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USE OF SIMULATION MODELLING FOR OPTIMISATION OF LOGISTICS SUPPLY CHAINS

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Abstract.
Logistics supply chains are highly sensitive to variations in flow intensity, network structure, stochastic disturbances and forecasting accuracy, which necessitates the development of integrated simulation-based optimisation approaches. This study developed and evaluated a unified modelling framework for analysing logistics system performance through the combined application of four complementary model families: discrete-event simulation (DES), agent-based modelling (ABM), system dynamics (SD) and machine-learning-assisted predictive models. Forty simulation scenarios representing different operational conditions were generated and systematically compared using the Supply Chain Performance Index (SCPI), which integrates key performance indicators, including cycle time, service level and system reliability. The DES approach revealed critical flow thresholds, demonstrating that an increase in arrival intensity (λ) from 0.5 to 2.0 resulted in a substantial increase in average cycle time from 14-17 to 48-57 minutes, while throughput declined from 185-198 to 101-112 units/hour. The ABM analysis indicated that decentralised coordination mechanisms improved system adaptability only when route distribution and warehouse utilisation remained balanced. SD models demonstrated high sensitivity to delayed feedback processes, backlog formation and demand variability, highlighting the importance of dynamic control strategies. Machine-learning-assisted models provided the highest predictive accuracy under simulated conditions, with LSTM models achieving the lowest prediction error and the greatest improvement in SCPI values. Nevertheless, DES, ABM and SD contributed essential complementary perspectives by capturing operational, behavioural and systemic characteristics that cannot be fully represented by predictive approaches alone. The proposed framework supports more comprehensive decision-making for designing resilient and efficient logistics systems under uncertain operating conditions.

Keywords:
traffic intensity; network topology; stochastic fluctuations; demand forecasting; machine learning models

Introduction

Modern logistics supply chains face increasing uncertainty due to variable demand, complex network structures, stochastic disturbances and the need for rapid decision-making. Traditional analytical approaches are often insufficient for predicting system behaviour and evaluating optimisation strategies before implementation. Simulation modelling addresses this limitation by reproducing logistics processes in a controlled virtual environment, enabling assessment of alternative configurations, bottleneck identification and performance improvement without disrupting real operations.

Previous studies have demonstrated the value of simulation approaches for various logistics challenges. Bezkorovainyi et al. (2021) analysed structural and topological optimisation of logistics networks, showing that mathematical representation of network connections improves transport process modelling. Nevliudov et al. (2023) applied simulation methods to multi-level intralogistics systems with mechatronic shuttles, demonstrating their effectiveness for route optimisation and component synchronisation. Papinko et al. (2025) highlighted the role of simulation modelling in evaluating logistics strategies under variable demand and resource constraints, while Abid et al. (2021) showed its ability to reproduce stochastic behaviour in reverse logistics systems.

Recent research has further emphasised the benefits of integrating modelling approaches. Rezeq et al. (2024) demonstrated that combining discrete-event simulation with optimisation methods improves humanitarian logistics planning, while Bozdoğan et al. (2022) applied agent-based modelling to analyse interactions in closed-loop supply chains. Ali et al. (2021) showed that machine learning enhances simulation models through improved information analysis, and Abaku et al. (2024) highlighted the potential of artificial intelligence for adaptive supply chain management.

Despite these advances, existing studies largely examine individual modelling approaches or specific logistics scenarios. A comprehensive framework that compares operational, behavioural, dynamic and predictive modelling approaches using common evaluation criteria remains insufficiently developed. Further research is therefore needed to determine how different simulation methods complement each other and how their integration can improve supply chain adaptability and performance.

Therefore, the present study develops and evaluates a unified simulation-based framework for logistics supply chain optimisation. The study establishes an integrated modelling approach capable of representing key logistics characteristics, including flow dynamics, network interactions, stochastic variability and predictive capabilities. The contribution of this research lies in the comparative assessment of discrete-event simulation (DES), agent-based modelling (ABM), system dynamics

(SD) and machine-learning-assisted predictive models using a common performance evaluation framework.

Method

The theoretical and modelling study used system analysis, dynamic and stochastic modelling approaches, and computer simulation of logistics processes. The research focused on four complementary modelling families: DES for operational flows, ABM for decentralised interactions, SD for aggregate feedback dynamics, and ML-assisted models for predictive forecasting and decision support.

These approaches were considered complementary rather than interchangeable, as each addressed a different aspect of logistics behaviour. DES modelled flows, queues, cycle time and throughput; ABM represented interactions among suppliers, warehouses, carriers and customers; SD captured inventory changes, backlog accumulation and information delays; and ML-assisted models provided predictive estimates of demand, delays and overload risks.

ABM represented decentralised interactions among logistics participants. Four agent types were included: suppliers, warehouses, carriers and customers. Each agent was assigned attributes including processing capacity, load, queue length, service time, transport availability and route priority. Decision rules defined order generation, flow consolidation, route selection and replenishment responses, enabling analysis of how local decisions influenced delays, throughput and reliability. Main ABM outputs included average delay, utilisation, route balance, service level and reliability index.

SD analysed aggregate logistics behaviour through stocks, flows and feedback loops. Stocks included inventory, backlog, orders in transit and accumulated delays, while flows represented order arrivals, processing, shipment and replenishment. The model assessed non-linear responses related to inventory accumulation, delayed corrections and bullwhip-type effects. Main SD outputs were inventory deviation, backlog growth, delay accumulation, service level and SCPI.

Model parameters were defined according to the purpose of each approach. DES included flow intensity, processing capacity, queues and throughput; ABM included agent attributes such as load, service time, transport availability and route priority; SD included stocks, flows and feedback mechanisms; ML models used simulated sequences of flow intensity, delays, throughput, service level, route load and reliability indicators to predict demand, delays and overload risks.

Detailed model parameterisation was defined to ensure reproducibility of the simulation experiments. In DES scenarios, order arrivals followed a Poisson process with flow intensity values λ=0.5, 0.75, 1.0, 1.25, 1.5, 1.6, 1.75 and 2.0 orders per time unit, while processing capacities were kept constant except in dedicated capacity

scenarios. Routing decisions followed a priority-based shortest-queue rule: incoming orders were assigned to the available node with the lowest expected waiting time, while alternative routes were activated when node utilisation exceeded 85%. In ABM scenarios, agents selected routes according to a combination of route priority (40%), current congestion level (40%) and transport availability (20%), allowing redistribution of flows under uneven loading conditions. Stochastic scenarios used exponential distributions for transport intervals with a mean value of 10 min and Markov transition probabilities between normal, high-load and overload states of 0.70, 0.20 and 0.10, respectively; transition probabilities increased to 0.45 for overload states under high disturbance scenarios. Demand fluctuations in SD models were introduced as external inputs with variability ranges of ±20% and ±40%, while feedback delays were modelled as short (5 time units) and long (15 time units) replenishment delays. These parameter values were selected to represent typical variability patterns in logistics systems and to reproduce stable, transitional and overload operating conditions observed in the simulation experiments.

The simulation design consisted of 40 scenarios divided into four blocks: DES, structural-network modelling, stochastic modelling and ML-assisted predictive modelling. Each block contained ten scenarios, with one principal factor varied while other baseline conditions remained constant. This design enabled comparison of flow intensity, network topology, stochastic disturbances and predictive performance.

Scenario generation was based on predefined baseline conditions and controlled parameter variation. DES scenarios varied flow intensity (λ=0.5-2.0) under fixed processing capacities, queue rules and routing logic. Network scenarios modified topology characteristics, while stochastic scenarios applied Poisson arrivals, exponential transport intervals and Markov state transitions. ML scenarios used simulated sequences containing flow intensity, delays, throughput, service level, route load and reliability indicators. A representative DES scenario (λ=1.0) was evaluated using cycle time, delay, throughput and SCPI.

DES, network and stochastic scenarios used a 100-hour simulation horizon with a 10-hour warm-up period. ML models used 100 time-step sequences and a 50-step forecasting horizon. Each scenario was replicated three times using fixed random seeds, and mean values with 95% confidence intervals were calculated where applicable.

ML models were trained and tested on simulated data generated from DES, network and stochastic scenarios rather than operational datasets. Input variables included order-flow intensity, delay, queue length, throughput, service level, route load, reliability index and previous demand values. Prediction targets were future demand, expected delay and overload risk. Data were divided into training, validation and test subsets using a 70/15/15 split while preserving temporal order.

LSTM and GRU models were configured with two recurrent layers (64 and 32 units), dropout of 0.20, Adam optimisation (learning rate 0.001), batch size 32

and early stopping based on validation loss. Mean squared error was used as the loss function, while MAE and MSE evaluated performance. The autoencoder was used as a predictive-support model for detecting abnormal demand-delay patterns through reconstruction error rather than direct forecasting.

All simulations were performed in AnyLogic, MathWorks and Python using appropriate modelling and analysis libraries. Stochastic processes included Poisson arrivals, exponential delays and Markov states. Controlled throughput parameters and flow conditions ensured reproducibility and consistent model comparison.

The simulations assumed a controlled analytical environment in which external disruptions were included only in predefined stochastic scenarios. Capacity, processing rules, transport availability and routing logic remained constant unless they represented the main varied factor. Demand was treated as an exogenous input, and stochasticity was introduced through predefined probabilistic mechanisms. ML results were therefore interpreted as model-based predictive estimates rather than external validation.

Because the study was based on simulated rather than operational logistics data, validation was conducted through model verification and conceptual validation rather than empirical validation. Verification included checking the consistency of model logic, parameter implementation, routing rules, queue behaviour, stochastic processes and feedback mechanisms. Conceptual validation was performed by comparing simulated responses with established logistics principles, such as increasing delays under higher flow intensity, reduced reliability in complex networks and instability caused by delayed information feedback. In addition, sensitivity analysis was used to examine whether changes in operational parameters and SCPI weighting schemes affected the main conclusions. Therefore, the results represent a verified simulation-based assessment of alternative modelling approaches under controlled scenarios rather than empirical validation against real-world logistics performance data.

Although the models represented different system characteristics, their results were compared using SCPI, which integrates cycle time, service level and reliability. This enabled assessment of overall logistics performance while preserving the specific purpose of each modelling approach.

For a generalised analysis of the results, service level, average cycle time, resource utilisation rate, delay frequency, transport operation reliability (Reliability Index), and the integral indicator of logistics network efficiency – Supply Chain Performance Index (SCPI) – were used. The SCPI was calculated for each of the 40 simulation scenarios, after which the values were normalised within the range [0, 1], which made it possible to compare different types of models in a single analytical space. The integral indicator was determined using formula (1):

$$SCPI = w_1\ T_"norm" + w_2\ S_"norm" + w_3\ R_"norm" \quad (1)$$
$$SCPI = w_1\ T_"norm" + w_2\ S_"norm" + w_3\ R_"norm"$$

where $T_"norm"T_"norm"$ is the reverse-normalised cycle time, $S_"norm"$, $S_"norm"$ is the normalised service level, and $R_"norm"R_"norm"$ is the normalised reliability index. The parameters w_1w_1, w_2w_2, and w_3w_3 represent the corresponding weighting factors assigned to each performance metric.

In the SCPI calculation, the cycle-time component was reverse-normalised because lower cycle time indicates higher logistics efficiency, while service level and reliability were directly normalised because higher values represent better performance. This ensured that all components had the same interpretation, with higher SCPI values indicating improved system performance.

The SCPI index combined average cycle time, service level and reliability index, representing temporal efficiency, demand fulfilment and operational stability. Equal weighting (0.333/0.333/0.333) was applied because no single performance dimension was assumed to be dominant. The normalisation procedure was based on the observed parameter ranges across all 40 simulation scenarios. For each indicator, the minimum and maximum values obtained from the complete simulation dataset were used as reference limits. Average cycle time (T_cycle) was treated as a cost parameter; therefore, its normalised value was calculated using reverse normalisation: $T_norm = (T_max - T_i\ )/(T_max - T_min\ )$ $T_norm = (T_max - T_i\ )/(T_max - T_min\ )$, where lower cycle time corresponds to higher efficiency. Service level and reliability index were treated as benefit parameters and were directly normalised as $X_norm = (X_i - X_min\ )/(X_max - X_min\ )$ $X_norm = (X_i - X_min\ )/(X_max - X_min\ )$, where higher values indicate better performance. Across the simulated scenarios, the reference ranges were: cycle time 14-57 min, service level 65-93%, and reliability index 74-95%. After transformation, all indicators were expressed on a common scale from 0 to 1, where values closer to 1 represented better logistics performance. The final SCPI value was calculated as the weighted sum of the three normalised components: cycle-time efficiency, service-level performance and reliability stability, using equal weights ($\alpha=\beta=\gamma=0.333$) because all three dimensions were considered equally important for overall system evaluation.

In this study, optimisation refers to identifying model configurations and scenarios that maximise the integrated SCPI value rather than solving a mathematical optimisation problem. The evaluated factors included flow intensity, network configuration, stochastic disturbance type and modelling approach, while the preferred solution corresponded to the configuration achieving the highest SCPI under the defined conditions.

The robustness of SCPI was assessed through sensitivity analysis using alternative weighting schemes (Table 1), including time-, service- and reliability-priority scenarios. The ranking of model groups remained stable across all weighting schemes, confirming that the conclusions were not determined by a single SCPI component.

Table 1. Sensitivity analysis of SCPI under alternative weighting schemes

Weighting scheme	Cycle time weight	Service level weight	Reliability weight	DES	ABM	SD	ML-assisted	Model ranking
Equal weights	0.333	0.333	0.333	0.675	0.723	0.647	0.805	ML>ABM>DES>SD
Time-priority	0.500	0.250	0.250	0.664	0.714	0.636	0.792	ML>ABM>DES>SD
Service-priority	0.250	0.500	0.250	0.681	0.731	0.651	0.811	ML>ABM>DES>SD
Reliability-priority	0.250	0.250	0.500	0.672	0.725	0.642	0.809	ML>ABM>DES>SD

Source: compiled by the author

The sensitivity analysis demonstrated that changes in SCPI weighting factors did not alter the relative ranking of the four model groups. ML-assisted models consistently achieved the highest SCPI values, while SD models showed the lowest stability, confirming that the comparative results were not dependent on a specific weighting scheme. To further assess robustness, key operational assumptions were varied, including flow intensity, processing capacity, routing rules and stochastic disturbances. Flow intensity was tested from low-load to peak-load conditions (λ=0.5-2.0), capacity was adjusted by ±20% from the baseline level, and routing sensitivity was evaluated by comparing shortest-queue and priority-based allocation rules under increased competition. Stochastic conditions were examined by varying demand fluctuations and state-transition assumptions. Although these changes affected absolute performance levels, the relative behaviour of the modelling approaches remained consistent: ML-assisted models maintained advantages under uncertain conditions, while DES, ABM and SD provided complementary insights into operational constraints, coordination mechanisms and feedback instability. The results confirm that the main conclusions are robust across reasonable variations in both indicator weighting and operational parameters.

ANOVA and Mann-Whitney U test methods were used for statistical verification of differences between model groups. Each simulation scenario was performed three times, followed by the averaging of results and the formation of 95% confidence intervals, which minimised the impact of stochastic fluctuations.

Results

Discrete-event simulation modelling of flow processes in logistics systems

Simulation experiments showed that the behaviour of flow processes in the logistics chain significantly depends on the intensity of order intake and the throughput capacity of service nodes. In baseline scenarios with low load, the system operated stably with minimal queues and short cycle times. However, as the intensity of the order flow increased, queues formed more quickly, increasing overall delays and causing the system to gradually approach overload mode. In peak scenarios, delays became avalanche-like, reflecting the presence of clearly defined bottlenecks in transport and warehousing operations. The most sensitive element was the order processing stage, where the speed of service determines the system's ability to maintain a stable state when the load changes. The key parameters of the DES scenarios are summarised in Table 2.

Table 2. Performance indicators of the logistics system in DES scenarios of varying intensity

Flow intensity (λ)	**Average cycle time T_{cycle} T_{cycle}, min**	**Average delay, min**	**Throughput capacity, units/hour**
Low (λ=0.5)	14-17	1.2-2.1	185-198
Average (λ=1.0)	22-27	5.4-7.8	162-175
High (λ=1.5)	34-41	11.6-15.3	128-139
Peak (λ=2.0)	48-57	19.7-26.4	101-112

Source: compiled by the author

An increase in λ leads to a nonlinear increase in cycle time, which corresponds to the classic characteristics of queuing systems with limited capacity. When switching from medium to high load, T_cycle increases by more than 50%, while throughput decreases by approximately 20-25%. This indicates a loss of system efficiency and the accumulation of unsolved queues. In peak mode, there is a sharp drop in performance and maximum growth in delays, which is an indicator of overload of node components. This behaviour is consistent with the theory of DES models, where exceeding the critical flow intensity causes a rapid deterioration in time indicators and an increase in the number of unserved orders. Figure 1 illustrates the dynamics of changes in time parameters depending on the load intensity.

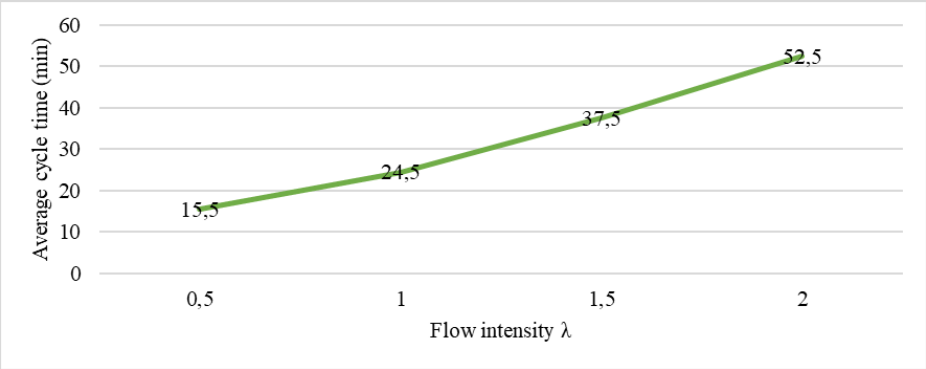


Figure 1. Nonlinear dependence of the average cycle time (T_cycle) on the flow intensity λ
Source: compiled by the author

In the range λ=1.4-1.6, there is a rapid accumulation of queues: even a slight increase in λ causes a significant lengthening of the cycle time, as the throughput approaches the limit level. Such a "critical break" is typical for DES models, where the overload of one node can cascade and degrade the performance of the entire logistics network. In the peak load zone (λ=2.0), the cycle time increases almost fourfold relative to the baseline scenario, which is consistent with the analytical patterns of queuing systems. In this mode, delays become cumulative, making the system sensitive to any fluctuations in demand or internal failures. The system remains stable at low and medium flows, but with further growth of λ, it quickly transitions to overload mode. The DES results obtained made it possible to identify critical load limits and determine bottlenecks, the elimination of which will improve the efficiency of logistics operations.

Structural-network simulation modelling of logistics systems in variable topological configurations

Structural network simulations have demonstrated that the behaviour of logistics flows significantly depends on the topology shape, the number of levels in the distribution network, and the routing rules that determine the priority or competitive distribution of cargo flows. In basic scenarios with a simple linear structure, the system maintained stable operation, ensuring uniform flow with a minimum number of overloads. However, with the transition to branched or multi-level networks, the effects of route competition and load fluctuations between nodes began to significantly affect time and performance indicators. The changes were particularly noticeable in networks with multiple parallel routes, which reduced

the risk of overload at a single node but at the same time increased the uneven distribution of traffic. Some routes were used much more frequently, forming local queues, while others remained underutilised. This caused load asymmetry and increased the likelihood of local delays. In multi-level structures with warehouses of different categories (central, regional, local), delays accumulate at the transitions between levels, where consolidation and redistribution of flows occur. The operation of the system in such modes showed a dependence of stability on the depth of the network: the more intermediate levels there are, the higher the time losses and the lower the Rindex reliability index. Table 3 presents the aggregated results of network simulations, which compared throughput, latency, and reliability index for different topology structures.

Table 3. Logistics network performance indicators depend on its structure

Network structure	Average delay, min	Throughput capacity, units/ hour	Rindex Rindex, %
Linear topology	4.8-6.1	178-185	93-95
Parallel routes	7.6-10.4	165-173	88-90
Branching	12.9-17.3	142-156	81-85
Multi-level logistics network	18.4-25.7	118-132	74-79

Source: compiled by the author

The topological properties of a logistics network determine its stability, throughput and time losses much more strongly than the level of flow intensity at DES. Increased network depth, the presence of consolidation nodes, and complex routing schemes create additional delay mechanisms and reduce the overall Rindex, increasing flow fragmentation and increasing the system's sensitivity to local overloads. The analysis also showed that networks with high structural complexity demonstrate lower adaptability to demand fluctuations and less uniform load distribution between nodes. The results confirmed that optimising the network structure is one of the key areas for improving the efficiency of logistics systems, especially under variable or high load conditions.

Stochastic simulation modelling of logistics processes incorporating random disturbances and probabilistic dynamics of the system

Stochastic simulations demonstrated that the logistics chain is highly sensitive to random variations in demand and fluctuations in vehicle arrival times. Even minor random deviations from average values caused cascading changes in system parameters, resulting in uneven loads and the formation of local delay peaks. In models with Poisson arrivals, the intensity of flows fluctuated around the set parameters λ, which caused uneven queue filling and a significant difference between the actual and predicted cycle times. In systems where transport intervals were formed based on exponential distributions, there were periods of sudden load growth, which provoked bursts of delays in key segments. Markov models with random transitions between the states "normal load", "high load" and "overload" demonstrated that the probability of transition to a critical state increases sharply with the regularity of demand fluctuations. Table 4 shows the average SCPI values and characteristic parameters of the probability distributions of delays.

Table 4. Stochastic indicators of logistics system performance

Type of stochastic disturbance scenarios	Average SCPI	Probability of overload, %	Median delay, min	95th percentile of delays, min
Poisson arrivals	0.74-0.79	18-26	6.2-7.8	17-21
Exponential transport intervals	0.69-0.75	27-34	8.4-9.9	22-28
Markov processes with stochastic states	0.61-0.68	38-44	10.2-12.7	31-36

Source: compiled by the author

Stochastic simulations showed that disturbance mechanisms strongly affected system stability. Poisson-based arrivals produced the most stable behaviour, whereas exponential transport intervals increased variability. Markov-based scenarios demonstrated the highest instability due to state transitions and delayed recovery effects. These findings highlight the need for adaptive control and buffering strategies under uncertain operating conditions. The delay distributions across stochastic scenarios are presented in Figure 2.

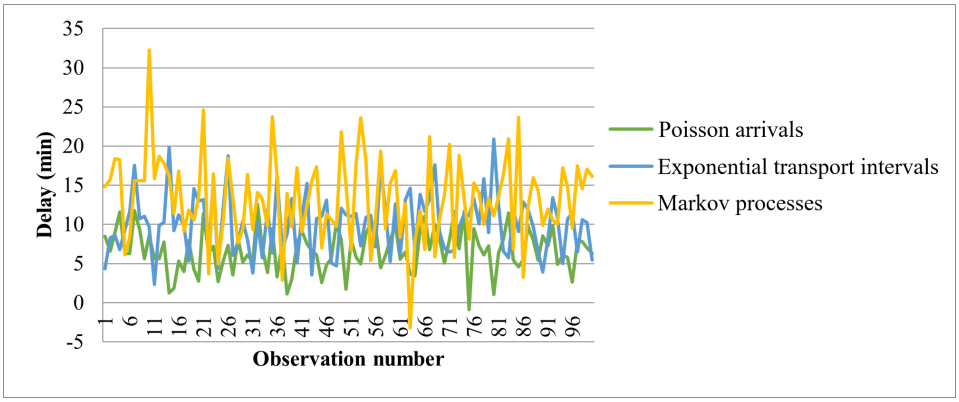


Figure 2. Delay distributions across stochastic scenarios
Source: compiled by the author

Models with Poisson arrivals demonstrate the most compact delay structure: values fluctuate within the range of approximately 5-15 minutes, forming a dense concentration around the central zone. Exponential intervals are characterised by a wider range of values – approximately 5-20 minutes – and more noticeable local jumps. Markov processes demonstrate the most unstable behaviour: the amplitude of fluctuations reaches approximately 25-30 minutes, and the frequency of peak values is significantly higher than in the other two models. The shape of the curve reflects the presence of a heavy tail and sharp transitions between states, which leads to the periodic accumulation of critical queues.

Random disturbances in demand and transport flows are one of the key factors in the deterioration of the logistics system's efficiency. All three stochastic disturbance scenarios demonstrate increased sensitivity to fluctuations, but the riskiest scenarios are those based on Markov transitions, where the system more often reaches critical states. The results obtained proved the need to develop buffering strategies and adaptive flow control methods to improve the stability of logistics networks.

Hybrid simulation modelling using ML algorithms

Hybrid simulation-analytical models, in which simulation data was integrated with machine learning algorithms, demonstrated a significant improvement in the accuracy of demand forecasting and delivery time parameters compared to classical approaches. The most promising models were those based on LSTM and GRU, which can reproduce long-term time dependencies and adapting to irregular fluctuations in order flows. Autoencoders effectively identified hidden structural patterns in delay dynamics, which improved the accuracy of overload risk assessment. In terms of demand forecasting, LSTM consistently showed the smallest error, especially in

modes with stochastic disturbances. GRU worked more efficiently in short time windows, demonstrating better performance compared to LSTM. Autoencoder models provided a high ability to filter noise and amplify informative signal components, which improved the forecast curves during sharp changes in traffic flows. The summary results are presented in Table 5.

Table 5. Predictive characteristics of ML models and their impact on SCPI

Model	MAE	MSE	Predicted accuracy, %	ΔSCPI (index change)
LSTM	0.084-0.097	0.011-0.015	91-94%	+0.07…+0.11
GRU	0.093-0.112	0.015-0.019	88-91%	+0.05…+0.08
Autoencoder	0.117-0.136	0.019-0.024	84-87%	+0.03…+0.06

Source: compiled by the author

Figure 3 shows how three types of ML models – LSTM, GRU, and autoencoder – reproduce demand dynamics over time. The reference simulated demand series was included as a baseline to evaluate how accurately each ML model reproduced temporal demand patterns.

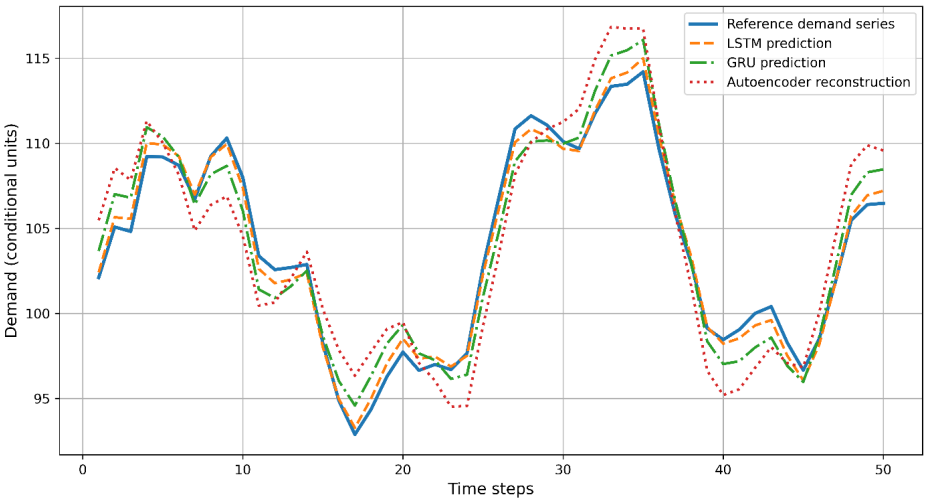


Figure 3. Forecast curves of ML models compared with the reference simulated demand series
Source: compiled by the author

LSTM most accurately reproduced simulated demand dynamics, capturing both short-term fluctuations and longer trends due to its ability to retain temporal dependencies. GRU showed stable but more inertial forecasting, with delayed

responses to rapid demand changes and smoother peak reproduction. The autoencoder demonstrated the weakest direct predictive performance because it lacks internal time memory and functions mainly as a reconstructive model; however, it remained useful for detecting anomalous demand-delay patterns. Overall, ML algorithms reduced uncertainty and improved logistics stability, with LSTM producing the greatest SCPI gain, GRU occupying an intermediate position, and autoencoders contributing mainly to early anomaly detection and peak-delay prevention.

Integral assessment of simulation model efficiency based on the SCPI index

The SCPI integral indicator of logistics system efficiency made it possible to compare the performance of four groups of simulation models – DES, ABM, SD and ML-oriented approaches – on a consistent scale [0;1]. The values calculated according to formula (1) revealed significant differences between the models: systems with more accurate forecasts and more stable time characteristics demonstrated higher integral scores. The statistical analysis revealed that the differences between the groups are statistically significant: the SCPI of ML models significantly exceeds the indicators of DES, ABM and SD, which is confirmed by the results of comparisons using ANOVA and Mann-Whitney U-test ($p<0.01$). The aggregated data are presented in Table 6.

Table 6. Integral values of SCPI for different types of simulation models

Type of model	Average SCPI	SCPI range	Scenarios with the lowest resilience	Scenarios with the highest resilience
DES	0.63-0.72	0.58-0.76	Peak loads ($\lambda \geq 1.6$)	Low and average λ
ABM	0.67-0.78	0.62-0.82	Uneven distribution of agents	Balanced routes
SD	0.59-0.71	0.55-0.74	Sharp changes in demand	Stable information streams
ML	0.74-0.86	0.68-0.89	Unpredictable stochastic peaks	Prognosed demand trends

Note: The SCPI value is calculated using formula (1) by normalising the cycle time, service level and reliability index.

Source: compiled by the author

Agent-based modelling examined how decentralised decisions among suppliers, warehouses, carriers and customers influenced logistics performance. The results showed that autonomous routing improved adaptability when agent distribution, route loads and warehouse utilisation remained balanced. However, uneven allocation of agents across the network reduced system flexibility, increasing congestion and

limiting the benefits of decentralised decision-making. These findings indicate that ABM-based coordination mechanisms are effective when supported by balanced resource distribution and responsive routing strategies (Table 7).

Table 7. Performance indicators of agent-based logistics scenarios

ABM scenario type	**Average delay, min**	**Service level, %**	**Route load balance, %**	**Reliability index, %**	**SCPI**
Balanced agent distribution	8.2-10.6	89-93	86-91	88-92	0.76-0.82
Moderate route competition	11.4-14.2	84-88	78-84	82-87	0.70-0.75
Uneven warehouse load	14.8-18.9	78-84	69-76	76-81	0.65-0.71
Asymmetric agent allocation	19.3-23.7	72-77	61-68	70-75	0.62-0.67

Source: compiled by the author

System dynamics modelling analysed aggregate logistics behaviour through stocks, flows and feedback loops. The results showed that stable demand and timely information exchange supported system equilibrium, whereas demand fluctuations and delayed replenishment feedback generated wave-like instability similar to the bullwhip effect. These findings demonstrate that SD models are particularly sensitive to information delays, inventory adjustments and feedback mechanisms, highlighting the importance of coordinated planning and timely decision-making in logistics systems (Table 8).

Table 8. Performance indicators of system dynamics scenarios

SD scenario type	Average delay, min	**Backlog level, units**	**Inventory deviation, %**	**Service level, %**	**SCPI**
Stable demand and regular information flow	9.6-12.4	11.5-15.8	6-9	84-88	0.68-0.74
Moderate demand fluctuation	14.1-18.6	18.9-24.7	11-16	78-83	0.62-0.68
Information delay in replenishment	18.7-23.2	25.3-31.1	17-23	71-77	0.58-0.63
Sharp demand change	23.8-29.5	31.6-38.4	24-31	65-70	0.55-0.60

Source: compiled by the author

Statistical analysis was conducted at the scenario level. Each scenario was replicated three times; these replications were used to calculate scenario-level means and 95% confidence intervals, while inferential comparisons were performed on the 40 scenario-level values to avoid pseudo-replication. One-way ANOVA was used because the analysis compared mean SCPI values across four independent model

groups. The assumptions were checked before testing: Shapiro-Wilk tests indicated no significant deviation from normality across groups (p=0.623-0.892), and Levene's test confirmed homogeneity of variances (p=0.604). Mann-Whitney U tests were additionally applied as pairwise non-parametric post-hoc comparisons because each group contained a limited number of scenarios (n=10) (Table 9).

Table 9. Statistical comparison of SCPI values across simulation model groups

Comparison	Mean SCPI or mean difference	95% CI	Test statistic	p-value	Adjusted p-value	Effect size
DES	0.675	0.653 to 0.697	F(3,36)= 32.57	2.33×10^{-10}	—	η^2=0.731; ω^2=0.703
ABM	0.723	0.696 to 0.750				
SD	0.647	0.617 to 0.677				
ML-assisted	0.805	0.775 to 0.835				
DES vs ABM	-0.048	-0.080 to -0.016	U=16.5	0.0115	0.0230	r_r b r_r b =-0.67
DES vs SD	0.028	-0.007 to 0.063	U=70.0	0.1431	0.1431	r_r b r_r b=0.40
DES vs ML-assisted	-0.130	-0.165 to -0.095	U=0.0	1.08×10^{-5}	6.50×10^{-5}	r_r b r_r b =-1.00
ABM vs SD	0.076	0.038 to 0.114	U=90.5	0.0015	0.0045	r_r b r_r b=0.81
ABM vs ML-assisted	-0.082	-0.120 to -0.044	U=7.5	0.0007	0.0029	r_r b =-0.85
SD vs ML-assisted	-0.158	-0.198 to -0.118	U=0.0	1.08×10^{-5}	6.50×10^{-5}	r_r b =-1.00

Note: Mean differences are calculated as the first model group minus the second model group. η^2 and ω^2 are reported for ANOVA; r_r b indicates rank-biserial correlation for Mann-Whitney U tests.

Source: compiled by the author

The results confirmed statistically significant differences in SCPI between the four model groups. The largest differences were observed between ML-assisted models and SD, DES and ABM scenarios, indicating the advantage of predictive modelling for scenarios where forecasting uncertainty strongly influences logistics performance.

The findings demonstrate that logistics system performance depends on the interaction of flow intensity, network structure, stochastic variability and predictive capability, with each modelling approach capturing a distinct aspect of this behaviour. DES identified operational limits and critical bottlenecks under increasing loads, ABM revealed the role of decentralised decisions and network balance, while SD captured the effects of delayed feedback and inventory fluctuations. ML-assisted models provided additional predictive capabilities by identifying demand patterns and potential overload risks, resulting in improved SCPI values under the evaluated scenarios. No single approach fully represents the complexity of logistics systems; rather, the integration of complementary simulation and predictive methods provides a more comprehensive basis for assessing stability, reducing delays and supporting adaptive logistics decision-making.

Discussion

The results demonstrate that the four model families capture complementary dimensions of logistics behaviour: DES identifies operational bottlenecks, ABM reveals the effects of decentralised decisions, SD describes feedback-driven instability, and ML-assisted models improve predictive control. System stability was shown to depend on the interaction between stochastic variability, network structure, operational constraints and predictive capabilities. This finding corresponds with Saracoglu (2023), who demonstrated that even minor random demand fluctuations can substantially influence system behaviour. Similarly, the present simulations showed a critical transition at λ=1.4-1.6, where cycle time increased rapidly and system stability declined.

The integration of simulation and machine learning is supported by Badakhshan et al. (2024), who identified DES and ABM as effective approaches for modelling supply chain uncertainty, while ML enhances prediction, classification and adaptive decision-making. In the present framework, DES, ABM and SD reproduced operational and dynamic logistics behaviour, whereas ML-assisted models provided predictive estimates of demand, delays and overload risks. This approach is consistent with Keshvarinia et al. (2025), who demonstrated the value of combining DES, real-time data and predictive ML within digital twin environments for disruption analysis and mitigation. The findings confirm that simulation approaches are valuable for identifying bottlenecks and instability thresholds, while ML improves predictive control and SCPI performance in complex logistics environments.

The influence of network structure observed in this study agrees with Wu and Wang (2023), who showed that topology configuration strongly affects long-term supply chain stability. In the simulations, linear networks maintained reliability at 93-95%, whereas multi-level configurations reduced reliability by almost one fifth

due to additional coordination and consolidation requirements. This relationship also corresponds with Pattanaik (2021), who emphasised the effect of cycle-time variation on throughput performance. The present results confirm that increased network depth and additional consolidation nodes contribute to higher delays and reduced flow coordination.

The ability of DES to identify operational vulnerabilities is consistent with Gebreabzgi et al. (2025) and Bottani and Casella (2024), who highlighted its effectiveness in detecting congestion and local inconsistencies that may remain hidden in aggregated approaches. In the current study, DES identified the critical overload point where $\lambda=2.0$ reduced throughput to 101-112 units/hour and initiated wider network degradation. ABM findings support Moreno et al. (2025) and Helo and Rouzafzoon (2023), who emphasised the role of autonomous interactions and decentralised decision-making in uncertain logistics systems. The simulated agent behaviour showed that adaptive responses under changing loads improved flow redistribution and represented resource shortages and surpluses more realistically. In addition, the sensitivity of service-oriented networks to transport and service variability reported by Bandari et al. (2024) was confirmed by increased instability under variable arrival intervals.

The predictive capabilities of ML-assisted models correspond with research on digital twins and intelligent logistics systems. Kim et al. (2025) highlighted the importance of predictive components for dynamic logistics forecasting, which aligns with the present finding that ML models achieved the highest efficiency improvement (+0.11) and supported early congestion detection. Similarly, Abideen et al. (2021) demonstrated that digital twins combined with reinforcement learning can improve logistics stability under demand fluctuations. The current results support this perspective, as hybrid predictive models reduced stochastic peaks and overload risks. The complementary relationship between simulation and ML also corresponds with Kogler and Maxera (2025), who noted that simulation provides structural understanding, whereas ML contributes behavioural prediction. This distinction was observed in the present study: DES identified stability limits, while predictive models estimated future responses to demand changes. The effectiveness of ML in highly stochastic environments reported by Tirkolaee et al. (2021) was further supported by improved controllability under Markov-based disturbance scenarios after predictive integration.

The benefits of hybrid simulation approaches are further supported by Castaneda et al. (2022), who demonstrated that combining simulation and optimisation improves decision-making under uncertainty. In the present study, forecast-based routing adjustments reduced delays and congestion at warehouse hubs. These findings also support Golinska-Dawson et al. (2023), who emphasised adaptability and multi-level analysis in sustainable logistics systems, as network complexity and consolidation structures reduced reliability to 74-79% in complex configurations.

The observed effects of structural complexity and digital integration correspond with broader logistics research. Llivisaca et al. (2022) highlighted the importance of structural models for logistics optimisation, consistent with increased delays in cross-route networks. Han et al. (2022) showed that complex supply chains are highly sensitive to stochastic disturbances, which agrees with the increase in median delay to 10-13 minutes under Markov-based scenarios. The importance of high-resolution digital modelling also corresponds with Varriale et al. (2021), who emphasised simulation and digital technologies, including IoT and blockchain, for real-time logistics control. Overall, the findings demonstrate that integrated network, stochastic and ML-based models provide a more complete representation of logistics dynamics under uncertainty.

From a practical perspective, the combined framework has relevance for military logistics, crisis response, dual-use supply chains and critical infrastructure resilience. DES can support identification of bottlenecks in time-sensitive supply flows, including fuel, medical supplies, equipment and spare parts; ABM can assist in analysing decentralised coordination among warehouses, transport units and response actors operating under incomplete information; SD can evaluate delayed feedback, backlog accumulation and demand surges during prolonged disruptions; and ML-assisted models can provide early warnings of overload risks, forecast demand and support preventive resource redistribution. Such integration is particularly valuable in security-related logistics environments, where the same infrastructure may simultaneously support civilian, humanitarian and defence-related functions.

Conclusions

The study developed and evaluated an integrated simulation framework combining discrete-event simulation (DES), agent-based modelling (ABM), system dynamics (SD), and machine-learning-assisted predictive models to analyse logistics performance under uncertainty. The results showed that each approach provides complementary insights: DES identified operational bottlenecks and critical load thresholds, ABM demonstrated the importance of balanced routing and warehouse utilisation, while SD captured the effects of delayed feedback, demand fluctuations and backlog accumulation. Increasing flow intensity from λ=0.5 to λ=2.0 increased average cycle time from 14-17 to 48-57 min and reduced throughput from 185-198 to 101-112 units/hour, confirming the sensitivity of logistics systems to overload conditions.

SCPI assessment showed that ML-assisted models provided the highest predictive performance under simulated conditions, with LSTM achieving MAE of 0.084-0.097, prediction accuracy of 91-94%, and the largest SCPI improvement (+0.07 to +0.11). However, predictive models complement rather than replace simulation

approaches, as DES, ABM and SD remain valuable for analysing capacity constraints, coordination mechanisms and long-term system dynamics.

The framework can support logistics planning by identifying bottlenecks, evaluating alternative configurations, predicting overload risks and improving resource allocation in complex or disrupted environments. The main limitation is that ML models were developed using simulated datasets and require future evaluation with operational logistics data. Further research should incorporate real-world datasets and adaptive control strategies for real-time logistics management.

Appendix A

Table 10a. Scenario matrix used in the simulation experiments

Code	Model family	Scenario condition	Scenario configuration	**Seeds**
DES-01	DES	Flow intensity	λ=0.5, low load	101-103
DES-02			λ=0.75, low-to-medium load	104-106
DES-03			λ=1.0, medium load	107-109
DES-04			λ=1.25, increased load	110-112
DES-05			λ=1.5, high load	113-115
DES-06			λ=1.6, near-critical load	116-118
DES-07			λ=1.75, overload tendency	119-121
DES-08			λ=2.0, peak load	122-124
DES-09		Service capacity	λ=1.5 with reduced service capacity	125-127
DES-10			λ=1.5 with increased service capacity	128-130
ABM-01	ABM	Agent distribution	Balanced agent distribution	201-203
ABM-02			Moderately uneven agent distribution	204-206
ABM-03		Route behaviour	Moderate route competition	207-209
ABM-04			Strong route competition	210-212
ABM-05		Warehouse load	Uneven warehouse load	213-215
ABM-06			High-priority warehouse overload	216-218
ABM-07		Network topology	Linear topology with autonomous routing	219-221
ABM-08			Parallel routes with autonomous routing	222-224
ABM-09			Branching network with autonomous routing	225-227
ABM-10		Agent allocation	Asymmetric agent allocation	228-230

Table 10a (continued)

Code	Model family	Scenario condition	Scenario configuration	**Seeds**
SD-01	SD	Demand behaviour	Stable demand and regular information flow	301-303
SD-02			Moderate demand fluctuation	304-306
SD-03			Sharp demand change	307-309
SD-04		Feedback delay	Short replenishment information delay	310-312
SD-05			Long replenishment information delay	313-315
SD-06		Inventory dynamics	Inventory depletion scenario	316-318
SD-07		Backlog dynamics	Moderate backlog accumulation	319-321
SD-08			High backlog accumulation	322-324
SD-09		Stochastic distur-bance	Demand fluctuation ±20%	325-327
SD-10			Demand fluctuation ±40%	328-330
ML-01	ML-as-sisted	Algorithm	LSTM, baseline demand sequence	401-403
ML-02			LSTM, stochastic demand sequence	404-406
ML-03			LSTM, peak-load sequence	407-409
ML-04			GRU, baseline demand sequence	410-412
ML-05			GRU, stochastic demand sequence	413-415
ML-06			GRU, peak-load sequence	416-418
ML-07			Autoencoder, baseline sequence	419-421
ML-08			Autoencoder, stochastic sequence	422-424
ML-09			Autoencoder, peak-load sequence	425-427
ML-10			Comparative evaluation of LSTM, GRU and au-toencoder outputs	428-430

Source: compiled by the author

Table 10b. Baseline simulation parameters

Parameter	**Value / range**
Total scenarios	40
Scenarios per model block	10
Replications per scenario	3
Simulation horizon	100 simulated operational hours
Warm-up period	First 10 simulated operational hours excluded
Order-flow intensity λ	0.5-2.0
Demand fluctuation range	±20% to ±40%

Table 10b (continued)

Parameter	Value / range
Delay distributions	Poisson, exponential and Markov-based
Cycle time unit	Minutes
Throughput unit	Units/hour
ML sequence length	100 time steps
ML forecasting horizon	50 time steps
Main comparative indicator	Supply Chain Performance Index, normalised to [0;1]
Statistical tests	One-way ANOVA and Mann-Whitney U test
Significance threshold	$p<0.05$ and $p<0.01$

Source: compiled by the author

Table 10c. Software and computational environment

Software / package	Function	Version
AnyLogic	DES, ABM and logistics process simulation	AnyLogic 8.9.8
MATLAB / Simulink	System dynamics modelling	MATLAB R2026a / Simulink R2026a
Python	Data processing, stochastic analysis and ML modelling	Python 3.12.13
NumPy	Numerical calculations and array processing	NumPy 2.4.5
SciPy	Statistical analysis and stochastic distributions	SciPy 1.17.1
SimPy	Discrete-event process simulation in Python	SimPy 4.1.1
TensorFlow	LSTM, GRU and autoencoder implementation	TensorFlow 2.21.0
Keras	High-level neural network API for ML models	Keras 3.14.1
Operating system	Computational environment	Windows 11 Pro, 64-bit

Source: compiled by the author

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