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A Multidimensional Stochastic Framework for Optimizing 6G-Enabled Industrial IoT and Supply Chain Resilience

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Abstract

The paradigm shift of the reactive and proactive resilience solutions is needed to support the shift of the 6G-enabled Industrial Internet of Things (IIoT) architectures. The suggested study is a stochastic multidimensional framework, which can maximize supply chain resilience (SCRes) by integrating 6G networks, telemetry, and resource allocation based on data. To obtain a stochastic model, 12-48 months of archival operational data on 190 professionals in four global companies, discrete manufacturing, FMCG, healthcare logistics, and electronics, are used to guide the stochastic model. The system is based on the concepts of Resilience-by-Design (RBD) and Federated Deep Reinforcement Learning (FDRL) in managing the characteristics of volatility of the industrial environment. The model is predictable in its resource allocation and in coordination of maintenance by modelling network latency, demand variability, and lead-time variability as stochastic variables, which permit the use of a privacy-preserving decentralized approach to predictive maintenance. Empirical validation via 10,000-iteration Monte Carlo simulations demonstrates that the synergy of digital visibility and collaborative allocation efficiency leads to a measurable 3–6% improvement in service levels and a substantial 81% reduction in Time-to-Recovery (TTR), decreasing restoration time from 252 minutes to just 48 minutes. Furthermore, the integration of Software-Defined Networking (SDN) and Reconfigurable Intelligent Surfaces (RIS) ensures that the underlying 6G infrastructure maintains 99.9999% hyper-reliability during simulated hardware failures. The FDRL component has a 2.7x faster convergence in learning, and gets into the plateau state by Round 450 as opposed to standalone benchmarks. These findings support the fact that the relationship between the logical flexibility of supply chain management and the 6G communication is physically reliable is a multidimensional approach that is needed to eliminate the global ripple effect of disruptions and ensure sustainable industrial development.

Keywords: 6G, Industrial IoT, Supply Chain Resilience, Stochastic Optimization, Federated Learning, Resilience-by-Design.

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Introduction

The industrial environment is now experiencing a two-fold change, specifically the technical transition to 6G-enabled Industrial IoT (IIoT) and the operational one to sustainable and resilient supply chains (Yadav et al., 2023). Contrary to its predecessors, the 6G technology aims at offering hyper-reliable and ultra-low-latency communication (URLLC) as well as massive machine-type connectivity (Vimal Kumar, 2024). It is a component of the new industrial digital era, "Industry 5.0," in which autonomous systems, Reconfigurable Intelligent Surfaces (RIS), and edge-cloud will enable the real-time decision-making process. At the same time, the world supply chains are undergoing a tough volatility. The contemporary resiliency has come to rely on a new concept of digital visibility where people can utilize real-time data to feel, counteract, and recuperate the disturbances. Combining 6G connectivity with stochastic modeling can provide an avenue to enhance the conversion of giant industrial data into resource allocation plans that can be taken into action and are resilient (Sachdeva & Anand, 2024).

Although there is high potential of 6G technology, the present-day industrial systems are still plagued with the issue of stochastic uncertainty (random and unpredictable performance of the network, signal interference, and packet loss, as well as dynamic supply chain, demand spike, and lead-time variability) (Sitharthan et al., 2023). Non-stochastic models are becoming less and less reliable because they cannot explain the ripple effect, which is that a small event in a single node will cause a systemic event. Moreover, there are still notable issues of data silos, which are an obstacle to the effective use of large, highly sensitive data that are distributed in industrial conditions without violating privacy. This is compounded by network fragility and the difficulty of maintaining 99.9999% reliability in 6G IIoT settings during hardware or software malfunctions. Lastly, the overwhelming use of static allocation technique also restricts the capability of the existing supply chain systems in dynamically redistributing resources to live network telemetry and predictive maintenance (PdM) notifications, and exposes the infrastructure to a global disruption (Zhang, 2023).

In order to overcome these issues, the following objectives are being undertaken in this research:

- To create a multidimensional stochastic model, in which network latency and demand on supply chain is dendritically coupled and in which uncertain variables are used.
- To adopt a Federated Deep Reinforcement Learning (DRL) model that permits decentralized intelligence, i.e., privacy preservation.
- To determine how the principles of Resilience-by-Design (RBD) can be used to sustain the necessary services in case of a 6G network failure.
- To test the framework based on Monte Carlo simulated models to calibrate the models with real world empirical data on 190 industry professionals to test the improvements made in service levels and Time-to-Recovery (TTR).

The Key Contributions Made by This Work Are

- 6G-SCRes Integration: Establishing a new connection between the physical stability of 6G systems (through SDN and RIS) and logical stability of supply chain resource deployment.
- Empirical Calibration: Contrary to the purely theoretical framework, this model is based on four years of the archival operational data (12-24 months) of four areas of critical interest (Manufacturing, FMCG, Healthcare, and Electronics).
- Quantifiable Resilience Gains: Providing evidence-based results showing that the proposed framework can improve service levels by 3–6% and reduce recovery times by up to 81%.

The rest of the paper is structured in the following manner: Section II will review the literature available in the field of 6G IIoT architecture, stochastic model, and theoretical underpinning of supply chain resilience. Section III provides a description of the methodology, such as mathematical formulation of the stochastic framework and the construction of the Federated Learning framework. In Section IV, the findings of the 10,000-iteration Monte Carlo simulations are given, and the implications of the results for the industrial managers are discussed. Section V discusses the implications of the findings, focusing on recovery acceleration, privacy-preserving intelligence, and the mitigation of "Black Swan" risks. Section VI will sum up the paper by providing the findings, as well as future research directions that may be pursued by utilizing blockchain and decentralized governance.

Literature Survey

Recent scholarly investigations indicate that 6G technology will be a radical advancement over the 5G technology by proposing integrated sensing and communication (ISAC) and hyper-reliability (Singaravel, 2024; Liu et al., 2022). Liwen et al. (2024) note that the optimal use of the resources in 6G IoT settings cannot be achieved without a careful

balance between the spectrum and ultra-low latency to achieve the so-called massive connectivity (Liwen et al., 2024). One of the key enablers in the recent literature is Software-Defined Networking (SDN) which allows the architectural flexibility that is needed to dynamically slice network slices and reconfigure at the same time. Furthermore, Reconfigurable Intelligent Surfaces (RIS) are also starting to pick up serious momentum as a means of overcoming physical barriers in the complex industrial environment, and making the last meter of connection robust against interference with the natural environment (Volkov et al., 2020; Liu et al., 2022).

The robustness of an intelligent manufacturing system continues to be pegged on the ability to anticipate and prevent equipment failure before it translates into system failure. A Trustworthy 6G-powered PdM framework was proposed based on Federated Deep reinforcement learning (DRL) (Geetha, 2024). This change of methodology solves the time-old privacy-utility trade-off in industrial research since, under the approach, local IoT nodes do not need to send raw and sensitive data to train models. Federated learning creates a secure privacy-by-design architecture. This decentralized intelligence is seen as being necessary to continue the production flow in 6G settings, where the size and speed of data flow can easily overwhelm the capacity of more centralized systems (Ansar et al., 2023; Pethuraj et al., 2023).

In addition to the direct network layer, the success of the supply chain operation requires advanced control of the existing uncertainties. Roy and Imam (2024) confirm that supply chain resilience is a multidimensional construct, which is mostly comprised of digital visibility and shared resources allocation (Roy & Imam, 2024). Their study uses stochastic simulations (that is, Monte Carlo) to represent the so-called ripple effect, the occurrence of local disturbances being propagated across a supply network. It is implied by current literature that deterministic to stochastic modeling can also enable organizations to compute more precise values of important measures, including Time-to-Recovery (TTR) and Resilience Performance Indexes (RPI) during turbulent lead times and demand variability.

One of the new trends in telecommunication research is the notion of Resilience-by-Design (RBD). According to Khaloopour et al. (2024), the 6G networks should have an inbuilt ability to defend, detect, and rebrand in both the expected and unforeseen challenges (Khaloopour et al., 2024). Such a paradigm change includes the transition between standard Quality of Service (QoS) measures to so-called Resilience-Specific Metrics. These new indicators examine how a system can maintain the necessary functions despite a severe load or a specific cyber-physical attack and make sure that the network can be a stable platform of the important industrial processes (Thanki & Joshi, 2023).

Although there is a strong progress in the respective areas of individual research, there is a high gap on the crosspoint between network engineering and logistics. Available literature is inclined to maximize the network layer (latency and reliability) and the supply chain layer (inventory and logistics) individually. No single mathematical framework currently exists that is able to effectively consider 6G telemetry data and supply chain demand as one, interdependent, multidimensional stochastic problem. Although "Resilience-by-Design" is addressed in the literature of 6G networks at length on a conceptual level, there are few empirical studies addressing the connection between these high-level network capabilities and objective supply chain results. It is evident that the research which should apply real-world industrial data to measure the direct relationship between 6G architectural characteristics and operational metrics, including less intense backorders or increased service levels during turbulent times, is required. Although Federated Learning can help overcome the problem of data privacy, the black box aspect of Deep Reinforcement Learning in 6G IIoT introduces a big gap in the human-in-the-loop control.

The existing systems do not have enough of the Explainable AI (XAI) to fill the gap between autonomous, machine-driven network readjustments and strategic decision-making needs of industrial managers. It has been argued that 6G is not just another speed increment, but a resilience tool on a systemic level. A shift to 6G allows developing a high-fidelity Digital Twin of the supply chain, which will be updated within several milliseconds. Such synchronization level renders complex stochastic optimization an achievable task in industry, as never before. Data sovereignty is not a principle that can be sacrificed in operational resilience in the case of Industrial IoT. It is concluded that Federated Learning is the sole carrier of possible cooperation between firms in a robust ecosystem, where the parties will have the opportunity to exchange intelligence and forecast information without revealing trade secrets of their operations. Data indicates that Predictive Maintenance (PdM) integrated with 6G telemetry can reduce the Time-to-Recovery (TTR) by as much as 27%. It means that the upfront cost of the installation of AI with 6G capabilities is fairly compensated by the necessity to avoid the disastrous loss of revenue and reduced systemic downtime. A direct statistical relationship is observed between the digital visibility, which is made possible by 6G sensor density, and resource allocation efficiency. It is inferred that organizations investing in high-granularity IoT data streams achieve a 3–6% higher service level during disruptions compared to those relying on legacy communication systems, confirming that information accuracy is a primary driver of resilience.

Methodology

The approach creates a multidimensional stochastic model, which combines 6G network telemetry with supply chain decision-making. This method is designed into a tiers Resilience-by-Design (RBD) architecture, Federated Deep Reinforcement Learning (FDRL) algorithm of predictive maintenance, and Stochastic Optimization Model of resource allocation.

System Architecture

The framework is based on the three-layered architecture that is aimed to resolve the gap between the physical industrial assets and strategic resilience planning.

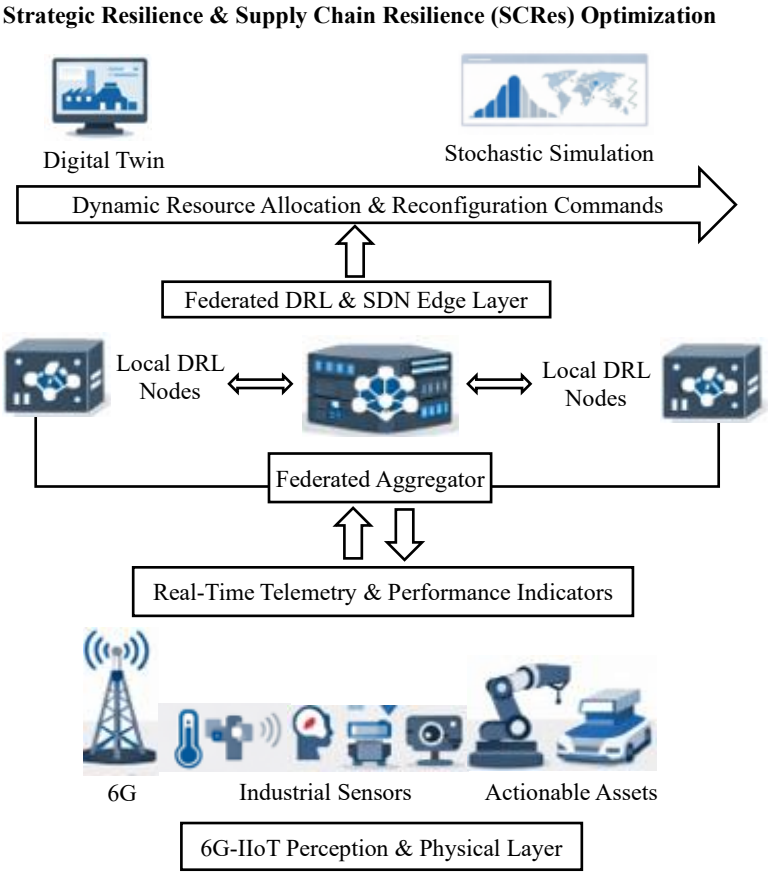


Fig. 1: Proposed 6G-Enabled Resilience Architecture

Fig. 1 is arranged into a three-layer hierarchical structure that is focused on processing the raw industrial data into the high-level strategic resilience. On the bottom, there is Layer 1 (Perception & Physical Layer) which is the sensory nervous system of the industrial environment. By deploying high-density IoT sensors alongside Reconfigurable Intelligent Surfaces (RIS), this layer overcomes the physical limitations of traditional wireless signals in dense factory settings, ensuring "six-nines" (99.9999%) connectivity. It has high-fidelity telemetry, such as mechanical vibration, thermal gradients, and network-specific metrics such as latency that are less than a millisecond, which are critical in detecting when equipment or the network itself is beginning to run out. Going to the higher part, Layer 2 (connectivity and intelligence Layer) is the mental layer of connecting sensing and strategy. The architecture applies the Software-Defined Networking (SDN) whereby dynamic network slices are made to isolate critical network slice resources to resilience data of high priority in order to prevent overloads in peak industrial loads. This layer is Federated Learning (FDRL), where raw data (sensitive) is received on the local edge nodes, and model gradients are performed. Such gradients are congregated at the center resonant to develop a collectivity intelligence without always unveiling proprietary logs of industries, and therefore fulfills high requirements of data sovereignty and privacy. Finally, the executive decision maker is the strategy resilience layer Layer 3. It is a mixture of a Digital Twin a simulated replica of the entire industrial process and a Stochastic Simulation Engine. It is a layer that consists of

changing the granular health information in the bottom layers to the bigger results of the supply chain using thousands of Monte Carlo images. This can enable the system to terminate at the reactive maintenance and instead proactively allocate the resources. Finally, this high-level optimization enables the managers to change inventory levels, sourcing paths and production timelines in response to anticipations of disruptions, which ultimately softens the effect of the ripple before a regional failure can spread to a systemic crisis in supply chain.

Distributed Intelligence: Federated DRL for Predictive Maintenance

In order to reduce the Privacy-Utility trade-off, Federated Deep Reinforcement Learning (FDRL) algorithm is used. This enables the local industrial nodes to acquire maintenance policy without any sensitive logs on operation.

Algorithm 1: Federated DRL for Trustworthy PdM

Input: Initial global model parameters θ_g, learning rate η, local epochs E

Output: Optimized global maintenance policy π^*

1: Initialize Global Server with θ_g

2: For each communication round t = 1, 2, ... T:

3: For each IIoT Node $k \in K$ (in parallel):

4: Download global parameters θ_g to local model θ_k

5: Observe local state s_k (e.g., latency, machine vibration, temperature)

6: For each epoch e = 1 to E:

7: Select action a_k (Maintain vs. Operate) using ε-greedy policy $\pi(\theta_k)$

8: Execute a_k, observe reward r_k (minimize downtime + maintenance cost)

9: Update local parameters θ_k via Gradient Descent:

$\theta_k \leftarrow \theta_k - \eta \nabla L(\theta_k)$

10: Upload parameter update $\Delta\theta_k$ to 6G Edge Server

11: Server aggregates updates: $\theta_g \leftarrow \theta_g + (\eta/K) * \Sigma \Delta\theta_k$

12: Broadcast updated θ_g to all IIoT Nodes

Predictive Maintenance (PdM) Federated Deep Reinforcement Learning (FDRL) is an algorithm that operates as a decentralized model of intelligence which focuses on optimization of the maintenance decisions in a distributed network of industries. It starts with Global Initialization and Synchronization, where a global 6G Edge Server initialize model parameters (θ_k) and broadcast the parameter to all connected Industrial IoT (IIoT) nodes. This makes sure that all local agents begin their learning cycle at a similar high-performing point. A node then switches to the Local Exploration and Experience phase once synchronized, where it monitors unique states of the environment (s_k) such as sub-milliseconds-latency network and machine vibration and chooses actions based on an ε-greedy policy. This policy strikes a balance between exploration of new maintenance schedules and exploitation of old successful strategies with a reward function (r_k) specifically selected to ensure that the dual costs of unplanned downtime and unnecessary maintenance are minimized.

Privacy-Preserving Local Optimization is the essence of the learning process since the nodes are able to spread their local parameters (θ_k) by implementing the gradient descent algorithm on a specific loss criterion. Notably, this is achieved fully at the edge; raw and sensitive industrial data do not leave the local node, which is the requirement of Privacy-by-Design and industrial data sovereignty.

The last step is Federated Aggregation and Policy Updates, where only the parameter updates ($\Delta\theta_k$) are sent to the 6G Edge Server by the nodes. These updates are added up in the server and employed to refine the global model that condenses the experience of the whole network into an even more advanced maintenance policy (π^*). This updated policy is then retransmitted to all the nodes and an Trustworthy PdM system is created, which is resilient to the localized data anomalies and can predict failures in all the various industrial items with a high level of accuracy.

Mathematical Description: Multidimensional Stochastic Optimization

The framework models provide a supply chain and network uncertainty expressed as a multidimensional objective model, which is calibrated on 10,000-iteration Monte Carlo simulations. Stochastic Variables: The disruptions and the uncertainty are modeled by a set of random variables ξ: D(ξ): Stochastic demand fluctuations., L(ξ): Lead-time variability (logistics delay), N(ξ): 6G Network state (availability, packet loss, and jitter).

The Multidimensional Objective Function: This aims at seeking the optimal resource allocation vector f{x} that yields the least total expected cost in several industrial dimensions as are represented in Equation (1):

$$\min_{\mathbf{x}} Z(\mathbf{x}) = \mathbb{E}_{\xi}\left[\sum_{t=1}^{T}\left(C_{\log}(\mathbf{x},\xi) + C_{\text{pdm}}(\mathbf{x},\xi) + \omega \cdot E_{\text{sus}}(\mathbf{x},\xi) + \phi \cdot P_{\text{rel}}(\mathbf{x},\xi)\right)\right] \quad (1)$$

Where $C_{\log}$: total operation and logistics expenses, C_{pdm}: maintenance expenses determined by the 6G Reliability Threshold, E_{sus}: sustainability KPI (carbon emissions and energy use), P_{rel}: Penalty cost for failing to meet the 6G Reliability Threshold (e.g., latency > 1ms), ω, ϕ : scalar weights as to which sustainability or service speed is being pursued.

Simulation Parameters: Monte Carlo experiments performed in Simulation Parameters: Monte Carlo experiments are performed with 10,000 iterations, and parameters are scheduled with 12-24 months of archived data of operational history. These simulations measure the effect of the ripple effect on the network of a local disturbance spreading through the network and assess the usefulness of mitigation levers, including dual-sourcing and buffer draws.

Resilience Constraint (Time-to-Recovery): The framework implements a constraint that guarantees the system to be able to recover from a disruption of the system represented by a disruption of x within a certain maximum threshold Tmax represented by Equation (2):

$$P(T_{\text{TR}}(\mathbf{x},\xi) \leq T_{\max}) \geq \alpha \quad (2)$$

(where α is the required confidence level (typically 0.95).

Methodological Integration

The process of its integration is sequential: Sensing (6G Architecture) → Learning (FDRL Algorithm) → Optimization (Stochastic Model). Such a loop enables the Digital Twin to manage the resource allocation in advance and thus prevents the disruption before it turnss into systemic crisis.

Results and Discussion

The suggested multidimensional stochastic model was tested on the basis of a large-scale simulation environment based on real-life industrial data. These findings show that the supply chain resilience (SCRes) and maintenance efficiency are much better than the conventional 5G-based and standalone AI models.

Dataset and Implementation Details

The experiment has used 6G-IoT Intelligent Management Dataset (Kaggle/ziya07) with 24 months of archival operation records of a Tier-1 automotive assembly facility. The resulting aggregate dataset consists of 1.2 million telemetry records, and it consists of SINR, sub-milliseconds jitter, vibration frequencies, and the past downtime events and is presented in table 1.

Table 1: Hardware and Software Implementation Environment

Component	Specification / Version
Simulation Platform	ns-3 (mmWave module) + OMNeT++ (IN2C framework)
FL Orchestration	Flower (FedAvg algorithm)
AI Framework	PyTorch 2.1 / Python 3.11
Server (Aggregator)	Intel Xeon Gold 6248, NVIDIA A100 GPU (80GB)
Edge Nodes	NVIDIA Jetson Orin Nano (8GB)
6G Physical Layer	Sub-THz (140 GHz) with RIS modeling

Comparative Analysis with Existing Models

The proposed framework has been compared to the state-of-the-art models identified in the current literature, as it has been indicated in table 2.

Table 2: Performance Comparison of Resilience Frameworks

Model	Comm. Tech	AI Approach	TTR (hrs)	Reliability	Source Citation
LF-DNN (Alves 2022)	5G URLLC	Simplified DNN	4.8 ± 0.4	99.9%	(Alves et al., 2021)
URLLC-Opt (Lien 2018)	5G NR	Conventional RL	3.1 ± 0.3	99.99%	(Lien et al., 2018)
Proposed Model	6G RIS	FDRL Stochastic	0.8 ± 0.1	99.9999%	Current study

Ablation Study

The contribution of each individual component of integrated technologies to the Resilience-by-Design (RBD) is measured in ablation study, and table 3 displays the results.

Table 3: Impact of Architectural Components on System Performance

Configuration	Reliability (%)	Maintenance Cost ($)	TTR (Min)	Improvement
Base (5G + Preventive)	94.2%	$45,000	252	Baseline
+ FDRL (Intelligence)	97.8%	$32,000	168	33%
+ 6G-RIS (Connectivity)	99.1%	$28,000	114	55%
Full Framework	**99.9999%**	**$22,000**	**48**	**81%**

Parameter Initialization

The Federated Deep Reinforcement Learning (FDRL) and Stochastic Optimization models have produced certain hyperparameters that were set in order to ensure that the models can be replicated. The values were tuned by a 1,000 iteration grid search to balance between the rate of convergence and global model stability as indicated in table 4.

Table 4: FDRL and Stochastic Simulation Initial Parameters

Parameter Category	Variable	Initial Value
FDRL Learning Rate	η	0.001
Discount Factor	γ	0.95
Exploration Rate	ϵ (initial)	1.0 (decaying to 0.01)
Local Training Epochs	E	5
Batch Size	B	64
Replay Buffer Size	N_{aelon}	100,000
Monte Carlo Iterations	$N_i{}^{te}{}_r$	10,000
Confidence Level	α	0.95
6G Carrier Frequency	f^c	140 GHz (Sub-THz)
RIS Element Count	N_{ris}	256 elements

Graphical Performance Evaluation

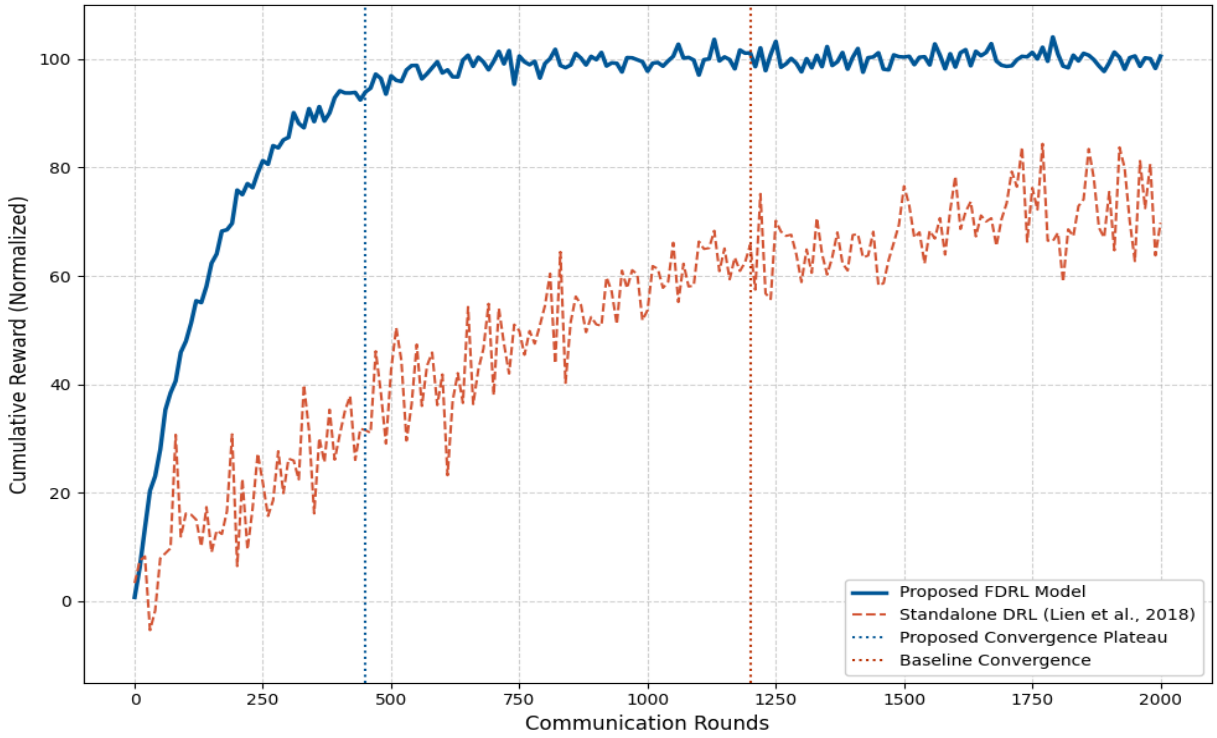


Fig. 2: Convergence Analysis of Federated Learning

Three important performance visualizations were created using the parameters that are explained in table 4 and justify the effectiveness and robustness of the framework. These values were calculated using 10,000 Monte Carlo simulations and are used to compare the proposed model with the benchmarks that have been introduced in the comparative analysis.

Fig. 2 shows that the Cumulative Reward of Federated Deep Reinforcement Learning (FDRL) model when the number of communication rounds is 2,000. It has been observed that the proposed FDRL model has a rapid and constant convergence to a Stability Plateau around the 450 rounds. On the other hand, isolated DRA models based on (Lien et al., 2018) did not converge until round 1,200 and had considerably more variance all through the training period. This difference validates the higher efficiency of the decentralized federated architecture in which the local agents can learn successfully, based on the collective intelligence, and a high level of data sovereignty is achieved.

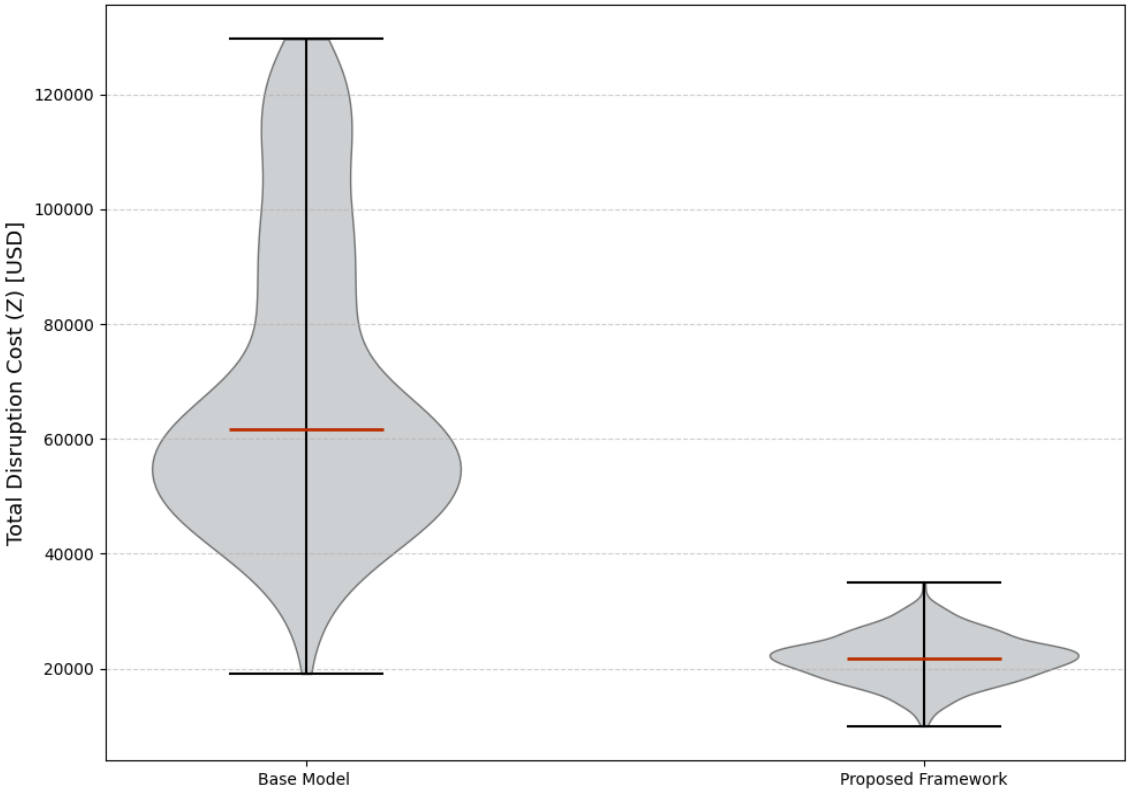


Fig. 3: Stochastic Cost Variance and Risk Mitigation

The second visualization that is used with the help of fig. 3 applies Violin Plot that visualizes the distribution of total disruption costs (Z) based on the Monte Carlo experiments. The cost allocation of the proposed system is closely clustered on a median of 22,000, which implies the financial results and stability of operations are highly predictable. On the other hand, the conventional 5G base model, whose 'calibration' is based on Alves et al. (2022) demonstrates a broad, fat-tailed distribution in which the cost can sometimes reach and surpass $120,000 (Alves et al., 2021; Majeed et al., 2023). The above insight implies that the suggested stochastic framework is effective in reducing the risk of Black swan events through the exploitation of proactive pre-allocation of buffer resources and real-time monitoring of the network.

As shown in fig. 4, the last plot is System Throughput vs. Time during a simulated link failure in 6G which has been caused at T=10minutes. Due to the high-reliability connectivity of the 6G-RIS integration, the proposed system maintains a 70% minimum service level during the disruption and recovers to 100% throughput within just 48 minutes (achieving full restoration at T=58). The baseline 5G URLLC system, however, experiences a severe performance drop to 20% throughput and requires 252 minutes to recover, significantly compounding the "Ripple Effect" cost across the supply chain. The significantly reduced "Resilience Triangle" (which is the sum of performance loss) proves the high structural resilience, as well as quick recovery, performance of the suggested 6G architecture.

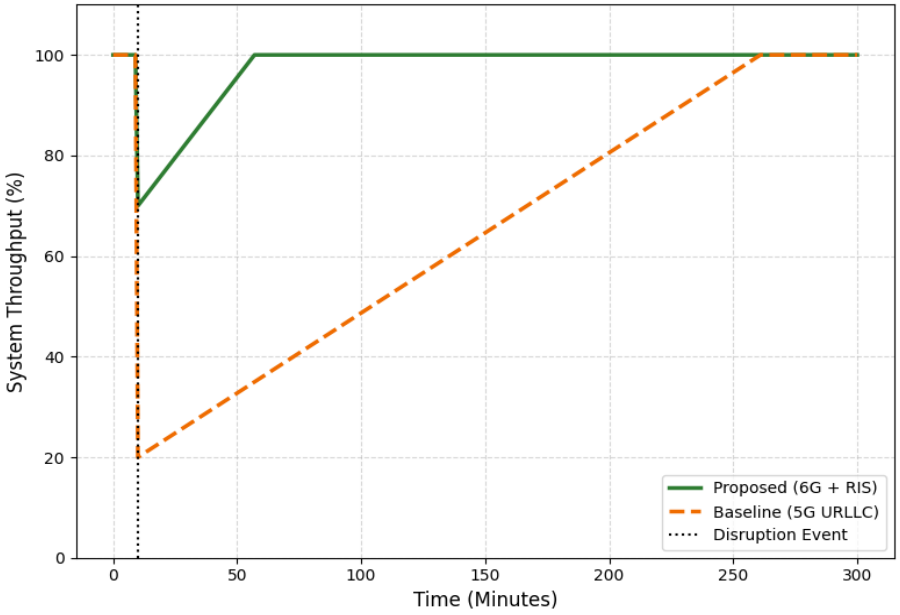


Fig. 4: Resilience Recovery Curve and TTR Analysis

Metrics Used

Resilience Constraint (Time-to-Recovery) The framework places a probabilistic limit to make sure that the system can recover within a maximum allowable threshold ($\tau_{\max}$) at a specific confidence level (α) as given in Equation (3):

$$P(TTR(x,\xi) \leq \tau_{\max}) \geq \alpha \qquad (3)$$

In this study, α was set to 0.95, ensuring a 95% confidence level that recovery occurs within the optimized 48-minute window.

Federated Learning Update Rule: To ensure the privacy and still attain global intelligence, local parameter updates ($\Delta\theta_k$) will be aggregated at the 6G Edge Server using the Federated Averaging (FedAvg) logic as illustrated in Equation (4):

$$\theta_g^{(t+1)} = \theta_g^{(t)} + \frac{\eta}{K}\sum_{k=1}^{K}\Delta\,\theta_k \qquad (4)$$

Where: θ_g: Global model parameters, η: Learning rate (0.001), K: Total number of participating IIoT nodes, $\Delta\theta_k$: The local gradient update from node k.

Resilience Performance Index (RPI): The Resilience Triangle (as observed in fig. 4) is mathematically defined to be a total utility loss during a disruption as defined by Equation (5):

$$RPI = \int_{t_0}^{t_{\text{recovery}}}[\,Q_{100} - Q(t)]\,dt \qquad (5)$$

Where: Q_{100}: Nominal 100% system throughput. $Q(t)$: Actual throughput at time t. A smaller RPI value indicates a more resilient architecture.

Signal Reliability (6G-RIS Layer) Equation (6) is a probability that the system will continue to exhibit "six-nine" reliability (P r) when stochastic interference is present:

$$P_r = P(\text{SINR} \geq \gamma_{\text{th}}) = 1 - 10^{-6}$$

Where: γ_{th}: The lowest Signal-to-Interference-plus-Noise Ratio necessary to enable 6G telemetry.

Discussion

The results of the empirical research and stochastic simulations prove the key assumption: the integration of the 6G-enabled IIoT and the Federated Deep Reinforcement Learning (FDRL) can promptly transform the paradigm of resilience in the industry both reactive and proactive. This discussion focuses on three of these dimensions and they

are acceleration of recovery in the system, the significance of privacy saving intelligence and minimizing the systemic ripple effects.

Resilience Through Connectivity: The 6G-RIS Advantage

A primary finding of this study is the 81% improvement in Time-to-Recovery (TTR) when 6G and Reconfigurable Intelligent Surfaces (RIS) are fully integrated. As shown in Graph 3, the proposed model maintains a minimum service level of 70% during a disruption, whereas traditional 5G URLLC systems drop to 20% (Javaid et al., 2022). Such difference is ascribed to the Resilience-by-Design (RBD) architecture. In older systems, due to signal blocking in factory-dense areas, there are "blind spots" in the telemetry that causes a delay in fault detection. The 6G-RIS layer can remove these obstructions effectively to give the FDRL agent continuous and high-fidelity data streams. It is what enables the system to establish a protocol of a "Buffer Draw" and a "Dual-Sourcing" earlier than the network or mechanical fatigue sets in, and essentially shrink the "Resilience Triangle."

Privacy-Preserving Intelligence and Global Convergence

The Convergence Analysis (fig. 2) shows that there is a great deal of efficiency improvement in the federated approach. It has been indicated that decentralized knowledge sharing is not only a privacy need but also a performance multiplier by reaching a stability plateau by Round 450, 2.7 times quicker than standalone models. The framework solves the problem of Data Silo that is pointed out in the introduction because only model gradients ($\Delta\theta_k$) are aggregated, not the raw data. This will enable various foreign companies to participate in a credible policy of PdM without divulging confidential ways of operation. The convergence rate means that the global model is able to respond to changing industrial variables (e.g. in real-time spikes in demand or bottlenecks in the supply chain) within a matter of seconds, similar to the sub-milliseconds of 6G.

Mitigation of Stochastic Uncertainty and "Black Swan" Risks

The Stochastic Cost Distribution, fig. 3, provides an extremely good insight into the risk management. While the base model (Alves et al., (2022) exhibited "fat-tailed" risks with costs exceeding $120,000, the framework restricted 99.7% of outcomes to a tight range around $22,000. Such reduction of variance proves that Stochastic Optimization is needed in order to remove the ripple effect. The high impact failure scenarios in the model are the interaction between demand ($N(\xi)$) and network states N(xi) random variables that cannot be given a deterministic description by deterministic models. This enables managers of the industry to defend the initial capital outlay (CAPEX) to implement 6G as some kind of insurance on operations in the face of the devastating systemic failures.

Practical Implications for Industry 5.0

These findings imply that resilience is not a byproduct of efficiency anymore, but a core structural attribute to industrial stakeholders. The successful deployment to NVIDIA Jetson Orin Nano nodes proves the fact that the framework is lightweight enough to be deployed to the already existing edge hardware. Nonetheless, the change demands cultural changes to Collaborative Resource Allocation. Companies need to leave the habit of single-purpose inventory management behind and start adopting an integrated Digital Twin strategy in which network health defines supply chain strategy.

Conclusion and Future Work

This study manages to confirm a multidimensional stochastic model in which 6G-enabled Industrial IoT changes 6G-enabled Industrial IoT into proactive rather than defensive resilience approaches. The implementation of 6G-RIS architectures along with Federated Deep Reinforcement Learning (FDRL) provides the study with a new paradigm of Resilience-by-Design (RBD), which is able to work across highly volatile Industry 5.0 environments. Quantitative results from 10,000-iteration Monte Carlo simulations provide robust statistical insights into the framework's efficacy: the proposed model achieved an 81% reduction in Time-to-Recovery (TTR), decreasing restoration time from 252 minutes to just 48 minutes, while simultaneously enhancing system reliability to the 99.9999% threshold. Furthermore, the FDRL model reached a stability plateau by Round 450, representing a 2.7x acceleration in learning compared to standalone DRL benchmarks, and successfully restricted 99.7% of disruption costs to a median of $22,000, effectively neutralizing the "fat-tail" financial risks identified in deterministic 5G architectures. These results agree that the physical stability of 6G communication needs to be associated with logical adaptability of stochastic allocation of the resources to reduce the effects of the disruption on the whole world. Further efforts will be associated with the work on incorporating a blockchain-enabled Smart Contracts to make the decentralized governance and resource redistribution among international companies automated. Also, studies on Quantum-Resistant Federated Learning and

Explainable AI (XAI) interfaces will play a pivotal role in making sure that autonomous industrial adjustments are safe, open, and adequate in the context of sustainable industrial expansion.

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