i, $f_j \in F$, $v_k \in V$. In this topology, facilities with multiple incoming paths and at least one outgoing path represent Hubs (H). The set of hub facilities H form the core of the PDN. Facilities with no incoming paths are typically termed as Collection centers (C), and facilities having no outgoing paths serve as destination centers (D). Facilities with fewer incoming and outgoing paths, including those from C and D, form the periphery of the PDN. It's important to note that any facility, irrespective of whether it belongs to C, D, or H, may receive parcels from E and dispatch parcels to E. Facilities from C and D exhibit specialized behavior compared to other facilities, while facilities from H also exhibit specialized behaviors to route a high volume of shipments to a large number of destinations. In addition to these topological concepts, the PDC uses the concept of a Trail (T), where each trail represents a sequence of paths. These trail definitions help orchestrate parcels and shipments (S) through the PDN.

We use our composable, parameterized, and simulatable agent abstraction to represent PDCM, which includes the environment, PDN, and various types of parcels and shipments (S). A schematic view of the agent topology is shown in Figure 3 (b). The Environment is an agent that acts as a parcel and shipment feeder to the PDN. Each parcel is represented using an agent whose attributes capture the heterogeneous characteristics of the parcel, such as weight, size, shape, and delivery service, along with its source and destination facilities. We consider a shipment as a composite agent that contains multiple parcel agents with the same destination. In this formation, environment agent can produce heterogeneous parcel and shipment agents in a specific order and interval either by conforming to parcel flows of the real system (i.e., collected from RLoop) or by depicting future or disrupted scenarios (as shown in Figure 2). For example, potential fluctuations in daily parcel flows, different parcel mix, different combination of parcel destinations and their arrival sequences can be introduced into the PDN for experimentations.

The PDN agent is a composite agent that contains facility agents and fleet agents through composition relations. It also captures paths and trails as attributes of the PDN agent (as they are not active elements). A path is captured as a list type attribute, and a trail is represented using a table structure. We make these compositions and attributes configurable through parameterization to introduce and remove paths and facilities to the PDN and define/redefine trails (conforming to path definition) to adjust and configure parcel orchestrations. Here, the behavior of the PDN is not explicitly specified; rather, it emerges from the behaviors of its constituent elements. The key interactions between the Environment and PDC, along with the interactions between facility and fleet agents within the PDC are shown using a swimlane diagram in Figure 3 (c). Essentially, as depicted in the figure, shipment agents originating from the environment agent move from one agent to another while navigating involved facilities and fleets of respective trails,

Table 1: Illustrative configuration.

Facility No	Facility Type	Inbound Doors	Outbound Doors	Chute Capacity (# of parcels)	Machine capacity (# of parcel)	Sort Schedules (Timing and Throughput)					
						Dawn (D)	Moonlight (M)	Noon (N)	Prime (P)	Sunset (S)	Evening (E)
F1	Ground Hub	40	110	1000	30000	.	[23,3:5000]	[10,14:5000]	[5,9:5000]	.	[17,21:5000]

Trail key	Origin Facility Number	Delivery Facility Number	Trails	Sorts	Service	Parcel Mix (Fraction)	Trail Volume (# of parcels)
T1	100	1000	[100, 110, F1, 1000]	['.', 'E', 'M', 'P']	Ground	0.7:0.2:0.1	1500
T2	101	800	[101, 109, 500, F1, 800]	['.', 'D, 'N', 'E', 'P']	Ground	0.7:0.2:0.1	500

which originate from the source facility and lead to their intended destination facility. In these transitions, container agents, such as fleets and facilities (along with their constituent agents), manages where and when these shipments will move to the next destination, how they will be sorted, and how much time they will take for sorting and so on. As depicted in Figure 3 (b), a facility is another composite agent that composes a set of agents representing its structural elements, such as inbound and outbound holding areas, constituent machines and assets like sorting machines, and different types of workers including loaders and sorters. The constituent agent representing the sorting machine is also a composite agent that contains agents representing its parts including infeeds, chutes, and scanners. The sorting machine also contains passive and configurable elements, such as sorting logic. The sorting logic orchestrates the parcel sorting by assigning destination chute of a parcel, which conforms to its trail definition. The agent behaviour for orchestrating shipment movements within a facility is depicted in Figure 3 (d). Similar to the Facility agent, Fleet is another active element in PDN, which is represented using a composite agent. It moves along the paths and can dynamically contain parcels that come in and go out based on their trail-definitions. Different modes of fleets can be described as truck, rail, air and ship. The further specializations are possible to introduce specific type of the vehicle, such as small, medium and large trucks.

3.3 Experimentation

The simulation capability of our agent-based model is essential for conducting what-if analyses to achieve resilience and adaptation-related criteria. By synchronizing the constructed PDCM with real data from RLoop and simulating PDCDT, we can understand possible bottlenecks and disruptions in PDC along with their root causes. Moreover, levers can be configured to represent disrupted situations, and observation of simulated KPIs can help understand the impact of disruptions on PDC. For example, the impacts of traffic congestion or facility breakdowns on overall PDN performance can be experimented with to develop proactive strategies and mitigate risks from such disruptions.Furthermore, by simulating hypothetical scenarios and assessing their impact on KPIs such as on-time delivery rates or resource utilization, our approach facilitates informed decision-making for enhancing adaptation capability.

Our digital twin and supporting simulation capability can explore changes in both network structure and policies. This includes the ability to explore different types of facilities and fleets, create new network formations using new paths, and modify the core structure by adding or removing hubs. From a policy perspective, our simulation allows for the exploration of new trails, different resource allocation strategies, and various sorting logic effectively. Our simulation assesses the impact of these changes both locally and across the entire network by observing KPIs associated with local entities like facilities and fleets, as well as global KPIs associated with the PDC agent. Through multiple explorations and comparisons, we can establish trade-offs and identify globally optimal solutions.

3.4 Implementation

We employed our actor/agent-based language, ESL (Clark et al. 2017), to define the PDCM in a format suitable for simulation, and in the process of making it commercially available through our product, TwinX

Table 2: Experimentation observations.

Scenario		Maximum Hub Capacity Utilization Rate (F1)		On-Time Delivery Rate		Average Package Transit Time (days)		Package Throughput Utilization (F1)		Average Dwell Time(hours)	
As-is		87.55%		99.99%		2.54		73.03%		5.7	
An illustrative disruption											
Scenario 1 : Disruption situation		98.63%		76.31%		7.94		84.63%		56.48	
Exploring alternatives to address disrupted situation (explorations for resilience)											
Scenario 2 : Intervention of adding new Sort		95.33%		99.3%		3.42		67.67%		27.26	
Scenario 3 : Intervention of increasing sorting capacity		97.56%		99.97%		2.62		60.46%		7.35	
Scenario 4 : Intervention of diverting path		95.78%		99.99%		2.53		73.28%		6.1	
Scenario 5 : Scenario 1+ Scenario 2 + Scenario 3	A	100%		42.16%		6.21		46.10%		104.61	
	B	100%		58.56%		5.03		48.27%		66.63	
Exploring resource allocation and network optimization (for adaptation)											
Scenario 6 : Scenario 5 (A) + 50% increase in Loaders		78.09%		99.98%		2.45		48.32%		2.76	
Scenario 7 : Scenario 5 (B) + 25% increase in Fleet		92.46%		99.98%		2.44		48.41%		2.85	
Scenario 8 : Remove Hub		Before F1 removal	After F1 removal	Before F1 removal	After F1 removal	Before F1 removal	After F1 removal	Before F1 removal	After F1 removal	Before F1 removal	After F1 removal
	F2	0.004%	32.90%	99.99%	99.99%	2.54	2.46	5.18%	31.34%	6.38	1.27

(Tata Consultancy Services 2022). We developed interfaces using Excel sheets and a user-friendly UI to configure the PDC, including parameters such as the number of facilities and fleets, their attributes, and paths. Additionally, we integrated four data extraction and injection plugins to capture the states of parcels, fleets, facilities, and resources. These plugins serve for synchronization between the real system and the PDCDT, specifically connecting the RLoop to DTLoop.

4 ILLUSTRATION

We illustrate the state-of-the-possibilities of our approach using a large-scale parcel delivery company (PDCX) that aims to improve on-time parcel delivery (which is related to customer satisfaction) while enhancing the utilization of facilities and resources (i.e., using operational costs effectively). Here, we first configure our digital twin to represent the as-is system of PDCX. Next, we introduce a disruption by emulating the arrival of high-volume parcels representing the festive session. Then, we explore a series of interventions to evaluate their effectiveness, showcasing the role of the constructed digital twin and its simulation capability in facilitating justification-backed informed decision-making.

4.1 Experimentation Setup

The experimental setup for our study focuses on a subset of PDCX, specifically centered around a major hub facility (F1). This subset comprises 857 facilities, 26,194 distinct parcel trails, and an approximate parcel inflow of 90,000 parcels per day. The network is constructed by considering ground delivery with normal priority service. We configured all involved facilities and fleets with values of the real facilities and fleets of PDC; a few sample values are shown in Table 1 for illustration (actual values are not shown due to confidentiality). Our simulation period spans 30 days.

4.2 Experimentation

Our experimentation encompassed a range of scenarios and interventions, all aimed at evaluating and improving KPIs of the PDC under different situations. Beginning with a baseline (as-is) scenario that represents the attribute values from the real system with regular business-as-usual operations, enabling a precise understanding of as-is system. Observation is captured in Table 2. Subsequently, we introduce

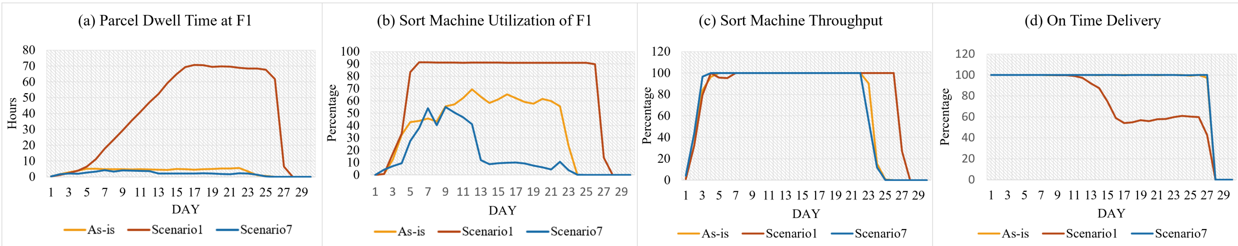


Figure 4: A comparison of As-is scenario, Scenario 1 and Scenario 7.

a disruption (Scenario 1), where the volume of selected parcel trails is increased by 5–10 times, which accounts to almost 38% of total parcel volume flowing through facility F1, to simulate peak periods and heightened parcel flows within the PDN. This scenario aims to evaluate the capacity of the PDC when demand is increased and identify any resulting bottlenecks or performance issues.

Comparing the "As Is" and "Disruption Scenarios" unveiled significant deviations in key performance indicators (KPIs). Notably, we observed an increase in dwell time under the disruption scenario due to congestion caused by the inflated parcel flow, by 8 times the time taken in as-is scenario (refer to Figure 4 (a)). Additionally, utilization graph in Figure 4 (b) shows that the sort machine of facility F1 experienced strain during peak periods, leading to almost 100% capacity utilization. In the disruption scenario, the throughput utilization of facility F1 (refer to Figure 4 (c)), indicates that the sort machine ran for extended durations, reaching maximum throughput consistently, compared to the as-is scenario where the machines operated at the same maximum throughput but for a shorter duration. Moreover, the disruption scenario demonstrated adverse effects on on-time delivery metrics by a huge decrement of almost 23% over a period of 30 days, highlighting the PDC's decreased ability to meet delivery deadlines during periods of heightened demand (refer to Figure 4 (d)). This decline in performance underscored the presence of bottlenecks within the PDC, impeding the smooth flow of parcel traffic and compromising operational efficiency.

Next, we pursue exploration of alternative strategies to mitigate these disruptions by simulating multiple scenarios to achieve a balanced network and address the identified bottlenecks effectively. To adapt to the increased parcel inflow, new sorting schedules were introduced to optimize the utilization of sorting resources. We added an additional sort schedule of 4 hours at facility F1 aiming to distribute the parcel load more evenly across available sort schedules. This resulted an improvement in overall on time delivery rate by almost 22% and reduced dwell times by 50% (refer to Table 2). We observed that extending sorting machine throughput capacity beyond standard rate helps to expedite parcel processing and reduce bottlenecks in the sorting process, thereby mitigating delays in delivery timelines. When we extended sort machine throughput capacity at Facility F1 by 15%, we observed notable improvement in overall parcel transit time and parcel dwell time at facility F1 when compared to the previous scenarios.

Furthermore, to address the challenges posed by overutilized facilities, we strategically rerouted the parcels to underutilized facilities for further processing. By redistributing 90% of the inflated parcel volume flowing through facility F1 to underutilized facilities, we sought to alleviate congestion and improve processing capacity in facilities experiencing high demand, thereby enhancing overall operational resilience. We also observed that the machine capacity utilization decreased markedly, addressing previous issues of overuse and resulting in reductions in both dwell time and parcel transit time. Moreover, the overall delivery rate saw a significant increase as a direct consequence of these operational optimizations.

We further explored alternative operational scenarios under resource constraints, by simulating two variations: Scenario (A), with a limited number of loaders, and Scenario (B), featuring a restricted fleet size, within the PDN. These simulations aimed to gauge the impact of resource limitations on operational performance. Augmenting loaders by 50% at facility F1 addressed resource constraints, bolstering parcel processing capacity during peak periods and resulting in significant improvements in on-time delivery rate, parcel transit time, and dwell time compared to Scenario (A). Similarly, increasing the fleet count by 25%

at facility F1 enhanced delivery capabilities, mitigating delays and enhancing timely delivery, leading to substantial improvements in on-time delivery rate, parcel transit time, and dwell time compared to Scenario (B). Identifying Facility F1 as overutilized within the PDN, we strategically retired it and redirected parcel flows to an underutilized nearby facility, Facility F2 (refer to Table 2). Leveraging its underutilized capacity ensured a smooth transition of parcel flows and minimized disruptions, with favorable outcomes observed in network-level KPIs such as dwell time and facility-specific KPIs including capacity and throughput utilization for both facilities.

Experimenting with these scenarios provided valuable insights into the effectiveness of various strategies for mitigating disruptions. The findings offer recommendations for optimizing PDN's operations and improving operational resilience to ensure timely parcel deliveries in dynamic environments.

5 CONCLUSION

We examined the intricate complexities faced by large parcel delivery companies by drawing on results from network theory and resilient adaptive systems. Having analyzed the state of art and practice, we showed its inadequacy in addressing the key needs of adaptiveness and resilience for the parcel delivery industry. We posited the digital twin concept and supporting technology as a means to overcome these gaps. We proposed a simulation-based data-driven justification-backed approach to evaluate existing strategy for meeting the stated goals and to identify suitable interventions if required. We illustrated utility and efficacy of the proposed approach using a complex use case from real-world. We encountered several challenges in constructing a hi-fidelity purposive digital twin of the parcel delivery network under consideration. For example, the available information such as parcel characteristics, fleet utilization data, resource availability, and resource productivity metrics was at best partial and pertained to what has happened and not to what could have happened. To overcome this limitation, we relied on domain experts to augment the existing information with a range of possibilities thus improving fidelity and completeness of the composite digital twin. Domain experts were able to ascertain correctness and completeness of the composite digital twin through a process of conceptual and operational validation. The digital twin thus validated was seen to be a significant advancement over analysis techniques that rely solely on past data for future predictions. We acknowledge the time-, effort- and intellect-intensive nature of digital twin construction process, and its vulnerability to the expertise of people involved. As part of our future work, we are actively exploring integrated use of Generative AI techniques to reduce the cognitive load of digital twin construction process and to improve the extent of automation thus enhancing scalability and efficiency of our approach.

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