

GENERATIVE AI-DRIVEN NETWORK DIGITAL TWINS: A NOVEL FRAMEWORK FOR MULTIVARIATE ANOMALY DETECTION AND DATA IMPUTATION IN 6G ECOSYSTEMS

Dr: Mohammed Ridha Faisal Faisal' Reya Majid Hameed 2

Ibn Khaldun Private University College, CyberSecurity

Techniques Engineering, Baghdad, Iraq¹

Middle Technical University, Electrical Engineering Technical College, Computer Techniques Engineering, Baghdad, Iraq²

Middle Technical University, Electrical Engineering Technical College, Computer Techniques Engineering, Baghdad, Iraq²

mohammed.ridha@ik.edu.iq, drengmrf@gmail.com'

rayamajid89@mtu.edu.iq²

ABSTRACT:

The symbiotic Internet of Things (S-IoT) networks, powered by 6G technologies, have created and will continue to create a revolution and complexity that necessitates a broader understanding of digital systems. Enabling distributed intelligence through the integration of centralized, peripheral, and cloud computing for automation relies on the support and symbiosis of artificial intelligence. This leads to all integral forms with respect to the largest scale models of the AI and their connection for the resource-limited devices, resulting in serious security vulnerabilities. The root cause is loose endpoints, which are increasingly becoming entry points for sophisticated cyberattacks. Data breaches are becoming increasingly apparent, and system disruptions further exacerbate these vulnerabilities. This study addresses this issue. This framework of the employs adaptive data preprocessing, with addition the outlier mitigation, class balancing using Adaptive Synthetic Sampling, and minimum-maximum normalization, followed by hierarchical integration and spatial pattern capture dynamics (such as packet length variation and TCP tag anomalies).

Introduction:

. Exceptional efforts are bringing us closer to preparing the essential elements of scientific and computer development, particularly in the field of the internet, such as the 6G era, for which we are currently conducting research. The complexity and dynamism of communication networks have increased rapidly [1].

Therefore, automated management is crucial in enhancing these efforts. Human oversight of this automation is also essential [2]. These ongoing and emerging challenges necessitate the planning of new infrastructures for network automation, especially closed-loop networks, the study represents the vision of the 6G-TWIN consortium in creating a fusion cyber-physical interconnected network, linking the physical world with its digital representation [3]. It explores network digital twinning and the finite element methods and application of integration into the 6G with AI architecture software.

The gap must be bridged between the increasing complexity of networks to improve user experiences across multiple domains at any time [4].

This study addresses the main challenges associated with this complexity and the approach taken by the 6G-TWIN consortium, outlining potential problems arising from this complexity and proposing future solutions[5].

System Architecture and Implementation:

General AI and non-destructive testing (NDT) are typically integrated across a distributed edge-to-cloud architecture:

Data Ingestion:

Edge nodes and broadcast stations continuously feed the digital twin with real-time telemetry data [6].

Generative Processing:

Cloud and edge servers use AI models to remove noise and reconstruct incomplete data, creating an accurate baseline state.

Simulation and Optimization:

The digital twin simulates multiple network configurations and trains virtual optimizers [7].

Execution and Control:

Optimized and validated policies are fed back into the actual 6G network to adjust routing, allocate resources, and mitigate service outages.

Key Performance and Research Benefits:

High-Precision Modeling: Studies indicate that General AI-powered digital twins (GenAI) can achieve scenario accuracy exceeding 98%, bypassing traditional rule-based limitations [8]. **Enhanced Resilience:** The ability to simulate rare and critical situations enables networks to proactively adapt and achieve up to 40% faster response times to anomalies [9]. **Resource Allocation:** Generative solutions have demonstrated 8.3% to 50% superiority over traditional solutions in intelligent resource allocation and noise resistance [10]. For a comprehensive analysis of architectural models, prototypes, and specific algorithmic approaches currently under investigation, please refer to the IEEE Xplore Digital Twin for Mobile Networks study [11]. It can also explore the theoretical boundaries and architecture roadmaps outlined in the ACM Generative AI Empowered Network Digital Twins study.

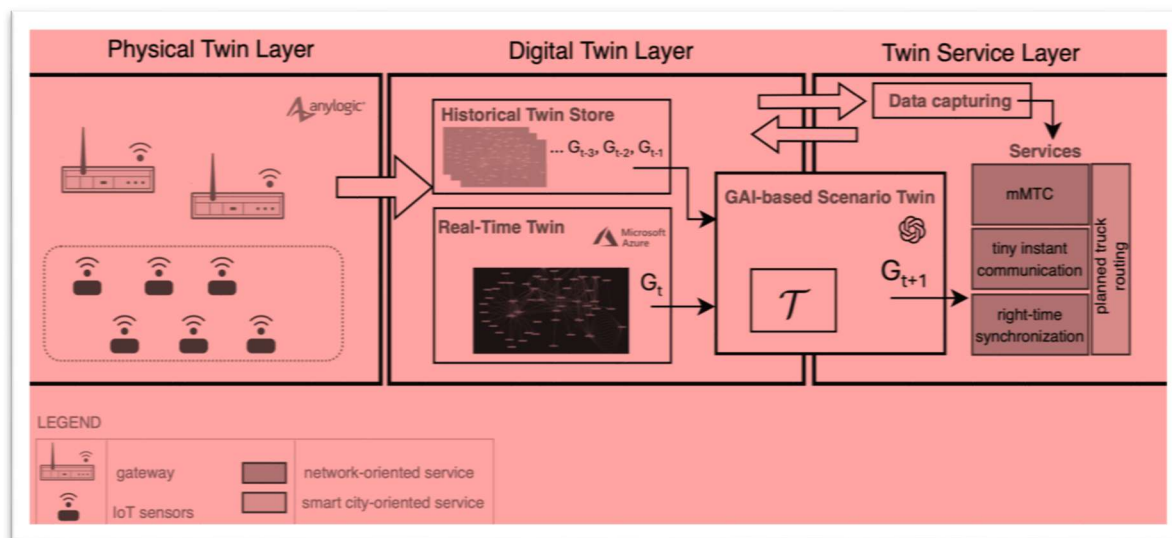


Figure (1): The hypothetical framework for the operation of a digital twin using artificial intelligence in a 6G network.

Component:

These individual components within the digital twins independently form an important part of the overall interconnected system through the battery twin used in an internet device [12].

(2) Historical Twin Store:

To refer to the data as $\{G_{t-m}, \dots, G_{t-2}, G_{t-1}\}$.

The dependents variables with respect to implemented scenario. The capacity of data store used [13].

In ADIX and efficiently structured to improve analysis for training of public service-level AI/machine learning models in this discipline [14].

(3) AI-Enabled Scenario Twins:

In this model, future probabilistic Internet of Things (IoT) twin models are generated by conducting a comprehensive study of all different scenario require for any potential [15].

The specific requirements for building upon these KPIs are artificial intelligence. the scenario priorities, as illustrated.:

$$p(w_p, w_d), D > D_{th}$$

$$p(w_l, w_d), L < L_{th}$$

$$p(w_p, w_a), A > A_{th}$$

(1)

The equations show that the p function prioritizes and calculates all weights by parameters. Random parameters to scenario's execution. D represents the hardware density to be implemented, and D_{th} represents the maximum hardware density [16]. Similarly, L indicates the maximum allowable response time in the scenario, and L_{th} represents the maximum response time. Similar approaches are applied the parameters (response timeout and packet timeout) and formulate scenarios key performance indicators within the same function, as shown below:

$$O = w_p T_p + w_d T_d + w_l T_l + w_a T_a \quad (2)$$

$$\text{Maximize } O = \sum_i w_i T_i \quad \forall i \in K \quad (3)$$

$$\sum_i w_i = 1 \quad (4)$$

$$p(w_x, w_y) \quad \forall (x, y) \in K \quad (5)$$

$$w_x, w_y > 0 \quad (6)$$

$$w_x, w_y > w_z, w_t \quad \forall (z, t) \in K \wedge (x, y) \quad (7)$$

Experimental setup:

The initial simulation information in this research is shown below.

TABLE (1): hypothetical simulation.

hypothetical	Values
No. of IoT sensors	{50, 250, 1000}
No. of gateways	{2, 8, 20}
Twinning rate	0.8
D_{th}, L_{th}, A_{th}	{50, 0.9ms, 97%}
Confidence interval	95%

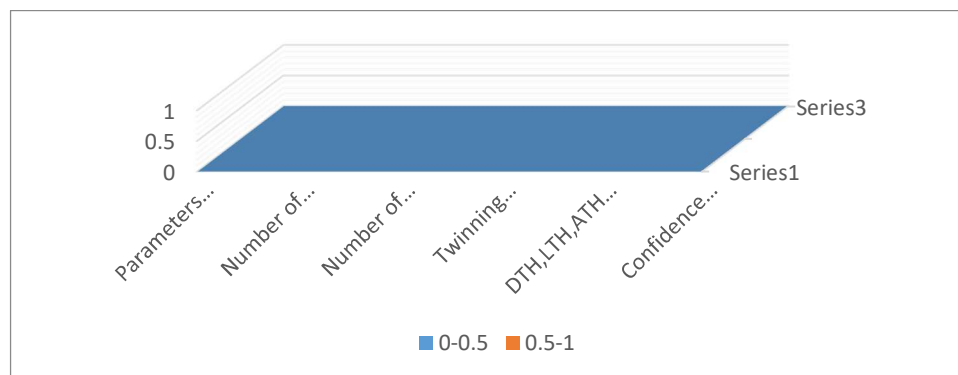


Figure (2): Parameters as function of Values.

TABLE (2): The sizes of Topolgy.

	Tested	Topologies	
	small	medium	large
device density	100	500	1000
Gateways	2	8	20

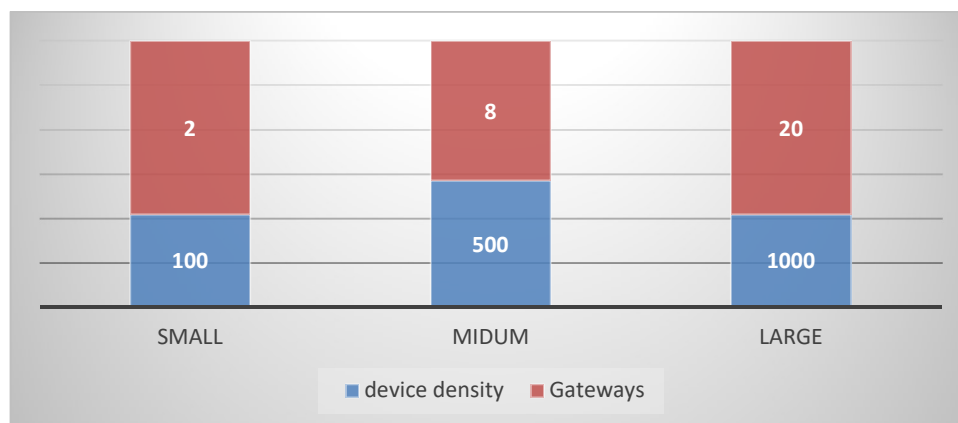


Figure (3): Device density as functions of Gateways.

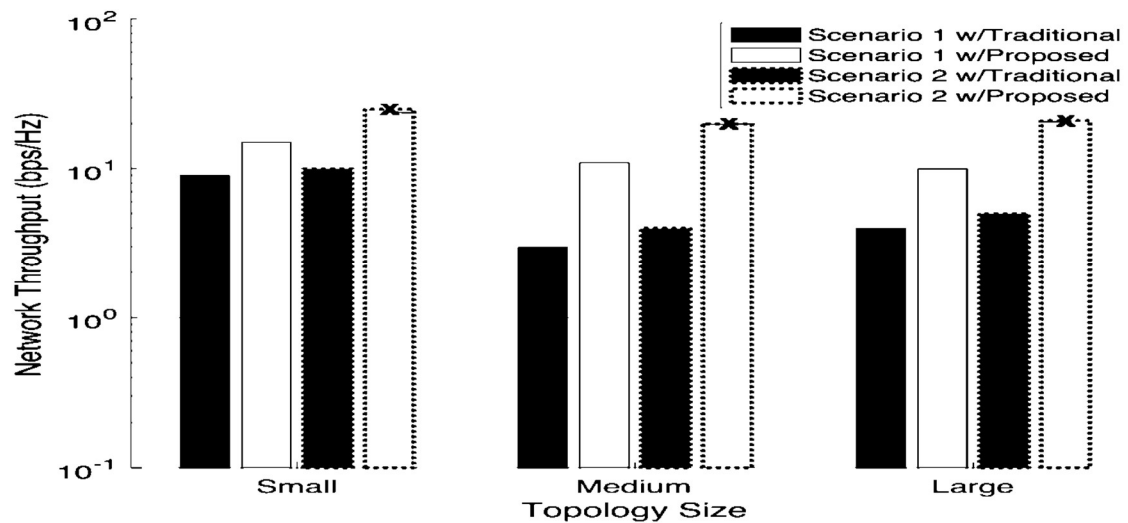


Figure (4): Comparison of network as function of variables.

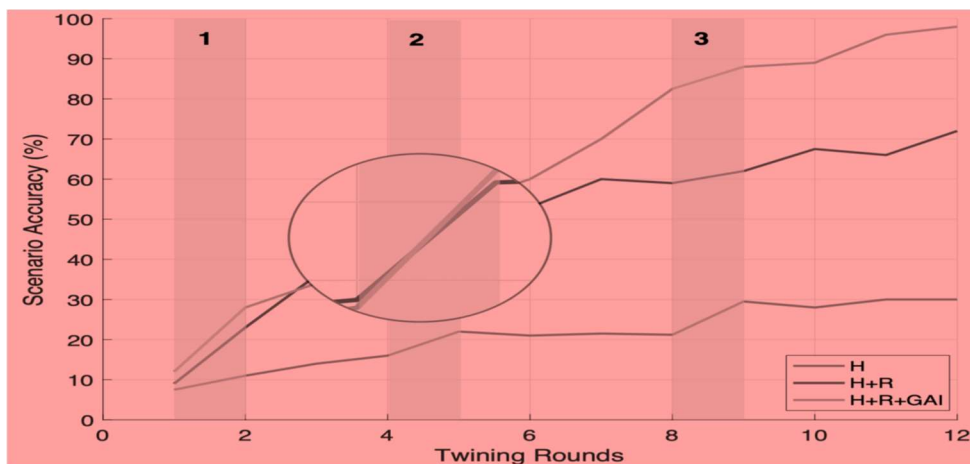


Figure (5): Accuracy as function for real-time twins, and generative AI.

CONCLUSION:

The importance of early and initial exploratory efforts has necessitated the development of new technologies that keep pace with advancements in the world of knowledge and serve rapid development. Therefore, 6G technology emerged relatively quickly due to the rapid growth in computing and highly sophisticated software development. This is driven by existing data-driven applications and the emergence of emergencies requiring solutions through new applications. Communications has become apparent. Increasingly complex and diverse network environments demand scientific approaches to the use of artificial intelligence, which strengthens and supports the scientific foundations of this trend. The development of the 6G-TWIN project primarily aims to address emerging and future scenarios. This objective is achieved by relying on two key aspects:

- (1) Continuous testing resilience (NDT) infrastructure in face both unforeseen and unexplored

constraints.

2) Aligning objectives with key priorities is crucial. Paying attention to two objectives can contribute to advanced achievement, and these two main constraints are:

First, mobility constraints that nodes may encounter, which are perfectly aligned with and equivalent to the predictive non-destructive testing methodology.

Second, power constraints, which are consistent with the interactive non-destructive testing methodology for adjusting the initial network components in real-time, responsive, and actual efficiency to predict overall power.

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