A Reinforcement Learning-based Adaptive Digital Twin Model for Forests

Robertas Damaševičius
CoE Forest 4.0
Vytautas Magnus University
Akademija, Lithuania
robertas.damasevicius@vdu.lt

Rytis Maskeliūnas
CoE Forest 4.0
Vytautas Magnus University
Akademija, Lithuania
rytis.maskeliunas@vdu.lt

***Abstract*—We present a Reinforcement Learning-based Adaptive Digital Twin (RL-ADT) model designed for forest ecosystems, utilizing advanced IoT data collection and spatiotemporal graph modeling. It focuses on dynamically representing forests for optimized health resource management and sustainability, simulating environmental interactions, and adapting to changing conditions for real-time monitoring and efficient resource usage. The implementation of the model substantially improved the energy and resource efficiency of the digital twin. The construction of spatiotemporal graphs within the model has led to a more accurate and precise representation of the complex interactions within forest ecosystems. This improvement in model fidelity is crucial to understanding and managing the dynamic nature of forests effectively. The adaptability of the RL algorithms is instrumental in managing the dynamic aspects of forests. The RL algorithm has optimized the trade-off between model accuracy and computational overhead, which is vital for the real-time application of the model in forest management. The insights gained from this study have substantial implications for the sustainable management of forest resources. By improving efficiency in resource use, technology aligns closely with sustainability goals and responsible stewardship of natural resources.**

***Index Terms*—Digital Twin, Forest Ecosystem Management, Reinforcement Learning, Spatiotemporal Data Analysis, Realtime Ecosystem Modeling, Resource Optimization in Forestry.**

I. Introduction

The concept of digital twins (DT) has emerged as a transformative tool for modeling and managing complex ecosystems. DT is a virtual representation of a physical system that allows for real-time monitoring, analysis, and simulation. In environmental applications, this technology has shown a significant potential to advance sustainable practices and improve ecosystem management [1]. The idea of DT, originally rooted in manufacturing and urban planning, has expanded to environmental sciences, offering a novel approach to understanding and managing ecosystems such as forests. This adaptation is crucial in the context of climate change and environmental conservation, where accurate modeling and adaptive management strategies are essential. Recent advances in the Internet of Things (IoT) and machine learning, particularly Reinforcement Learning (RL), have further expanded the capabilities of DTs. RL's adaptability and learning capabilities make it an ideal tool for managing dynamic and complex systems like forests. By integrating RL with DT, we can create models that not only represent the forest ecosystem but also learn from it, adapt to changes and optimize management strategies in real time [2]. In forestry, the integration of DTs promises a paradigm shift towards more sustainable and efficient forest management. The concept, initially formulated for smart cities, involves the creation of virtual dynamic replicas of the physical environment. These replicas are continuously updated with real-time data, reflecting the intricate and ever changing dynamics of forest ecosystems [3].

This integration introduces significant challenges in the DT modeling process, primarily due to the inherently dynamic nature of forest environments. The main challenge lies in developing a data-driven model that accurately represents the forest ecosystem. This model must continuously process and integrate data flows from a multitude of sources to create an accurate snapshot of the environment at any given time [4]. It is essential that the model achieves and maintains convergence with the actual forest environment. This convergence is hampered by the asynchronous nature of updates from various data sources, which may not correspond to the same temporal point, leading to potential discrepancies in the DT model [4]. The need for up-to-date and accurate data requires high-frequency data collection. This approach, while ensuring the responsiveness of the DT model to environmental changes, can lead to high resource use and energy consumption [5].

Addressing these challenges involves these considerations:

- Traditional relation-based modeling approaches do not provide precise representations, especially given the complex and asynchronous nature of forest data. Enhanced modeling methods are imperative to ensure exact alignment of the DT with its physical counterpart. The model must account for the temporal misalignment and dynamicity inherent in forest ecosystems.
- The necessity of collecting high-frequency data in forests can strain resources and increase energy consumption, particularly when updates to the model do not reflect significant environmental changes. Thus, there is a critical need to develop adaptive data update methods. These methods should be capable of discerning the right-time data required for capturing the dynamics of the forest environment efficiently, with minimal energy consumption.

The need for high synchronization between the DT model and the actual forest environment poses significant challenges. This synchronization requirement becomes particularly critical given the dynamic nature of forests, where variables such as climate conditions, plant growth, and wildlife activities change frequently. To maintain accurate mirroring, it is essential that data collection devices transmit information with increased frequency under these fluctuating conditions [6]. This may lead to an increase in resource and energy consumption on the part of DT, a predicament reminiscent of the trade-off between the Age of Information and energy efficiency widely discussed in the IoT literature [4].

Therefore, the dilemma arises in balancing the need for high-fidelity synchronization with the imperative of energy and resource efficiency in the DT model. This research seeks to address the critical research question: "How can we ensure precise modeling of DT models in forest ecosystems while also providing low-overhead and energy-efficient updates?" To address this challenge, our study introduces an innovative approach that incorporates spatiotemporal graph modeling specifically tailored for forest environments [7]. This method is complemented by an adaptive twinning mechanism based on RL, which is poised to redefine the landscape of environmental monitoring and sustainable forest management [8].

The primary objective of this study is to develop and validate a DT model based on reinforcement learning specifically designed for forest ecosystems. This model aims to take advantage of the latest advancements in IoT, machine learning, and DT to create a dynamic, adaptive representation of a forest environment. The scope encompasses:

- Designing a DT framework that accurately models complex interactions within a forest ecosystem.
- Integrating IoT technologies for real-time data collection and monitoring of forest parameters such as soil moisture, tree growth, and environmental conditions.
- Developing an RL algorithm capable of making informed decisions to optimize forest resource management.
- Exploring the potential scalability of the model.

This study contributes to the field of environmental technology by providing a novel approach to sustainable forest management, improving our understanding of ecosystem dynamics, and offering a tool for proactive forest conservation.

The paper is organized as follows: Section II reviews the existing literature on DTs, IoT in environmental monitoring, and Reinforcement Learning, establishing the theoretical foundation for the study. Section III describes the Adaptive DT Model, including data collection, model design, and algorithm development. Section IV discusses the practical aspects of implementing the model in a forest environment, including the simulation and training of the Reinforcement Learning algorithm. Section V presents the findings of the study, evaluates the performance of the model, and discusses its implications for forest management and sustainability. Section VI examines the potential challenges and limitations of the model. Section VII summarizes the key findings of the study and suggests directions for future research.

II. Literature Review

A. Digital Twin Technologies in Complex System Modeling

DT technologies have increasingly become central in the modeling of complex systems. Integration of DTs into IoT networks, as highlighted by Park and Park (2024), exemplifies the growing trends and challenges in the modeling of complex systems [7]. Chiu et al. (2024) further illustrate the potential of DTs to simulate expansive design spaces within complex systems [9]. Daly et al. (2024) discuss the synergy between physical and virtual realms in DTs and their impact on innovation [10]. The application of DT extends to urban planning, as demonstrated by Merlo and Lavoratti (2024), who emphasize the role of urban digital twins in supporting analysis and planning [11]. Furthermore, the work of Kabbaj et al. (2024) showcases the effectiveness of DTs in robot control within complex systems [12]. These studies collectively underscore the transformative role of DT technologies in the modeling and management of complex systems.

B. Reinforcement Learning in Environmental Applications

RL has emerged as a powerful tool in environmental applications, offering efficient and adaptive solutions to various challenges. In the field of 5G networks, Smirnov and Tomforde (2024) demonstrated the effectiveness of Deep RL in improving the quality of experience in real-time rate control [13]. Aranguren and Aguilera (2024) explored the application of RL in optimizing gas injection in shale reservoirs, highlighting the potential of RL in environmental optimization problems [14]. A similar approach has been proposed and evaluated in [15] for a DT in a green city context. Hossain, La, and Badsha (2024) applied Cooperative Multi-agent RL algorithms in autonomous transportation, emphasizing the importance of RL in critical environmental applications [16]. Furthermore, Yun et al. (2024) proposed a learning-based sensing and computing decision model for data freshness in edge computing-enabled networks, demonstrating the versatility of RL in environmental contexts [17].

C. IoT in Forest Ecosystem Monitoring

The application of IoT in forest ecosystem monitoring has become increasingly crucial. Pioneering methodologies that utilize IoT technologies such as Raspberry Pi models and a series of sensors demonstrate significant advances in this field [18], [19]. The decentralized and distributed nature of IoT networks improves the monitoring and response capabilities to environmental changes [20]. Kabala and Battipaglia emphasize the importance of managing forest ecosystems on a global scale with the help of IoT [21]. Integration of UAV networks with IoT technologies shows great promise in real-time monitoring of natural habitats and ecosystems [22]. Otu et al. (2024) further highlights the role of IoT in diverse applications such as insect pest population monitoring and livestock health monitoring, underlining its versatility [23].

These studies collectively illustrate the transformative impact of IoT in improving forest ecosystem monitoring, offering innovative solutions for sustainable forest management.

III. METHODOLOGY

A. Architecture

The Reinforcement Learning-Based DT Model for Forest Ecosystems comprises two integral layers: the Physical Twin Layer and the Digital Twin Layer.

1) Physical Twin Layer: The Physical Twin (PT) layer embodies the tangible components of the forest ecosystem, including its flora, fauna, soil composition, and climatic factors. Within this scope, we consider the ecological dynamics and environmental interactions of the forest. Here, IoT devices, designated as PTs, are strategically deployed throughout the forest to collect various data, such as soil moisture levels, tree growth patterns, wildlife activity, and atmospheric conditions. This study focuses on data-driven modeling and management of updates to this model. We assume that this layer, through a robust network infrastructure, can provide all the necessary information. To construct this layer, we utilize advanced ecological simulation tools, complemented by network simulators to emulate the communication infrastructure within the forest environment.

2) Digital Twin Layer: This layer uses continuous data streams from the PTs to forge a real-time DT model of the forest. The distributed data collection across various forest zones ensures the synchronization of the DT model with the PTs. The DT layer is not just a passive receiver of data; it includes services such as ecosystem management tools that leverage data analytics and machine learning techniques to actively influence and control the forest environment.

In this context, we introduce a novel approach combining spatial-temporal graph modeling with a RL-based Adaptive Digital Twinning (RL-ADT) mechanism. This innovative combination aims to achieve precise modeling of the forest ecosystem while efficiently managing the resource-intensive twinning process. The RL-ADT mechanism, in particular, adapts and learns from forest data, optimizing management strategies in response to the dynamic and complex nature of forest ecosystems. This approach marks a significant advancement in environmental monitoring and sustainable forest management, showcasing the potential of integrating cutting-edge technology with natural ecosystems. Fig. 1 describes the high-level architecture of the RL-based DT Model for Forest Ecosystems.

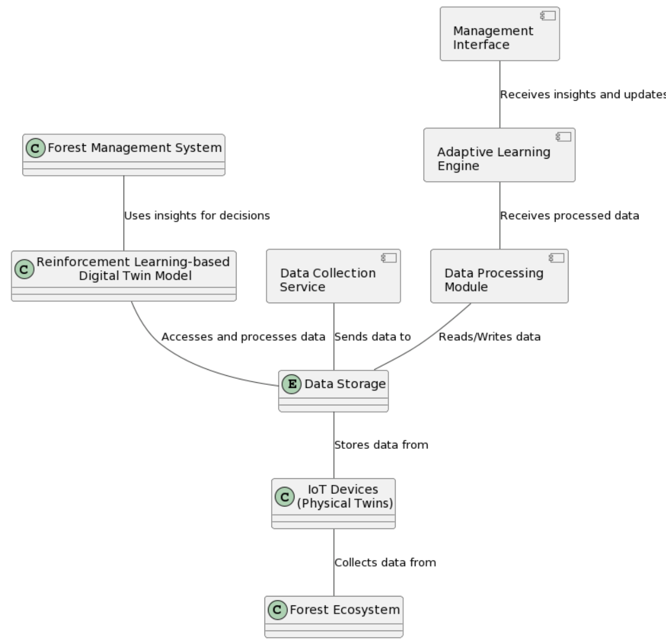

Fig. 1. Container Diagram for Forest Ecosystem DT Model

B. Dynamic Eco-Spatio-Temporal Graph Modeling

In the domain of forest ecosystem management, Dynamic Eco-Spatio-Temporal Graph Modeling emerges as a pivotal methodology. This approach involves the creation of intricate spatiotemporal graphs, using the eco-spatial environment as its fundamental building block.

The Eco-Spatial graph, denoted as $S = (V, E, w)$, is a weighted directed graph designed for spatial modeling within the forest context. In this graph, V represents the set of vertices, E the set of edges, and w the weight function. The vertices encapsulate various elements of the forest ecosystem, such as clusters of trees, water bodies, and animal habitats. Edges symbolize spatial relationships between these elements, while weights reflect ecological distances or interactions, such as proximity or ecological impact.

The feature matrix of this graph is expressed as $X \in \mathbb{R}^{N\times F\times T}$, where N is the number of vertices in the S graph, F the number of features that represent ecological parameters, and T the time steps. The graph signal at a specific time t, denoted X_t, encompasses the data collected from the IoT devices within the forest at that time. This structured approach ensures that each snapshot of the model presents a uniformly updated and synchronized representation of the forest environment at any given moment.

These spatiotemporal graph models, symbolized as G, are meticulously stored using the Neo4j graph database. Within Neo4j, each IoT device within the forest is conceptualized as a node $v \in V$, fostering two types of relationships: spatial and temporal. These are represented as `[:spatial]` and `[:temporal]`, respectively. The data collected from the forest is stored within the node properties, with the weight function $w(e)$ allocated to the `[:spatial]` relationship property and the time differential to the `[:temporal]` relationship property.

This Dynamic Eco-Spatio-Temporal Graph Modeling for Forest Ecosystems, leveraging advanced graph theory and database technology, offers an innovative and efficient method for understanding and managing the complex dynamics of forest ecosystems. It facilitates a deeper understanding of ecological interrelations and enables more effective, data-driven decision making in forest management.

C. RL-based Adaptive Twining for Forest Ecosystems

In the context of forest ecosystems, the concept of Reinforcement Learning-Based Adaptive Twining (RL-ADT) is instrumental in ensuring efficient synchronization between the physical forest environment and its DT. The twinning rate, the frequency of synchronization attempts, varies due to external factors such as network latency and packet loss, which are particularly pertinent in diverse and expansive forest environments. The RL-ADT mechanism in forest ecosystems dynamically adjusts the update strategy to optimize the accuracy of the DT while minimizing resource consumption. Using Deep Q Learning, the mechanism strategically decides which nodes (representing various elements of the forest) need updates. The state at a given time t, denoted as s_t, is defined as the spatio-temporal graph signal within a specific time window δ, symbolized as $(X_{ijk})_{t-\delta \leq k \leq t}$. This window represents the number of updates made in the past that are considered in determining the update strategy. The update action, represented as a_t, is a vector of length N (the number of nodes), indicating whether an update is necessary for each node. The action space A is defined as:

$$A = \{a_{ij} | a_{ij} \in \{0, 1\}\} \tag{1}$$

The reward function r_t for an update action is calculated based on the mean square error between the current values of the DT X_t and the subsequent values X_{t+1}, with an energy consumption penalty:

$$r_t = \frac{1}{N+F} \sum_{i=0}^{N} \sum_{j=0}^{F} \sqrt{(X_{i,j,t+1} - X_{i,j,t})^2} - P(a_t) \tag{2}$$

The penalty function $P(.)$ accounts for the memory operations needed to apply the action and is defined as:

$$P(a_t) = \sum_{i=0}^{N} a_t \left(1 + 1 + 1 + |\{e_{ij} | e_{ij} \in E\}|\right) \tag{3}$$

This formulation takes into account the number of memory operations on data and terms in the equation corresponding to the retrieval, node, and edge creations in the spatio-temporal graph. Therefore, the RL-ADT mechanism ensures an effective balance between accuracy and resource efficiency in maintaining the DT of the forest ecosystem.

Algorithm 1 RL-based Adaptive Twining Mechanism

```
Initialize replay memory to capacity D
Initialize action-value function Q with random weights
Observe initial state s_1
for each time step t do
    Select action a_t = { random action with probability ε,
                        { argmax_a Q(s_t, a) otherwise
    Execute action a_t and observe reward r_t and next state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in replay memory
    Sample random minibatch of transitions from replay memory
    Calculate target for each minibatch transition
    Perform a gradient descent step on (y_i - Q(s, a))^2 with respect to the network parameters
    Update state s_t ← s_{t+1}
end for
```

IV. Implementation

A. Simulation Setup for Forest Ecosystem

To simulate the forest ecosystem and its network infrastructure, we use SUMO and OMNET++ simulators [13], adapted to the context of forest environments. Within SUMO, the forest environment and its elements are modeled, with junctions representing the locations of IoT devices. This simulation is integrated with the OMNET++ simulation through the TraCI interface [24]. In OMNET++, IoT devices are configured to transmit their collected data to the DT device via the MQTT protocol [25], simulating real-world data flow within a forest network. Through this simulation set-up, we generate datasets that capture forest behavior patterns and packet delivery times. A simulation environment is developed using Python to evaluate the proposed RL-based Adaptive Twining in a forest context. The adaptive twining mechanism based on RL is implemented using the KerasRL library, and the spatiotemporal graph models for the forest ecosystem are developed using Neo4j [26], which provides a comprehensive framework for simulating, evaluating, and optimizing the DT model in the context of forest ecosystem management.

B. Update and Memory Query

In this study, we evaluate the performance of the DT model based on reinforcement learning tailored for forest ecosystems. Our focus is on assessing various aspects: the DT accuracy performance of the spatiotemporal graph model in comparison to traditional modeling, the efficiency of querying performance within the spatiotemporal graph storage method, the cumulative reward dynamics of the RL-based Adaptive Twining mechanism across different learning rates, and the average energy consumption and total RAM usage, particularly under varying payload sizes and in the presence or absence of the RL-based Adaptive Twining.

Initially, we concentrate on comparing the accuracy of the spatio-temporal graph model against the conventional entity update mechanism. This is evaluated by examining the mean square error (MSE) between snapshots captured during simulations and actual snapshots of the forest's dynamic states. Our findings reveal that while the spatiotemporal graph model maintains consistent error levels, traditional methods exhibit increasing error rates with increasing number of nodes. The spatio-temporal approach effectively preserves time-associated data, leading to snapshots that closely align with real forest conditions. The traditional approach suffers from temporal misalignment between entities, resulting in higher MSE, which is exacerbated as the number of nodes increases. This can be attributed to delays in data transmission from the PTs to the DT, which magnifies the misalignment.

Subsequently, we delve into comparing storage methodologies, specifically contrasting graph databases with relational databases, particularly in the context of the spatiotemporal graph model under conditions of increasing query size. Our findings, depicted in Fig. 3, show that relational databases exhibit increased latency in data retrieval as query sizes grow, primarily due to the intensive join operations on data files. In contrast, graph databases, by maintaining relationships between nodes separately, circumvent these costly join operations. The simulation results demonstrate a significant 55% reduction in total querying latency when utilizing spatiotemporal graphs in graph databases. This efficiency in querying latency is not only pivotal in reducing overhead but also crucial in the swift generation of states, an essential component in the management of forest ecosystems through DTs.

C. Adaptive Memory Management Strategies

In our study, we conduct a comprehensive evaluation of the cumulative reward of reinforcement learning-based adaptive twining (RL-ADT) in forest ecosystems under various learning rates, as illustrated in Fig. 4. We observe that at a learning rate of 0.5, the algorithm struggles to converge, whereas a reduced rate of 0.05 facilitates successful convergence. This phenomenon can be attributed to the fact that lower learning rates are better suited for generalization in complex scenarios, a crucial aspect given the expansive state-space characteristic of forest environments.

We evaluated the average energy consumption and total RAM utilization of the DT both with and without the implementation of RL-ADT, under varying payload sizes depicted in Fig. 5. The RL-ADT mechanism demonstrates its efficacy by selectively circumventing updates that negligibly impact the DT's accuracy. The algorithm judiciously determines the need for each update, considering its effect on accuracy and resource usage. Consequently, it achieves data updates at optimal times, resulting in a 23% reduction in total RAM usage compared to scenarios where all updates are processed asynchronously. Interestingly, even in cases where payload sizes range between approximately 2100 to 2400 bytes, where RAM usage values are comparable, a significant 27% decrease in average energy consumption is observed with the RL-ADT. This reduction is attributed to the higher energy demands of memory operations and the application of a penalty for these operations in the reward function.

Furthermore, our analysis extends to the synchronization aspect, where we measure the discrepancies in the incoming and outgoing traffic characteristics, referencing the number of vehicles in the simulation as a baseline, as shown in Fig. 6. Sampling observations from physical twins, we categorize them as hit-or-miss cases based on the temporal discrepancy in capturing specific observations on the DT side. The findings indicate that both the traditional and RL-ADT approaches exhibit a trajectory similar to the baseline, with a noticeable deviation in the traditional method that exacerbates over time. This divergence is likely caused by data accumulation awaiting updates, creating a bottleneck in resource availability, an issue RL-ADT addresses through selective data updating using a deep Q Network (DQN). The observed disparities in hit cases arise because not all received data are reflected in the model, highlighting a trade-off between accuracy and timeliness. Contrary to initial expectations, the traditional method, despite its trajectory change, does not produce a lower difference in values. This outcome can be linked to the temporal misalignment between entities in the model, as previously discussed.

V. Results and Discussion

A. Model Performance Evaluation

Fig. 2 represents the cumulative reward function across a number of episodes for three different learning rates in a reinforcement learning context. The figure suggests that a moderate learning rate (0.005) leads to better long-term learning, a slightly higher learning rate (0.05) may lead to a learning plateau, and a high learning rate (0.5) can cause instability and prevent the algorithm from converging on an optimal policy.

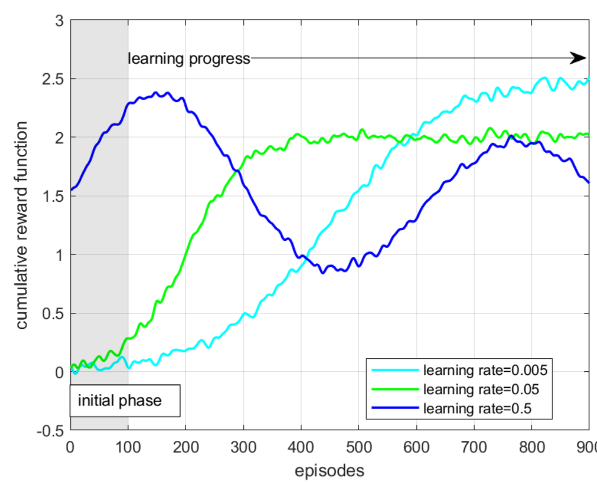

Fig. 2. Cumulative reward

B. Resource Optimization Analysis

Fig. 3 compares query latency between graph databases (graph DB) and relational databases (relational DB) in different query sizes. For both types of databases, as the query size increases, the query latency also increases. This is expected behavior as larger queries typically take longer to process. The graph database shows significantly lower latency compared to the relational database at all query sizes. This suggests that the graph database is more efficient in handling queries, which may be due to the nature of graph databases where relationships are directly stored, potentially reducing the time needed for join operations. The relational database exhibits a higher querying latency in all query sizes. The increase in latency as query size grows is more pronounced compared to the graph database, indicating that relational databases may not scale as efficiently with increased query complexity or size, likely due to more complex join operations that are typical in such databases. Interestingly, at query sizes of 150×10^6 bytes and 250×10^6 bytes, there is a noticeable spike in latency for the relational database. These spikes suggest that there may be thresholds at which the processing time for relational databases significantly increases, potentially due to the data structure or the algorithmic complexity of handling larger datasets.

The latency for the graph database appears relatively stable between the 100×10^6 and 150×10^6 bytes query sizes, suggesting a level of efficiency in handling incremental query size increases within this range. The relational database does not show a consistent pattern of increase; the latency does not increase linearly or predictably with the size of the query. For example, the latency at 200×10^6 bytes is lower than at 150×10^6 bytes, which could be due to caching, query optimization, or other performance-enhancing mechanisms. Overall, the plot indicates that graph databases may offer performance advantages over relational databases in terms of latency, particularly as query sizes increase. However, spikes and inconsistencies in relational database performance suggest that there may be additional factors at play that affect query processing time.

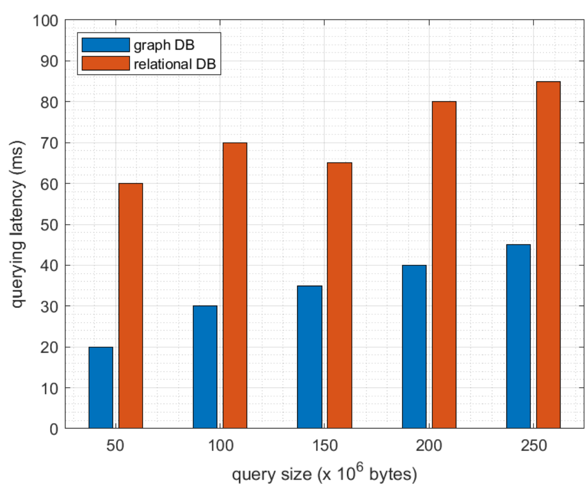

Fig. 3. Querying Latency vs Query Size

C. Energy Use Impact Assessment

Fig. 4 shows two trends of average energy consumption (in millijoules) and total RAM usage (in percentage) versus the payload size (in bytes) for a DT system with and without the implementation of RL-ADT. Here are the observed trends and features: Both with and without RL-ADT, the energy consumption increases as the payload size increases. This is expected since larger payloads typically require more processing power, which in turn consumes more energy. Similar to energy consumption, the total RAM usage also increases with the increase in payload size for both cases. Trends indicate that the implementation of RL-ADT can lead to savings in energy and memory usage, which could be significant in scenarios where resource optimization is crucial. In summary, the plot indicates that RL-ADT can contribute to resource efficiency in a DT system, both in terms of energy and memory usage.

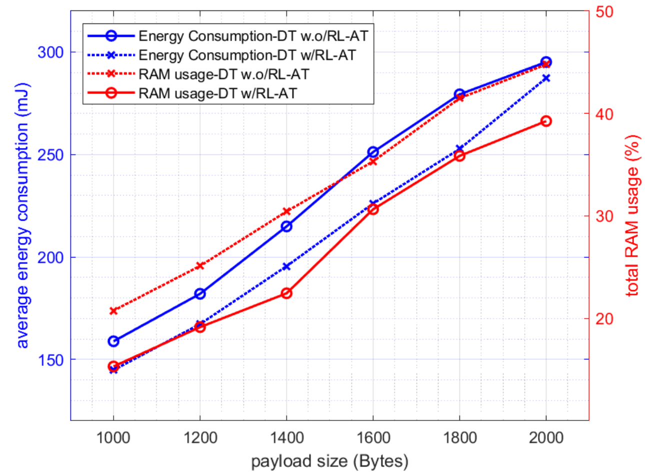

Fig. 4. Energy and RAM usage for digital twin with and without RL-ADT

VI. Challenges and Limitations

The endeavor to construct a DT for forest ecosystems embodies a complex fusion of environmental science and computational modeling. One of the paramount challenges is the accurate representation of the vast heterogeneity of forests, where each tree, underbrush, and wildlife species plays a critical role in the ecosystem's vitality. Collecting comprehensive data to feed into the DT is a herculean task, due to the sheer scale and inaccessibility of forest terrains. The dynamic nature of these ecosystems, with continuous growth, seasonal changes, and interactions with the climate, further complicates this endeavor. Ensuring the data's timeliness and relevance necessitates an infrastructure capable of rapid data acquisition and processing, presenting both technological and logistical hurdles. RL offers a promising avenue for modeling and managing forest ecosystems through DTs. However, applying RL to such complex and dynamic systems introduces unique challenges. The model must decipher intricate ecological relationships and feedback loops, translating them into actionable strategies that align with conservation goals. The nonstationary nature of forests, where past conditions may not be indicative of future states, demands an RL algorithm that is both adaptive and foresighted. The inherent uncertainty and variability within forest ecosystems also pose significant difficulties in defining and quantifying appropriate reward structures that can guide the RL model towards beneficial outcomes for both the forest and its myriad inhabitants. While the conceptual framework of a forest ecosystem DT is robust, scaling it from a controlled, simulated environment to a real-world application is fraught with challenges. The computational complexity of the model increases with the size of the area being monitored and managed, potentially leading to prohibitive processing times and resource requirements. The real-world application requires the integration of the DT with existing forest management practices and policies, which may be resistant to change. The model must be resilient to anomalies and capable of operating under suboptimal conditions, such as sensor failures or data transmission errors, which are inevitable in the unpredictable forest environment. The path to widespread adoption of such a system will involve not only technical refinement but also a concerted effort to demonstrate its utility and reliability to stakeholders in the field of forest management.

VII. Conclusion

Our exploration into the development of a Reinforcement Learning-Based Adaptive Digital Twin (RL-ADT) for forest ecosystems has yielded several key findings. In particular, the implementation of RL-ADT has been shown to significantly enhance the energy and resource efficiency of the DT model. The construction of spatio-temporal graphs has improved the fidelity of the model, allowing a more precise representation of the complex interactions within forest ecosystems. The adaptability of RL algorithms has proven crucial in managing the dynamic nature of forests, particularly in optimizing the trade-off between model accuracy and computational overhead.

The insights gained from this study have substantial implications for sustainable forest management. The DT model offers a powerful tool for forest conservation efforts, providing real-time monitoring and data-driven insights that can inform and improve decision-making processes. The RL-based framework has the potential to revolutionize the way forests are managed by predicting the results of various conservation strategies, optimizing resource allocation, and responding adaptively to changing environmental conditions. By improving efficiency, this technology aligns closely with the goals of sustainability and responsible stewardship of natural resources.

Although promising, the current study also opens avenues for future research. More work is needed to refine the data collection methods, ensuring accurate and comprehensive input for the DT models. Exploring more complex RL algorithms may provide better generalization capabilities and decision-making strategies. The scalability of the model presents another frontier of research: investigating how to effectively apply the DT concept to larger and more diverse forest areas without sacrificing performance. Lastly, integrating the DT with emerging technologies such as drone surveillance and advanced satellite imaging could further enhance the model's capabilities. Engaging with forest management professionals will also be crucial in tailoring the DT to real-world scenarios, ensuring its relevance and applicability in the ongoing effort to manage and preserve our forested landscapes.

Funding

This research paper has received funding from Horizon Europe Framework Programme (HORIZON), call Teaming for Excellence (HORIZON-WIDERA-2022-ACCESS-01-two-stage) - Creation of the centre of excellence in smart forestry "Forest 4.0" No. 101059985.

References

[1] S. Kosse, P. Hagedorn, and M. König, "Analyzing modularity in construction digital twins for developing a dynamic modular reference architecture," *Computing in Civil Engineering 2023*, 2023.

[2] A. Khdoudi, T. Masrour, I. El Hassani, and C. El Mazgualdi, "A deep-reinforcement-learning-based digital twin for manufacturing process optimization," *Systems*, 2024.

[3] G. Di Domenico, L. Cesaretti *et al.*, "Forests management in the metaverse: the potential of forest digital twin and blockchain for preventing crimes," *Nuove frontiere e sfide*, 2023.

[4] S. Agostinelli, "Optimization and management of microgrids in the built environment based on intelligent digital twins," Ph.D. dissertation, 2024.

[5] Brochado, E. Rocha, and D. Costa, "A modular iot-based architecture for logistics service performance assessment and real-time scheduling towards a synchromodal transport system," *Sustainability*, 2024.

[6] Y. Gao, D. Chang, C. Chen, and M. Sha, "A digital twin-based decision support approach for agv scheduling," *Engineering Applications of Artificial Intelligence*, 2024.

[7] H. Park and S. Park, "Emerging trends and challenges in iot networks," *Electronics*, vol. 13, no. 3, p. 513, 2024.

[8] H. Lan, S. Cheng, H. Lu, C. Chang, and S. Li, "A novel process-based digital twin for intelligent fish feeding management using multi-mode sensors and smart feeding machine," *Preprints*, 2024.

[9] C. Chiu, C. Lai, and Y. Liu, "An optimal computing allocation strategy for swarm-based algorithm in simulation-based optimization problem with stochastic constraint," *Asia-Pacific Journal of Operational Research*, 2024.

[10] N. Daly, T. Chhatbar, M. Schmid, and M. Castanier, "Modeling & validation of a digital twin tracked ground vehicle," 2024.

[11] A. Merlo and G. Lavoratti, "Documenting urban morphology: From 2d representations to metaverse," *Land*, 2024.

[12] M. Kabbaj *et al.*, *The Usefulness of Digital Twin in Manipulator Robot Control*, 2024.

[13] N. Smirnov and S. Tomforde, "Real-time rate control of webrtc video streams in 5g networks: Improving quality of experience with deep reinforcement learning," *Journal of Systems Architecture*, 2024.

[14] C. Aranguren and R. Aguilera, "Application of self-learning enhancing huff and puff gas injection optimization in shale reservoirs through sequence-based proxy reservoir simulation and reinforcement learning," *Geoenergy Science and Engineering*, 2024.

[15] L. V. Cakir, K. Duran, C. Thomson, M. Broadbent, and B. Canberk, "Ai in energy digital twining: A reinforcement learning-based adaptive digital twin model for green cities," 2024.

[16] M. Hossain, H. La, and S. Badsha, "Rampart: Reinforcing autonomous multi-agent protection through adversarial resistance in transportation," *Journal on Autonomous Transportation and Infrastructure*, 2024.

[17] S. Yun, D. Kim, C. Park, and J. Lee, "Learning-based sensing and computing decision for data freshness in edge computing-enabled networks," *arXiv preprint arXiv:2401.13936*, 2024.

[18] R. Zakari, W. Shafik, K. Kalinaki, and C. J. Iheaturu, *Internet of Forestry Things (IoFT) Technologies and Applications in Forest Management*. CRC Press, 2024.

[19] R. Damaševičius, N. Bacanin, and S. Misra, "From sensors to safety: Internet of emergency services (ioes) for emergency response and disaster management," *Journal of Sensor and Actuator Networks*, vol. 12, no. 3, 2023.

[20] S. Vashisth and A. Goyal, "A comparative analysis for designing security mechanism for resource-constrained internet of things devices," 2024.

[21] J. Kabala and G. Battipaglia, "Update to ttprocessing: the r-package to handle the treetalker monitoring data," *Dendrochronologia*, 2024.

[22] J. Hassan and S. Alsamhi, *Applications of Machine Learning in UAV Networks*, 2024.

[23] A. Otu, O. Onwusaka, C. Meseko, and E. Effa, "Learning from one-health approaches to explore links between farming practices, animal, human and ecosystem health in nigeria," *Frontiers in Nutrition*, 2024.

[24] J. Guo, "Impacts of the coordination of dtms with different local control objectives considering their spatial layout," 2023.

[25] M. Mishra and S. Reddy, "Performance assessment and comparison of lightweight d2d-iot communication protocols over resource constraint environment," *Multimedia Tools and Applications*, 2024.

[26] J. Rahimifard, "Temporal and spatio-temporal graphs in neo4j," 2023.