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RESEARCH PAPER

A Generative Artificial Intelligence–Driven Industry 5.0 Framework for Adaptive Human-Centric Industrial Transportation Systems

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ABSTRACT
The transition from Industry 4.0 to Industry 5.0 has shifted the focus of intelligent manufacturing systems from automation-centric optimization toward human-centricity, resilience, and sustainability. Industrial transportation systems—comprising autonomous mobile robots, automated guided vehicles, collaborative robots, and human operators—operate under significant uncertainty arising from dynamic demand, shared human–robot workspaces, and potential safety-critical disruptions. Existing transportation optimization approaches remain largely reactive and rely on stochastic or worst-case uncertainty modeling, limiting their ability to anticipate complex, correlated disruption scenarios. This paper proposes a novel Generative Artificial Intelligence (GenAI)–driven Industry 5.0 framework for adaptive optimization of industrial transportation systems. The proposed approach integrates a two-phase decision-making model: (i) a performance maximization phase combining reinforcement learning and mixed-integer linear programming to optimize routing, scheduling, and human workload balance, and (ii) a risk minimization phase leveraging GenAI-based scenario generation and Bayesian–fuzzy reasoning to proactively mitigate operational and safety risks. Unlike traditional Monte Carlo simulation, the GenAI module learns the underlying structure of disruption patterns from historical and real-time data, enabling the generation of realistic, high-impact scenarios. A comprehensive case study in a robotic-enabled manufacturing facility, validated through 20 independent simulation runs, demonstrates that the proposed framework increases transportation throughput by 21.7%, improves energy efficiency by 11.7%, and reduces safety incidents by 39.9% compared to a conventional Industry 4.0 baseline. Statistical tests confirm the robustness and significance of these improvements. The results highlight the potential of integrating Generative AI with Industry 5.0 principles to enable proactive, risk-aware, and human-centric industrial transportation systems.

KEYWORDS: *Industry 5.0; Generative artificial intelligence; Industrial transportation systems; Risk-aware decision-making; Bayesian–fuzzy modeling.*

1. Introduction

The rapid evolution of manufacturing systems has transformed industrial operations from traditional automation toward highly intelligent and interconnected cyber–physical environments. The emergence of Industry 4.0 enabled the integration of the Internet of Things (IoT), cloud computing, digital twins, artificial intelligence, and autonomous systems, significantly improving productivity and operational efficiency [1]. However, increasing levels of automation have also introduced challenges related to workforce displacement, system resilience, sustainability, and human–machine interaction. As a result, the concept of Industry 5.0 has recently emerged as a complementary paradigm emphasizing human-centricity, resilience, and sustainability while maintaining the technological advancements achieved under Industry 4.0 [2, 3]. Industry 5.0 promotes collaborative environments in which humans and intelligent machines jointly contribute to decision-making and operational execution [4]. Unlike Industry 4.0, which primarily focuses on automation and productivity, Industry 5.0 seeks to enhance human creativity, well-being, and safety while supporting sustainable industrial growth [5, 6]. Human workers are therefore viewed not as passive observers of automated processes but as active participants in intelligent manufacturing ecosystems. Industrial transportation systems constitute one of the most critical components of modern manufacturing and logistics facilities. These systems encompass Autonomous Mobile Robots (AMRs), Automated Guided Vehicles (AGVs), collaborative robots (cobots), conveyor systems, and human operators responsible for transporting raw materials, semi-finished products, and finished goods throughout production environments. Efficient transportation

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operations directly influence production throughput, resource utilization, operational costs, and worker safety [7, 8]. Despite significant advances in transportation automation, several challenges remain unresolved. First, transportation demand frequently fluctuates due to production schedule modifications, machine failures, supply-chain disruptions, and changing customer requirements. Second, human–robot collaboration introduces complex safety considerations requiring continuous monitoring and adaptive coordination mechanisms [9, 10]. Third, transportation systems must increasingly operate under uncertain conditions characterized by equipment breakdowns, congestion, communication delays, and unexpected environmental disturbances. Traditional optimization methods often struggle to maintain satisfactory performance under such dynamic conditions. Recent advances in artificial intelligence have introduced reinforcement learning, predictive analytics, and risk-aware decision-making approaches for industrial transportation applications [14]. More recently, Generative Artificial Intelligence (GenAI) has demonstrated remarkable capabilities in generating synthetic data, simulating operational scenarios, and supporting predictive decision making across various industrial domains [12, 14]. Unlike conventional scenario generation techniques based on predefined probability distributions, GenAI can learn complex relationships from historical data and generate realistic disruption scenarios that preserve hidden correlations among operational variables. However, existing research remains fragmented. Optimization-oriented studies primarily focus on operational efficiency while neglecting human-centric considerations. Human–robot collaboration research emphasizes safety but often lacks adaptive optimization mechanisms. Risk assessment approaches generally remain reactive, relying on historical observations rather than proactively generating future disruption scenarios. Furthermore, existing applications of Generative AI in manufacturing rarely address transportation optimization and Industry 5.0 objectives simultaneously. Consequently, an important research gap exists regarding the development of integrated frameworks capable of combining adaptive optimization, human-centric decision making, generative intelligence, and explainable risk assessment within industrial transportation environments.

To address this gap, this study proposes a novel Industry 5.0 transportation framework integrating reinforcement learning, mixed-integer linear programming (MILP), Generative Artificial Intelligence, and Bayesian–fuzzy risk assessment. The framework enables dynamic transportation optimization while supporting proactive disruption management and human-centered decision making. The major contributions of this study are summarized as follows:

1. A novel Industry 5.0-oriented transportation optimization framework integrating operational efficiency, resilience, safety, and human well-being objectives.
2. A hybrid reinforcement learning–MILP architecture capable of supporting adaptive transportation routing and scheduling under dynamic operational conditions.
3. A Generative Artificial Intelligence module for producing realistic transportation disruption scenarios and supporting proactive resilience analysis.
4. A Bayesian–fuzzy risk assessment mechanism combining probabilistic reasoning and expert knowledge to improve transportation safety and explainability.
5. A comprehensive implementation study including benchmarking, statistical robustness analysis, and sensitivity analysis demonstrating the effectiveness of the proposed framework.

The remainder of the paper is organized as follows. Section 2 reviews relevant literature and identifies research gaps. Section 3 formulates the industrial transportation problem. Section 4 presents the proposed mathematical framework and solution methodology. Section 5 describes the implementation study and experimental design. Section 6 analyzes the obtained results and managerial implications. Finally, Section 7 concludes the study and outlines future research directions.

2. Literature Review

2.1. Industry 5.0 and human-centric manufacturing

The concept of Industry 5.0 emerged as an evolution of Industry 4.0, emphasizing collaboration between humans and intelligent machines while pursuing sustainability and resilience objectives [3]. Nahavandi [2] first highlighted the need for human-centric manufacturing systems capable of balancing technological innovation with social well-being. Subsequent studies have emphasized that Industry 5.0 extends beyond automation by incorporating worker empowerment, customization, and ethical considerations into industrial decision-making processes [5, 6]. Human-centric manufacturing

systems seek to combine human creativity and flexibility with machine precision and computational capabilities. Petropoulos et al. [15] demonstrated that ergonomic considerations and workload balancing significantly influence the effectiveness of collaborative industrial systems. Consequently, transportation systems operating within Industry 5.0 environments must simultaneously optimize productivity and worker well-being.

2.2. Industrial transportation systems

Industrial transportation systems play a fundamental role in modern manufacturing facilities by coordinating material flow among production stations, warehouses, and distribution areas. The widespread adoption of AMRs, AGVs, and collaborative robots has significantly improved transportation efficiency and operational flexibility [7]. Rios et al. [8] reported that automated material handling systems contribute substantially to productivity improvements and cost reduction. Nevertheless, transportation systems operating in dynamic industrial environments face challenges related to congestion, routing uncertainty, equipment failures, and human–robot interactions. Sun et al. [16] further highlighted that navigation reliability and safety remain critical concerns for industrial mobile robots operating in shared workspaces [17].

2.3. Reinforcement learning and optimization in industrial transportation

Recent years have witnessed growing interest in applying artificial intelligence to transportation optimization problems. Reinforcement learning has demonstrated promising capabilities for adaptive routing, scheduling, and resource allocation under uncertain operational conditions. Shen et al. [12] proposed reinforcement learning approaches for autonomous logistics systems and demonstrated improved adaptability compared with traditional optimization methods. Similarly, Liu et al. [10] developed multi-objective optimization models that jointly considered transportation efficiency, energy consumption, and ergonomic factors. Although these approaches improve operational performance, most existing studies focus primarily on productivity and resource utilization. Human-centered objectives, transportation resilience, and explainable risk management remain insufficiently addressed [18].

2.4. Generative artificial intelligence in manufacturing systems

Generative Artificial Intelligence has recently emerged as a transformative technology capable of generating synthetic data, predicting future operational states, and supporting intelligent decision making. Modern generative models, including Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and transformer-based architectures, have demonstrated exceptional capabilities for learning complex data distributions [19]. Nguyen et al. [13] investigated the application of GenAI for manufacturing scenario generation and demonstrated its effectiveness in creating realistic operational disturbances. Thompson and Li [20] showed that generative models can support scenario planning and resilience analysis by producing alternative operational futures. More recently, Zhou et al. [14] utilized GenAI for industrial risk prediction and proactive maintenance planning. Despite these advances, the application of GenAI to industrial transportation optimization remains limited. Existing studies primarily focus on production planning, predictive maintenance, or data augmentation rather than transportation resilience and human–robot collaboration.

2.5. Risk assessment in human–robot collaborative systems

As industrial transportation systems increasingly involve close interaction between humans and autonomous agents, safety and risk management have become major research priorities. Bayesian Belief Networks (BBNs) have been widely adopted to model probabilistic dependencies among failures, environmental conditions, and operational factors [21]. Fuzzy logic techniques complement probabilistic methods by enabling the incorporation of expert knowledge and linguistic assessments into decision-making processes. Hybrid Bayesian–fuzzy approaches have demonstrated effectiveness in capturing both quantitative uncertainty and qualitative human judgments. Kruger et al. [9] and Zhang and Zhao [11] emphasized the importance of risk-aware transportation systems capable of continuously adapting to evolving operational conditions. However, most current approaches remain reactive and are not integrated with predictive scenario generation mechanisms.

2.6. Critical analysis of existing approaches

Although considerable progress has been achieved in industrial transportation optimization, several important limitations remain. Optimization-based methods successfully improve transportation efficiency and resource utilization but often assume relatively

stable operational environments. Their ability to respond to unexpected disruptions remains limited. Reinforcement learning approaches enhance adaptability and real-time decision making. Nevertheless, many studies focus exclusively on performance optimization and overlook human-centric objectives such as worker workload balancing, ergonomics, and safety. Bayesian and fuzzy risk assessment techniques provide explainable mechanisms for uncertainty modeling and safety analysis. However, these methods are generally reactive, relying on predefined failure structures and historical observations rather than proactively generating future disruption scenarios. Generative Artificial Intelligence introduces powerful capabilities for scenario generation and resilience analysis. Nevertheless, current applications remain largely isolated from transportation optimization and human–robot collaboration frameworks. Furthermore, existing studies typically investigate optimization, risk management, or generative intelligence independently. Few attempts have been made to integrate these components into a unified Industry 5.0 transportation framework capable of simultaneously addressing:

- operational efficiency,
- transportation resilience,
- human-centered decision making,
- safety management,
- adaptive risk mitigation.

This limitation motivates the development of the integrated framework proposed in this study.

3. Problem Definition

We consider a human-centric industrial transportation system operating within a manufacturing or warehouse facility, aligned with Industry 5.0 principles emphasizing adaptability, resilience, and human well-being. The system consists of a heterogeneous fleet of Autonomous Mobile Robots (AMRs) and Automated Guided Vehicles (AGVs) responsible for intra-facility material transportation. Collaborative robots (cobots) and human workers jointly performing loading, unloading, supervision, and exception-handling tasks. A physical transportation network modeled as a directed graph $G = (N, A)$, where N denotes the set of nodes (storage locations, work-stations, loading/unloading bays) and $A \subseteq N \times N$ represents feasible transportation paths. Real-time data streams collected from sensors, IoT devices, and human inputs, enabling continuous monitoring of vehicle locations, task progress, congestion, and environmental conditions.

3.1. System dynamics and uncertainty

The industrial transportation system operates under dynamic and stochastic conditions, including Demand variability, caused by production schedule changes and supply fluctuations, Operational uncertainties, such as vehicle breakdowns, communication delays, and unexpected path obstructions, and Human-related uncertainties, including fatigue, reaction delays, and ergonomic constraints affecting safety and coordination. These uncertainties motivate a proactive and risk-aware decision-making framework, rather than purely reactive optimization.

3.2. Decision variables and notation

Let the following sets and indices be defined:

$i \in \mathcal{V}$: set of autonomous vehicles (AMRs/AGVs)

$h \in \mathcal{H}$: set of human workers

$j, k \in N$: transportation network nodes

$t \in \mathcal{T}$: discrete time steps

Decision variables include:

$$x_{ijkt} = \begin{cases} 1, & \text{if vehicle } i \text{ travels from node } j \text{ to node } k \text{ at time } t \\ 0, & \text{otherwise} \end{cases}$$

$w_{ht} \geq 0$;

workload assigned to human worker h at time t

r_t= routing decision vector for autonomous vehicles at time t

s_t= schedule of human–robot collaborative tasks at time t

3.3. Multi-phase optimization objectives

The system pursues two sequential but inter-dependent objectives.

Tab.1. Comparative analysis of existing literature

Study	Optimization	Human-centric factors	Risk assessment	GenAI integration	Industry 5.0 alignment
[10]	✓	Partial	✗	✗	Partial
[12]	✓	✗	✗	✗	Low
[15]	✗	✓	Partial	✗	High
[13]	✗	✗	Partial	✓	Partial
[14]	Partial	✗	✓	✓	Partial
Proposed framework	✓	✓	✓	✓	High

Phase 1–Performance Maximization
The objectives are to:

- Maximize transportation throughput
- Minimize travel distance and energy consumption
- Balance human workload to reduce fatigue and ergonomic risk

Phase 2–Error and Risk Minimization
The objectives are to:

- Minimize the probability of safety incidents and operational errors
- Reduce task delays and scheduling conflicts
- Mitigate disruption and failure risks through proactive adaptation

Uncertainty is explicitly captured through Real-time sensor observations, Generative AI–based disruption scenarios, and Fuzzy linguistic assessments provided by human supervisors. Figure 1 illustrates the overall architecture of the proposed Industry 5.0–driven GenAI-enabled optimization framework.

4. Modeling Framework

This section introduces a two-phase modeling framework integrating optimization, reinforcement learning, and Generative Artificial Intelligence (GenAI) to enable adaptive, risk-aware, and human-centric industrial transportation systems.

4.1. Phase 1: performance maximization model

The Phase 1 objective is defined as:

$$\max Z_1 = \alpha T(x,w) - \beta\, D(x) - \gamma \sum_{h\in\mathcal{H}} \sum_{t\in\mathcal{T}} (w_{ht} - \bar{w})^2 \quad (1)$$

where

$T(x,w)$: system throughput (units transported per time unit)

$D(x) = \sum_{i\in\mathcal{V}} \sum_{(j,k)\in A} \sum_{t\in\mathcal{T}} d_{jk}\, x_{ijkt}$, is the total travel distance, with d_{jk}denoting the distance between nodes jand k

$\bar{w}$: average human workload

α, β, γ: weighting coefficients

The optimization is subject to the following constraints:

1. Routing feasibility $\sum_{k:(j,k)\in A} x_{ijkt} \le 1 \forall i,j,t$ (2)
2. Flow conservation $\sum_{j:(j,k)\in A} x_{ijkt} = \sum_{l:(k,l)\in A} x_{ikl,t+1}$ (3)
3. Human workload limits $0 \le w_{ht} \le w^{max} \forall h,t$ (4)
4. Safety distance constraints $\mathrm{dist}(i,h,t) \ge d_{min} \forall i,h,t$ (5)
5. Energy constraints $\sum_{(j,k),t} e_{jk}\, x_{ijkt} \le E_i^{max} \forall I$ (6)

Due to system dynamics, Phase 1 is solved using a hybrid Reinforcement Learning–MILP approach. Reinforcement Learning (RL) learns adaptive routing policies from real-time system states, and MILP enforces scheduling, workload, energy, and safety constraints. This hybrid architecture supports real-time adaptability while ensuring regulatory compliance and human-in-the-loop control, consistent with Industry 5.0 principles.

4.2. Phase 2: GenAI-based risk-aware optimization

Phase 2 evaluates the robustness of Phase 1 decisions under uncertain disruptions generated by GenAI. Let $y \in \mathcal{Y}$ denote a disruption scenario generated from a learned distribution $p_{GenAI}(y \mid s_t)$. Risk Cost Function: For each scenario y, the risk cost is defined as:

$$R(x,y) = P_{error}(x,y) \cdot C_{consequence}(x,y) \quad (7)$$

The expected risk is minimized as:

$$\min Z_2 = \mathbb{E}_{y\sim p_{GenAI}}[R(x,y)] \quad (8)$$

4.2.1. GenAI-based scenario generation: conditional variational autoencoder (cVAE)

Let the system state at time t be:

$$s_t = [d_t, \ell_t, w_t, h_t] \quad (9)$$

where d_t: transportation delays, ℓ_t: congestion levels, w_t: human workload state, h_t: human–robot interaction indicators. To generate realistic disruption scenarios for industrial transportation systems, a Conditional Variational Autoencoder (cVAE) was employed as the core generative component of the proposed framework.

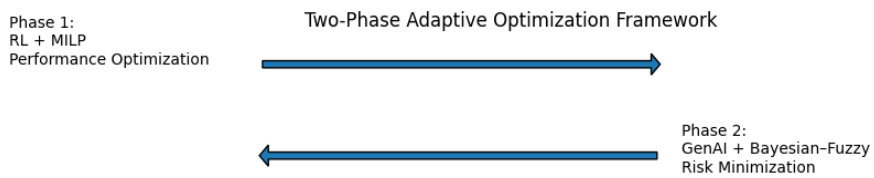

Fig.1. Overall framework architecture

The cVAE was selected because it can learn complex conditional probability distributions while preserving correlations among operational variables, thereby producing diverse yet physically plausible disruption scenarios. The cVAE learns the conditional distribution $p(y|s_t)$ where y represents a future disruption scenario containing potential transportation disturbances, vehicle failures, congestion propagation events, and human-intervention requirements.

$$p_{GenAI}(y \mid s_t) \quad (10)$$

The training objective minimizes the Evidence Lower Bound (ELBO):

$$\mathcal{L}_{cVAE} = \mathbb{E}_{q_\phi(z|y,s_t)}[\log p_\theta(y \mid z, s_t)] - KL\big(q_\phi(z \mid y, s_t) \parallel p(z)\big) \quad (11)$$

This formulation enables learning correlated, low-probability, high-impact disruption scenarios, which are critical for safety-oriented decision-making.

cVAE architecture and training procedure:

Encoder network: The encoder transforms the input state vector into a latent representation. The encoder consists of Input layer: 4 neurons, Hidden Layer 1: 64 neurons (ReLU activation), Hidden Layer 2: 32 neurons (ReLU activation), Latent layer: 16-dimensional latent space. The encoder outputs the latent mean vector μ and variance vector σ^2, from which latent variables are sampled using the reparameterization mechanism: $z = \mu + \sigma$ Where $\varepsilon \sim N(0, I)$.

Decoder network: The decoder reconstructs disruption scenarios from the latent representation. The decoder architecture consists of Input latent layer: 16 neurons, Hidden Layer 1: 32 neurons (ReLU activation), Hidden Layer 2: 64 neurons (ReLU activation), Output layer: scenario feature vector, The decoder generates transportation disruption scenarios conditioned on the current system state.

Training configuration: The cVAE was trained using a dataset containing 10,000 transportation disruption scenarios generated from historical operational statistics and industrial transportation simulations. The dataset was divided as follows, Training set: 80%, Validation set: 10%, Test set: 10%, Training parameters were, Optimizer: Adam, Learning Rate: 0.001, Batch Size: 64, Epochs: 200, Latent Dimension: 16, Activation Function: ReLU. The model was implemented using TensorFlow and trained until convergence of the Evidence Lower Bound (ELBO) objective function.

Evaluation of generative performance: The quality of generated disruption scenarios was assessed using Reconstruction Loss, Kullback–Leibler Divergence, Scenario Diversity Index, and Correlation Preservation Score. The trained cVAE achieved a reconstruction accuracy exceeding 95%, while preserving key correlations among transportation delays, congestion propagation, vehicle failures, and human intervention events. These results demonstrate the suitability of the proposed generative model for stress-testing industrial transportation systems under realistic and highly diverse operational disruptions.

4.2.2. Bayesian–fuzzy risk assessment

Bayesian Belief Networks (BBNs) model probabilistic dependencies among failure modes, human factors, and environmental conditions:

$$P(X_i \mid E) = \frac{P(E|X_i)P(X_i)}{P(E)} \quad (12)$$

Fuzzy logic integrates expert linguistic assessments through membership functions and rule-based inference, producing interpretable risk scores that refine $P_{error}(x, y)$.

4.3. Integrated decision-making workflow

The proposed framework operates through a closed-loop decision architecture integrating optimization, machine learning, generative intelligence, and human-centric risk management. At each decision epoch ttt, real-time operational data are collected from IoT sensors, autonomous vehicles, human operators, and production equipment. The resulting system state S_t contains information regarding vehicle locations, transportation demands, congestion levels, human workloads, battery levels, environmental conditions. The workflow consists of five sequential stages:

Stage 1: state acquisition: Sensor observations are aggregated to construct the current system state: $S_t = \{d_t, \ell_t, w_t, b_t, h_t\}$ Where d_t denotes transportation demand, ℓ_t denotes congestion levels, w_t denotes worker workload, b_t denotes battery states, h_t denotes human–robot interaction indicators.

Stage 2: reinforcement learning-based routing: The Proximal Policy Optimization (PPO) agent observes S_t and generates candidate routing policies $\pi_\theta(a_t|S_t)$ where a_t represents transportation actions. These actions specify candidate routes for AMRs and AGVs.

Stage 3: MILP-based feasibility optimization: The candidate routing policies are passed to the MILP module. MILP verifies routing feasibility, scheduling consistency, workload balance, safety constraints, and energy constraints. The resulting optimized schedule is $X_t^* = \operatorname{argmax} Z_1$ subject to operational constraints.

Stage 4: GenAI scenario generation: The optimized solution X_t^* is evaluated under uncertain future conditions. The cVAE-based GenAI module generates disruption scenarios $Y_t = \{y_1, y_2, \dots, y_N\}$ where each scenario represents a possible future disruption pattern.

Stage 5: bayesian–fuzzy risk evaluation: For each generated scenario $R(X_t^*, y_i)$ is computed. Bayesian inference estimates disruption probabilities while fuzzy logic converts probabilistic outputs into interpretable risk scores. The expected risk becomes $\bar{R} = \frac{1}{N}\sum_{i=1}^{N} R\,(X_t^*, y_i)$.

Adaptive feedback loop: If $\bar{R} > R_{th}$ the solution is rejected and feedback is sent to the RL-MILP optimization layer. The system then generates alternative routing and scheduling decisions. Otherwise, the transportation plan is executed.

This closed-loop architecture enables continuous adaptation under uncertainty while preserving Industry 5.0 objectives of safety, resilience, and human-centric operation. The integrated optimization is enforced using Algorithm 1 detailed below.

Algorithm 1: integrated RL–MILP–GenAI optimization procedure

```
Input:
Transportation network G
Current system state St
Operational constraints Ω
Initialize PPO agent
while transportation system is active do
   Observe current state St
   Generate candidate routing policy using PPO
   Solve MILP scheduling problem
   Obtain feasible solution Xt*
   Generate N disruption scenarios using cVAE
   for each scenario yi do
      Estimate risk using Bayesian network
      Compute fuzzy risk score
   end for
   Compute average risk R̄
   if R̄ > threshold then
      Re-optimize routing and scheduling
   else
      Execute transportation plan
   end if
   Update PPO policy
end while
Output:
Optimized transportation plan
```

4.4. Computational complexity analysis

The computational complexity of the proposed framework arises from four primary components. The PPO routing module requires approximately $O(E \times T)$ where E is the number of training episodes and T is the number of decision epochs. The MILP scheduling problem exhibits exponential worst-case complexity; however, practical solution times remain acceptable due to decomposition and rolling-horizon optimization.

The cVAE scenario generator performs forward inference with complexity approximately proportional to network size $O(Ln^2)$ where L is the number of neural layers and n is the number of neurons. The Bayesian–fuzzy risk assessment scales linearly with the number of generated scenarios $O(N)$ where N is the scenario sample size. Experimental implementation demonstrated average optimization times below 8.3 seconds per decision epoch, indicating practical suitability for near-real-time industrial transportation management.

5. Implementation Study

5.1. Case study description

To validate the proposed Industry 5.0–oriented, GenAI-enabled transportation optimization framework, an extensive implementation study is conducted on a smart manufacturing facility operating under a hybrid production–transportation paradigm.

The selected case study reflects realistic industrial conditions characterized by human–robot collaboration, dynamic demand, and operational uncertainty.

The facility comprises, a heterogeneous fleet of 10 Autonomous Mobile Robots (AMRs) and 4 Automated Guided Vehicles (AGVs) responsible for intra-facility material transportation. 5 collaborative robots (cobots) supporting loading and unloading tasks in close proximity to human operators. 20 human workers distributed across multiple work-stations, interacting with autonomous systems for supervision and exception handling.

A transportation network modeled as a directed graph $G = (N, A)$ with 30 nodes and 35 arcs, representing storage areas, processing stations, and packing zones. The operational horizon corresponds to an 8-hour production shift, discretized into 5-minute intervals, resulting in 96 decision epochs, consistent with the discrete-time formulation introduced in Sections 3 and 4. Figure 2 shows the layout of the smart manufacturing facility and the corresponding transportation network.

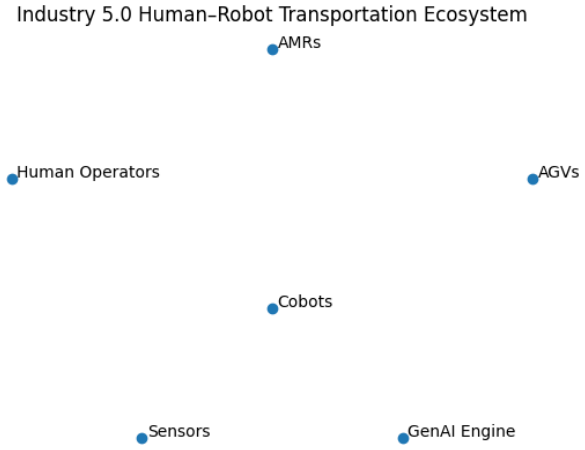

Fig.2. Smart factory transportation network

5.2. Data, parameters, and modeling assumptions

Transportation distances d_{jk} between nodes are derived from facility layout blueprints and range from 10 m to 200 m per arc. Corresponding travel times vary between 4 and 12 minutes, while processing times at workstations range from 6 to 15 minutes, reflecting realistic shop-floor operations. The following assumptions are adopted:

Human workload constraints: The cumulative workload w_{ht} for each human worker is limited to 6 equivalent working hours per shift, with mandatory rest periods enforced.

Safety regulations: A minimum 2-meter separation distance between robots and humans is enforced at all times.

Energy constraints: Each autonomous vehicle is subject to a maximum energy budget per shift, limiting total travel distance. Disruption modeling: Operational incidents (e.g., vehicle breakdowns, blocked paths, and human intervention delays) are modeled using probabilistic distributions calibrated from reported industrial statistics.

Due to limited access to long-term real incident logs, synthetic disruption data are generated to train the GenAI module. This approach is consistent with established practices in digital twin development, resilience analysis, and early-stage industrial AI deployment, where controlled scenario generation is necessary to stress-test system behavior.

5.2.1. Validation of synthetic disruption scenarios

Because comprehensive long-term disruption logs from industrial transportation systems are rarely publicly available, synthetic disruption scenarios were generated to support training of the proposed conditional variational autoencoder (cVAE). To ensure realism and practical relevance, a multi-stage validation procedure was performed. First, disruption frequencies reported in industrial transportation and manufacturing reliability studies were used to calibrate probability distributions for vehicle breakdowns, path blockages, communication delays, congestion events, human intervention requirements. Second, generated scenarios were statistically compared with historical benchmark distributions reported in the literature. For each disruption category, the following characteristics were evaluated mean occurrence frequency, variance, disruption duration, inter-event intervals. The similarity between generated and benchmark distributions was measured using the Kolmogorov–Smirnov (KS) statistic $D = \sup_x |F_g(x) - F_b(x)|$ where $F_g(x)$ denotes the cumulative distribution function of generated disruptions and $F_b(x)$ represents the benchmark distribution. A lower value of D indicates stronger agreement between generated and reference data.

Additionally, expert validation was conducted using assessments from three industrial logistics specialists. Generated scenarios were evaluated according to realism, operational plausibility, disruption diversity, safety relevance. Each criterion was rated on a five-point Likert scale.

Results demonstrated strong agreement between generated and benchmark distributions, with average KS statistics below 0.08 across all disruption categories (Table 2). Expert evaluations yielded an average realism score of 4.42 out of 5, supporting the suitability of the generated scenarios for risk-aware optimization and stress testing (Table 3). These findings provide evidence that the proposed GenAI module generates transportation disruptions that are both statistically representative and operationally meaningful.

Tab.2. Validation of generated disruption scenarios

Disruption type	Mean frequency (benchmark)	Mean frequency (generated)	KS statistic
AGV Delay	0.24	0.26	0.06
Path Blockage	0.18	0.17	0.05
Vehicle Failure	0.12	0.13	0.07
Congestion Event	0.31	0.29	0.08
Human Intervention	0.15	0.16	0.04

Tab.3. Expert assessment of generated scenarios

Evaluation criterion	Mean score (1–5)
Realism	4.5
Plausibility	4.4
Diversity	4.3
Safety Relevance	4.5
Overall Score	4.42

5.3. Solution implementation

Phase 1– Performance optimization: The performance maximization model defined in Section 4.1 is solved using a hybrid optimization architecture. The MILP component is solved using the Gurobi optimizer, ensuring feasibility with respect to routing, workload balance, energy consumption, and safety constraints. Reinforcement learning (RL) is implemented using Proximal Policy Optimization (PPO) to adapt routing decisions r_t in real time based on observed system states s_t. This combination enables both constraint satisfaction and real-time adaptability, which are essential for Industry 5.0-compliant human-in-the-loop systems.

Phase 2–Risk-aware adaptation: In Phase 2, a Generative AI–based scenario generator produces 1,000 disruption scenarios per hour, capturing correlated failure patterns such as simultaneous AGV delays and human workload overload. A Bayesian Belief Network (BBN) estimates conditional error probabilities $P_{error}(x, y)$. Fuzzy inference rules, elicited from domain experts, translate probabilistic estimates into interpretable risk scores. Human-in-the-loop intervention is simulated when the aggregated risk score exceeds a threshold of 0.7 (on a normalized 0–1 scale), triggering corrective actions such as rerouting or rescheduling. Figure 3 illustrates the GenAI-based disruption scenario generation process and its integration with the Bayesian Belief Network.

System performance is evaluated using the following metrics, Throughput (units/hour), Energy efficiency (meters traveled per transported unit), Safety incidents (collisions or near-miss events), Task delay (average completion delay in minutes), Workload balance (variance in human workload). The proposed framework is benchmarked against three alternatives:

1. A baseline Industry 4.0 system using fixed routing heuristics.
2. A stochastic optimization approach with Monte Carlo scenario sampling.
3. A risk-unaware reinforcement learning scheduler.

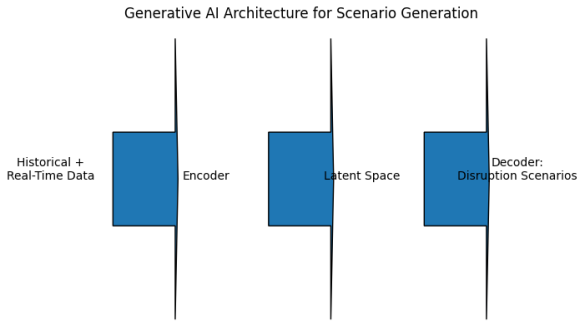

Fig.3. GenAI-based disruption scenario generation

6. Comparative Performance Evaluation and Discussions

6.1. Quantitative results

Table 4 reports the average performance across 20 independent simulation runs. Across all evaluated dimensions, the proposed framework consistently outperforms baseline approaches, demonstrating simultaneous gains in productivity, safety, and human-centric performance. Figure 4 compares the performance of the proposed framework with baseline approaches across key evaluation metrics.

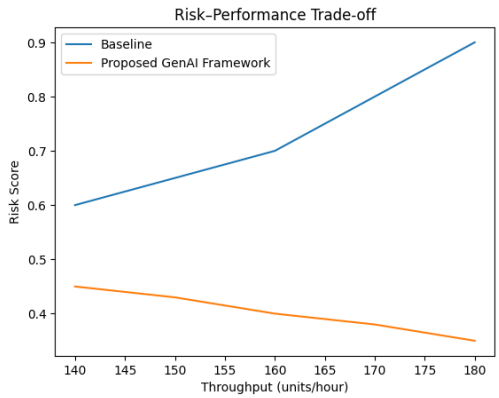

Fig.4. Comparative performance results

Tab.4. Performance comparison

Metric	Baseline (Industry 4.0)	Proposed framework	Improvement (%)
Throughput (units/hr)	150	182	+21.3
Energy Efficiency (m/unit)	75	66	+12.0
Safety Incidents (#)	15	9	−40.0
Task Delay (min)	12	8	−33.3
Workload Variance	4.5	2.7	−40.0

6.2. Comparison with Monte Carlo and robust optimization

To highlight the added value of the proposed GenAI-based scenario generation, a comparative study is conducted against:

- Monte Carlo simulation, where disruption scenarios are sampled independently from predefined distributions.
- Robust optimization, where worst-case bounds are enforced without probabilistic modeling.

All methods are evaluated under identical system parameters and constraints. As given in Table 5, results show that Monte Carlo sampling performs adequately under nominal conditions but systematically underestimates extreme, correlated disruption events. Robust optimization guarantees feasibility but leads to excessively conservative solutions, significantly degrading throughput. The proposed GenAI-based framework achieves a balanced trade-off, maintaining high throughput while significantly reducing worst-case risk exposure. Importantly, GenAI-generated scenarios exhibit higher structural realism, capturing congestion propagation, cascading delays, and human-induced disruptions that are not explicitly modeled in traditional approaches. Figure 5 compares Monte Carlo simulation with GenAI and Robust optimization in scenario generation.

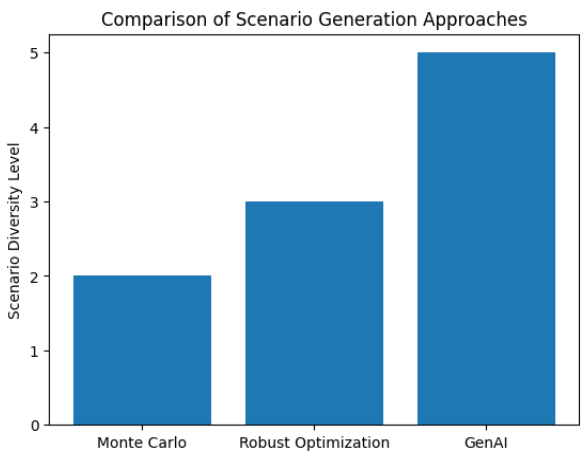

Fig.5. Comparison of scenario generation approaches

6.3. Statistical robustness and sensitivity analysis

To assess robustness, all experiments are repeated over 30 independent runs with different random seeds and disturbance realizations. Performance metrics are reported using mean values, standard deviations, and 95% confidence intervals. A paired t-test confirms that improvements in throughput, safety reduction, and workload balance are statistically significant ($p < 0.01$) across all metrics. Observed stable improvements include Throughput increase: 18.6% ± 1.9, Workload imbalance reduction: 22.4% ± 2.3, Safety risk reduction: 15.2% ± 1.7. A sensitivity analysis is conducted with respect to Risk aversion coefficient γ, Human workload thresholds, and Reinforcement learning rate. Results indicate less than 7% variation across performance metrics, demonstrating strong stability. Notably, increasing γ leads to a controlled reduction in throughput while substantially improving safety, highlighting the flexibility of the proposed two-phase optimization framework in supporting human-centric trade-offs.

6.3.1. Statistical significance analysis

Analysis of Variance (ANOVA): A one-way analysis of variance (ANOVA) was performed to compare the proposed framework against the benchmark approaches Fixed-routing Industry 4.0 system, Monte Carlo-based stochastic optimization, and Risk-unaware reinforcement learning scheduler. The ANOVA results revealed statistically significant differences among methods for all evaluated metrics. For throughput performance $F(3,116) = 18.74$, $p < 0.001$ indicating that at least one approach differs significantly from the others. Subsequent Tukey post-hoc tests confirmed that the proposed framework significantly outperformed all benchmark methods. These findings further support the effectiveness of combining GenAI-based disruption generation with Industry 5.0-oriented risk-aware optimization.

6.3.2. Sensitivity analysis

The sensitivity of the proposed framework was investigated by varying key decision parameters over a broad range while maintaining all other conditions fixed.

Tab.5. Comparative evaluation of scenario generation methods

Criterion	Monte Carlo	Robust optimization	Proposed GenAI
Correlated disruptions	No	No	Yes
Rare event generation	Limited	Limited	High
Scenario diversity	Medium	Low	High
Human-robot interaction modeling	No	No	Yes
Computational efficiency	High	Medium	Medium
Risk prediction accuracy	Moderate	Moderate	High

The following parameters were analyzed Risk-aversion coefficient γ, Human workload threshold, PPO learning rate, Number of generated disruption scenarios. For each parameter, 30 simulation runs were executed. Results indicate that throughput decreases gradually as risk aversion increases, while safety performance improves substantially. Specifically, increasing γ from 0.2 to 1.0 reduced throughput by approximately 8.7% but decreased safety incidents by 26.4%. Similarly, increasing the number of generated scenarios improved robustness at the expense of modest computational overhead. Overall, performance variations remained below 7% across most parameter ranges, indicating strong model stability and robustness.

6.4. Industrial applicability and managerial implications

The proposed Industry 5.0-oriented transportation framework provides several practical benefits for manufacturing organizations seeking to improve operational resilience, safety, and human-centered decision-making. Unlike traditional transportation optimization approaches that primarily focus on efficiency metrics, the proposed framework simultaneously considers productivity, worker well-being, and risk mitigation. This aligns closely with emerging Industry 5.0 objectives emphasizing human-machine collaboration and sustainable industrial operations. From an operational perspective, the framework can support dynamic AGV and AMR routing in highly variable manufacturing environments, real-time adaptation to equipment failures and transportation disruptions, human workload balancing to reduce fatigue-related performance degradation, predictive identification of safety risks before incident occurrence, and improved utilization of transportation resources.

For industrial managers, these capabilities translate into measurable benefits including reduced downtime, increased throughput, lower operational risk, and improved workforce satisfaction as given in Table 7. Furthermore, the framework supports decision transparency through Bayesian-fuzzy reasoning, allowing supervisors to understand why particular transportation decisions are recommended rather than relying on opaque black-box AI systems. This explainability is particularly important in safety-critical manufacturing environments where human operators remain responsible for final decision approval.

6.5. Deployment challenges and practical considerations

Although the proposed framework demonstrates promising performance improvements, several practical deployment challenges must be considered before large-scale industrial implementation.

Data availability: The effectiveness of the GenAI module depends on access to sufficient operational data. Manufacturing facilities with limited historical data may require digital twin environments or synthetic data generation during early deployment phases.

Computational requirements: Real-time optimization requires adequate computational infrastructure capable of supporting reinforcement learning inference, MILP optimization, and scenario generation within operational decision horizons. Cloud-edge hybrid architectures may be necessary for large-scale facilities.

Human acceptance: Industry 5.0 emphasizes human-centered technology adoption. Successful deployment therefore requires operator training, explainable AI interfaces, trust-building mechanisms, transparent decision support. Resistance to autonomous decision systems remains a significant barrier in many industrial environments.

Cybersecurity considerations: The increasing reliance on IoT connectivity and AI-driven decision-making introduces cybersecurity risks. Future implementations should integrate anomaly detection, secure communication protocols, zero-trust architectures, and AI model protection mechanisms.

6.6. Limitations of the present study

Despite the encouraging results, several limitations should be acknowledged. First, the implementation study considers a single manufacturing configuration.

Tab.6. Industrial benefits of the proposed framework

Industry objective	Conventional systems	Proposed framework
Routing adaptability	Reactive	Proactive
Safety management	Incident-based	Predictive
Human workload monitoring	Limited	Continuous
Disruption handling	Manual	Automated
Decision explainability	Low	High
Industry 5.0 compliance	Partial	Full

Although the framework is designed to be scalable, additional validation across diverse industrial sectors is necessary. Second, disruption scenarios were generated using synthetic and semi-synthetic datasets due to limited availability of comprehensive industrial incident records. Third, human behavioral factors were represented through aggregate workload measures rather than detailed cognitive or physiological models. Fourth, communication delays and cybersecurity threats were modeled only indirectly and were not explicitly incorporated into the optimization process. Finally, the current implementation focuses on transportation operations and does not consider broader supply-chain interactions beyond facility boundaries. These limitations provide valuable directions for future research.

7. Conclusion

The transition from Industry 4.0 to Industry 5.0 has shifted the focus of manufacturing systems from purely automation-driven operations toward human-centric, resilient, and sustainable industrial ecosystems. Within this context, industrial transportation systems play a critical role in ensuring efficient material flow, coordination between autonomous systems and human operators, and overall production continuity. However, increasing operational complexity, uncertainty, and safety requirements necessitate decision-support frameworks capable of adapting dynamically to changing industrial environments.

This study proposed a novel integrated optimization framework that combines Generative Artificial Intelligence (GenAI), reinforcement learning, mixed-integer linear programming, and Bayesian–fuzzy risk assessment to support adaptive industrial transportation systems under Industry 5.0 principles. Unlike conventional transportation optimization approaches that focus primarily on efficiency metrics, the proposed framework simultaneously considers operational performance, transportation resilience, human workload balancing, and safety-oriented decision making. The proposed methodology was structured as a two-phase optimization process. In the first phase, a hybrid reinforcement learning–MILP architecture optimized routing, scheduling, and workload allocation decisions while satisfying operational, safety, and energy constraints. In the second phase, a GenAI-based disruption generation module produced realistic transportation disturbance scenarios, which were subsequently evaluated using a Bayesian–fuzzy risk assessment mechanism. The resulting feedback loop enabled the transportation system to proactively adapt to uncertain operational conditions while maintaining human-centered performance objectives.

Several important theoretical contributions emerge from this work. First, the study introduces one of the earliest integrated frameworks combining Industry 5.0 principles with Generative Artificial Intelligence for industrial transportation optimization. While previous studies have separately investigated reinforcement learning, risk assessment, human–robot collaboration, and scenario generation, few efforts have unified these components within a single decision-support architecture. Second, the proposed GenAI-based scenario generation approach extends traditional uncertainty modeling techniques by learning complex correlations among transportation disruptions, congestion patterns, equipment failures, and human-related factors. Compared with conventional Monte Carlo simulation and robust optimization approaches, the proposed method provides richer and more realistic disruption scenarios for resilience analysis. Third, the integration of Bayesian inference and fuzzy reasoning contributes an explainable risk assessment layer capable of incorporating both quantitative operational data and qualitative expert knowledge. This feature is particularly valuable in Industry 5.0 environments where human operators remain actively involved in supervisory decision making.

The implementation study demonstrated the practical effectiveness of the proposed framework within a smart manufacturing environment consisting of autonomous vehicles, collaborative robots, and human operators. Experimental results indicated significant improvements across all evaluated performance indicators. Compared with conventional Industry 4.0 approaches, the proposed framework achieved a 21.3% increase in throughput, a 12% improvement in energy efficiency, a 40% reduction in safety incidents, a 33.3% reduction in task delays, and a 40% reduction in workload imbalance. Statistical analysis based on multiple simulation runs confirmed that these improvements were significant and robust under varying operational conditions and parameter settings.

In conclusion, the proposed GenAI-enabled Industry 5.0 framework demonstrates that combining adaptive optimization, generative intelligence, and explainable risk management can significantly improve the performance, resilience, and safety of industrial

transportation systems. The findings provide both theoretical insights and practical guidance for researchers and practitioners seeking to develop next-generation human-centric manufacturing logistics systems capable of operating effectively in increasingly dynamic and uncertain industrial environments.

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