IMPLEMENTATION OF DIGITAL TWIN OF LOGISTICS SUPPLY CHAIN BASED ON ANT-LOGISTICS FOR ASSESSING RESILIENCE TO PEAK LOADS

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Abstract. The paper proposes a framework for constructing a digital twin (DT) of a multi-node logistics supply chain using the ANT-Logistics cloud transport management system as the operational data layer. The DT architecture integrates a network of $M(t)/M/1/N$ queuing nodes with the real-time routing and GPS-monitoring capabilities of the ANT-Logistics TMS platform, which over a decade of deployment across more than 900 enterprises has documented 15-45% mileage reductions and up to 74% reductions in service-denial rates under surge conditions. The digital twin continuously ingests live telemetry exported via the ANT-Logistics REST API v2 and recalibrates Chapman-Kolmogorov state-probability equations governing each logistics node. The ant colony optimisation (ACO) controller redistributes cargo flows before congestion propagates chain-wide. Simulation experiments across 512 parameter scenarios varying non-stationary load amplitudes λ_1, queue capacities N, and ACO hyper-parameters demonstrate that the Ant-Logistics DT reduces peak-hour queue lengths by 44.9%, cuts service-denial probability from 9.2% to 2.1%, and raises average resource utilisation from 75% to 87.2% compared with static routing baselines. The results establish a reproducible methodology for resilience assessment of last-mile and distribution supply chains under volatile demand patterns.

Keywords: digital twin, logistics, supply chain, optimisation, stationary flow, peak load.

Introduction

The accelerating complexity of last-mile and distribution supply chains has exposed a critical gap between static routing models and the dynamic, non-stationary reality of cargo flows. Promotional peaks, seasonal surges, and geopolitical shocks routinely push logistics networks beyond their design envelopes, causing cascading queue build-ups that conventional transport management systems (TMS) cannot pre-empt [1]. Resilience – defined as the capacity of a supply chain to absorb demand disturbances and recover target service levels – has therefore migrated from a strategic aspiration to an operational engineering requirement [2].

Digital twins (DTs) have emerged as a paradigm-shifting instrument for bridging physical logistics operations and analytical decision models [3]. DT maintains a continuously synchronised virtual replica of a physical system, enabling real-time state monitoring, counterfactual scenario analysis, and closed-loop adaptive control. In logistics contexts, DT applications have ranged from warehouse layout optimisation [4] to intermodal terminal scheduling [5] and cold-chain integrity monitoring [6]. However, most published DT frameworks treat the routing layer as static or rely on heuristic rule sets, leaving unexploited the potential of bio-inspired optimisation algorithms to provide genuinely adaptive flow redistribution.

The ANT-Logistics platform - a cloud-based TMS developed in Ukraine and deployed across more than 900 enterprises in distribution, e-commerce, pharmaceutical, and municipal waste-collection sectors – embodies a practical instantiation of swarm-inspired logistics. The platform core routing engine employs unique mathematical algorithms that account for over 80 operational parameters, including time windows, vehicle capacity, road-segment travel-time forecasts, and real-time GPS deviation from the plan [5]. Its decade-long market track record provides an exceptionally rich empirical basis for calibrating a digital twin architecture.

Concurrently, queuing theory, and specifically the $M(t)/M/1/N$ formulation for single-channel systems with non-stationary Poisson arrivals, has been validated by the present authors as an accurate model for individual logistics service nodes such as loading bays, customs checkpoints, and distribution hubs [8]. The Chapman-Kolmogorov differential equations governing state-probability evolution under time-varying load revealed that even moderate non-stationarity amplitudes cause disproportionate degradation in queue length, waiting time, and service-denial probability - findings that motivate the present network-level DT extension.

The present paper therefore pursues three complementary objectives: (i) to formalise a digital-twin architecture that maps ANT-Logistics operational data onto a network of $M(t)/M/1/N$ queuing nodes;

(ii) to embed an ACO controller as the adaptive routing layer of DT; and (iii) to quantify resilience gains under peak-load scenarios through large-scale simulation.

Materials and methods

Queuing networks as models of logistics chains originate from David George Kendall's classification of service systems and the product-form network theorem developed by Frank Spitzer Jackson [8]. Extensions to non-stationary arrival processes summarized by Ward Whitt [9] are particularly relevant for logistics, where demand shows strong intra-day, weekly, and seasonal fluctuations. The $M(t)/M/c/K$ model, solved numerically through Chapman-Kolmogorov equations, captures such temporal variability without relying on steady-state assumptions typical for classical $M/M/c$ analysis [6; 8]. Recent studies by Rakesh Kumar [10] and Mykola Uryvsky together with Anastasiia Kryklyva [11] further extend queuing analysis to self-similar input streams and heterogeneous service channels [17].

Research on digital twins in logistics has expanded with the rise of Industry 4.0. Michael Grieves and John Vickers [3] formulated the conceptual triad of a physical system, its virtual model, and a bidirectional data connection that defines modern digital twin architectures. Later studies demonstrated practical benefits: Zhenyu Jiang implemented a port-logistics digital twin integrating IoT sensing with agent-based simulation, reducing vessel waiting time by 23%, while Thijs Defraeye applied digital twins to perishable supply chains by combining sensor telemetry with thermodynamic decay models. However, these approaches do not incorporate swarm-intelligence routing within the digital-twin control layer.

Ant Colony Optimisation (ACO), proposed by Marco Dorigo and Luca Maria Gambardella [12], addresses complex routing problems through pheromone-based search on network graphs. Subsequent developments, summarized by Marco Dorigo and Thomas Stützle [13] and extended by Rohit Joshi, show that ACO outperforms genetic algorithms and simulated annealing in dynamic vehicle-routing scenarios with volatile demand [5; 6; 18].

The ANT-Logistics platform has also been introduced into academic training. Nataliia Olkhova [14] reported improved employability among students trained with the system. Using queuing-network simulation, Hennadii Prokudin [15] and co-authors identified single-channel nodes as key bottlenecks in cargo delivery chains during peak load. Nevertheless, no previous research has developed a digital twin for ANT-Logistics or combined its operational telemetry with a formal queuing-network and ACO-based optimization model.

Mathematical model and digital twin architecture

Single-Node Queuing Model

Each logistics service node – a loading bay, depot gate, customs station, or delivery point - is modelled as an $M(t)/M/1/N$ queuing system. The arrival process is characterised by a time-varying intensity:

$$\lambda(t) = \lambda_0 + \lambda_1 \cdot \sin(\omega t + \varphi), \tag{1}$$

where λ_0 – baseline arrival rate (orders·min^{-1});
λ_1 – peak-surge amplitude;
$\omega t = 2\pi_i/T$ – angular frequency of the demand cycle;
φ – initial phase.

Service times are exponentially distributed with parameter μ, giving density $f(\tau) = \mu \cdot \exp(-\mu\tau)$. The time-dependent utilisation factor is:

$$\rho(t) = \lambda(t)/\mu \tag{2}$$

System stability requires that the cycle-averaged utilisation satisfies:

$$\bar{\rho} = \frac{1}{T}\int_0^T \rho(t)dt < 1 \tag{3}$$

The state probability vector $p(t) = [p_0(t), p_1(t), ..., p_N(t)]$ evolves according to the Chapman-Kolmogorov differential equations [16]:

$$\frac{dp_0}{dt} = -\lambda(t) \cdot p_0(t) + \mu \cdot p_1(t) \tag{4a}$$

$$\frac{dp_i}{dt} = \lambda(t) \cdot p_{i-1}(t) - (\lambda(t) + \mu) \cdot p_i(t) + \mu \cdot p_{i+1}(t), i = 1, \ldots, N-1 \tag{4b}$$

$$\frac{dp_n}{dt} = \lambda(t) \cdot p_{n-1}(t) - \mu \cdot p_n(t) \tag{4c}$$

with the normalisation constraint

$$\sum_{i=0}^{N} p_i(t) = 1 .$$

The key performance indicators derived from the state probabilities are defined in Table 1.

Table 1

Performance indicators of the $M(t)/M/1/N$ node model

Indicator	Symbol	Formula
Average queue length	$Lq(t)$	$Lq(t) = \Sigma_{i=1}^{N} (i-1) \cdot p_i(t)$
Mean waiting time	$Wq(t)$	$Wq(t) = Lq(t)/\lambda(t)$
Service-denial probability	$P_{rej}(t)$	$P_{rej}(t) = p_n(t)$
Time-averaged denial probability	$P_{rej}avg$	$\bar{P}_{rej} = (1/T) \cdot \int_0^T p_n(t)\,dt$

Network Extension and Digital Twin Architecture

A logistics supply chain is modelled as a directed graph $G = (V, E)$, where each vertex v in V represents a service node governed by an $M(t)/M/1/N$ queuing model, and each arc e in E represents a transport link with stochastic travel-time $\tau_e(t)$. The DT architecture consists of four coupled layers. Physical layer:

The live ANT-Logistics TMS deployment, exporting vehicle GPS coordinates, order completion events, and queue length estimates via the ANT-Logistics REST API v2 at 60-second polling intervals. State estimation layer: The Chapman-Kolmogorov solver ingests API telemetry, infers $\lambda(t)$ for each node using a sliding-window maximum-likelihood estimator, and integrates equations (4a-4c) forward over a 30-minute prediction horizon.

Control layer: The ACO routing engine evaluates pheromone-weighted arc costs and generates redistributed route assignments whenever any node's predicted $P_{rej}(t + \Delta t)$ exceeds the threshold $\theta = 0.05$.

Feedback layer: Validated re-routing decisions are injected back into the ANT-Logistics dispatcher console via the platform's route-import API endpoint, closing the control loop within one polling cycle.

This architecture is deliberately non-invasive with respect to the ANT-Logistics platform: it relies exclusively on documented public API methods and standard export formats, ensuring applicability to any enterprise currently using the Basic or Extended subscription tier.

Ant colony optimisation routing algorithm

The ACO controller maintains a pheromone matrix $T = \{\tau_{ij}\}$, where τ_{ij} represents the accumulated desirability of routing a cargo unit from node i to node j. At each decision epoch (every 60 s), a colony of $m = 50$ artificial ants constructs candidate routing solutions. The probability that ant k traverses arc (i, j) is:

$$p_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{1 \in J_i^k} [\tau_{i1}]^{\alpha} \cdot [\eta_{i1}]^{\beta}} \tag{5}$$

where $\eta_{ij} = 1/c_{ij}$ – heuristic desirability (inverse arc cost);
J_i^k – set of feasible successors for ant k at node I;
α, β – influence parameters controlling the relative weight of pheromone trail versus heuristic information.

The composite arc cost is:

$$c_{ij}(t) = w_1 \cdot \bar{\tau}_{ij}(t) + w_2 \cdot P_{rej,j}(t) + w_3 \cdot d_{ij} \tag{6}$$

where $\bar{\tau}_{ij}(t)$ – predicted travel time on arc (i,j) derived from the ANT-Logistics traffic-forecast module;
$P_{rej,j}(t)$ – current service-denial probability at destination node j from the DT state estimator;
d_{ij} – arc distance;
w_1, w_2, w_3 – weighting coefficients summing to unity.

After all ants have constructed solutions, pheromone levels are updated by global evaporation followed by elite-ant reinforcement:

$$\tau_{ij} \leftarrow (1-\rho)\cdot \tau_{ij} + \sum\nolimits_k \Delta\tau_{ij}^k \tag{7}$$

where $\rho \in (0,1)$ – evaporation rate;
$\Delta\tau_{ij}^k = Q/C^k$ if ant k used arc (i,j), with C^k being the total cost of ant k's solution;
Q – scaling constant.

Parameter values were determined through a grid search: $\alpha = 2$, $\beta = 3$, $\rho = 0.15$, $Q = 100$, $w_1 = 0.4$, $w_2 = 0.4$, $w_3 = 0.2$.

Simulation design and results. Experimental Design.

The logistics network used for simulation consists of seven nodes: one central distribution depot (Node 0), three intermediate transit hubs (Nodes 1-3), and three terminal delivery zones (Nodes 4-6), interconnected by twelve directed arcs. This topology is representative of a mid-scale FMCG distribution network as documented in ANT-Logistics deployment case studies (e.g., FAYNO Group, KRON, Raiffeisen Bank Aval cash-collection service). The following parameters were varied in a full-factorial design:

- base arrival intensity λ_0: 0.5, 1.0, 1.5, 2.0 orders·min^{-1};
- peak-surge amplitude λ_1: 0.0, 0.2, 0.4, 0.6 orders·min^{-1};
- service intensity μ: 1.0, 1.5, 2.0, 2.5 orders·min^{-1} per node;
- node queue capacity N: 5, 10, 15, unlimited.

This yields 4x4 = 256 baseline scenarios. Each scenario was run under two routing regimes – static ANT-Logistics plan-route (control) and DT-guided ACO re-routing (treatment) – producing 512 simulation runs. Each run covered $T = 480$ min (one working shift), with Chapman-Kolmogorov integration performed at $\Delta t = 1$ min resolution using the SciPy odeint solver.

Baseline Results: *Impact of Non-Stationary Load*

Table 2 reproduces key aggregate results for the reference node (Node 0, $\lambda_0 = 1.5$, $\mu = 2.0$, $N = 10$), extending the single-node findings of the authors' prior work [18] to the network context.

Table 2

Node-level performance as a function of peak-surge amplitude (λ_0 = 1.5, μ = 2.0, N = 10)

λ_1, orders·min^{-1}	Avg. queue length Lq	Avg. waiting time Wq, min	Failure probability P_{rej}	Loading $\bar{\rho}$
0.0	2.14	1.43	0.018	0.750
0.2	2.36	1.57	0.024	0.751
0.4	3.12	2.08	0.047	0.753
0.6	4.58	3.05	0.092	0.754

The results confirm that non-stationarity disproportionately degrades queue performance: doubling λ_1 from 0.2 to 0.4 increases P_{rej} by 96%, and the step from 0.4 to 0.6 nearly doubles it again.

ACO Digital Twin Intervention Results

Table 3 compares network-level performance indicators under static routing and ACO DT-guided routing, aggregated across all 256 parameter combinations for the high-surge subset ($\lambda_1 = 0.6$). ACO DT was activated whenever any node's predicted P_{rej} exceeded the threshold $\theta = 0.05$.

ACO DT achieves a 44.9% reduction in peak queue length and a 77.2% reduction in service-denial probability at the cost of 11.4 re-routing interventions per shift, each resolved within the 60-second polling cycle. The 16.3% gain in resource utilisation indicates that the ACO controller actively redistributes slack capacity from lightly loaded nodes to absorb surge demand.

Table 3

Network performance: static routing vs. ACO digital-twin routing (λ_1 = 0.6, all $\lambda_0/\mu/N$ combinations)

Performance Indicator	**Static Routing**	**ACO DT Routing**	**Δ*a*.**	**Δ*v*.**
Peak queue length (max L_q)	8.73	4.81	-3.92	-44.9%
Avg. waiting time W_q, min	3.05	1.47	-1.58	-51.8%
Failure probabilityP_{rej}	0.092	0.021	-0.071	-77.2%
Loading $\bar{\rho}$	0.750	0.872	+ 0.122	+ 16.3%
ACO re-routing events per shift	-	11.4	-	-
Avg. API round-trip latency, s	-	1.8	-	-

Table 4 presents a sensitivity analysis of ACO performance with respect to the key hyper-parameters α, β, and ρ, evaluated at the reference scenario ($\lambda_0 = 1.5$, $\lambda_1 = 0.6$, $\mu = 2.0$, $N = 10$).

Table 4

Sensitivity of ACO DT performance to hyper-parameter variation

α	β	ρ	**Avg. Wq (min)**	P_{rej}	$\bar{\rho}$
1	2	0.10	1.98	0.031	0.851
2	3	0.15	1.47	0.021	0.872
3	4	0.20	1.63	0.026	0.864
1	5	0.30	2.11	0.038	0.843

The optimal configuration $\alpha = 2$, $\beta = 3$, $\rho = 0.15$ yields the lowest P_{rej} and highest $\bar{\rho}$. Higher β over-weights heuristic distance; higher ρ erodes pheromone memory under shifting demand.

Coupling the ANT-Logistics TMS data layer with a queuing-theory state estimator and ACO controller produces a digital twin that substantially outperforms static dispatching. The 77.2% reduction in service-denial probability directly prevents missed delivery windows, stock-outs, and retail-partner penalties in FMCG networks.The framework leverages ANT-Logistics's native capabilities: REST API v2 GPS telemetry feeds the physical layer; the traffic-forecast module supplies arc travel times; and the route-import endpoint injects re-routing decisions with 1.8 s latency. Extended-tier subscribers additionally gain GraphQL dashboards and event webhooks.

The 16.3% utilisation gain aligns with ANT-Logistics field data: Lindstrom Ukraine saved 32,000 km·year^{-1} and Raiffeisen Bank Aval saved over 500,000 km·year^{-1} across 900 + routes [5], both consistent with ACO-driven capacity release. Key limitations include: exponential service-time assumption (heavier-tailed empirical distributions require $M(t)/G/1/N$ extensions); calibration on simulated rather than live data; and absence of vehicle breakdown and weather-shock modelling.

Future work will pursue Erlang-k service-time generalisations, online reinforcement-learning tuning of ACO hyper-parameters, and integration with the ANT-Logistics temperature-monitoring module for cold-chain applications.

Conclusions

1. A digital-twin architecture for logistics supply-chain resilience assessment was proposed, formalising the mapping between the ANT-Logistics TMS operational data model and a network of $M(t)/M/1/N$ queuing nodes governed by Chapman-Kolmogorov state-probability equations. The architecture relies exclusively on documented API interfaces available to all ANT-Logistics enterprise subscribers, making it non-invasive and immediately deployable.
2. Non-stationarity of the input flow was confirmed as the dominant driver of supply-chain fragility: an increase in demand-surge amplitude from $\lambda_1 = 0.2$ to $\lambda_1 = 0.6$ orders·min^{-1} raises the service-denial probability from 2.4% to 9.2% (a 283% relative increase), corroborating at the multi-node network level the single-node findings reported in the authors' prior work.

3. The embedded ACO routing controller, parameterised at $\alpha = 2, \beta = 3, \rho = 0.15$, reduced peak queue length by 44.9%, average waiting time by 51.8%, and service-denial probability by 77.2%, while raising resource utilisation by 16.3% compared with static ANT-Logistics plan-routing across 256 parameter scenarios at $\lambda_1 = 0.6$.
4. The average API round-trip latency of 1.8 s confirms that the DT control loop can be closed within a single 60-second polling cycle, making the framework operationally viable for real-time deployment on logistics networks of comparable topology.
5. The proposed Ant-Logistics DT provides a reproducible, platform-grounded methodology for resilience quantification and adaptive flow management in last-mile and distribution supply chains, directly applicable to FMCG, pharmaceutical, e-commerce, and municipal-logistics sectors served by ANT-Logistics and analogous TMS platforms.

Author contributions

Conceptualization, formal analysis and writing – Savchenko L.; original draft preparation, methodology – Zagurskiy O, Lemishko D.; project administration – Opalko V. All authors have read and agreed to the published version of the manuscript.

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