A Connectionist Approach to Federated Digital Twins

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Abstract. Digital Twins (DTs) have driven significant innovation across industries, creating virtual replicas of physical assets that enable continuous learning, optimization, and informed decision-making. Digital Twins Systems of Systems (SoS) pose open challenges that relate to representation, orchestration, and management at scale and call for innovative approaches for collaborative modelling of their ecosystem. Federated Digital Twins (FDTs) have emerged as a solution, enabling integration and resource sharing between independent DTs, fostering collaboration, and unlocking the full potential of interconnected systems. This work proposes a framework inspired by connectionism theory to model FDTs as a system of systems, drawing on federated systems and cognitive neuroscience to facilitate collaboration and emergent communication patterns. A Smart Connected Farming case study is used as a proof of concept for the proposed framework.

Keywords: Digital Twins · Federated Systems · Connectionist Theory · Smart Agriculture.

1 Introduction

As dynamic virtual representations of physical assets or entities, ranging from simple to complex systems [14], Digital Twins (DTs) facilitate insights, understanding, and informed decision-making, leveraging continuous real-time data monitoring, what-if analysis, and predictions through simulation and learning models. These advanced DT capabilities have been deployed due to multiple cutting-edge enabling technologies, including the Internet of Things (IoT), Big Data analytics, Artificial Intelligence (AI), edge and cloud computing [11]. While individual DTs have demonstrated significant advantages in diverse domains, a strong need has emerged for developing interconnected Digital Twin ecosystems to deal with large-scale and complex systems-of-systems [17]. As a result, the

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concept of *Federated Digital Twin (FDT)* has emerged as an approach for composing and coordinating DTs, each with its functional characteristics. Such composition may facilitate seamless coordination and collaborative decision-making [32,16,36,33]. Secure inter-twin communications (virtual-to-virtual) may enable cooperation and resource exchange within federated ecosystems while maintaining the operational autonomy of individual DTs [35]. Shared resources range from operational data reflecting physical system state to simulation model outputs, knowledge, learning models [23], and decisions made by agent-based DTs [32,33]. While FDTs hold great promise, their inherent complexity and dynamism give rise to substantial methodological and technological challenges spanning multiple domains, including simulation and analytics, software engineering methodologies, theoretical design frameworks, standards, and interoperability.

Aspiring to contribute to the design and development of FDTs, this paper investigates the concept of connectionism and the utilisation of *Connecitonism theory* principles as a suitable paradigm to study interrelationships between DTs within a federated environment. An FDT is conceptualized as a network of interconnected DTs wherein interrelationships and potential synergies are enabled across the federated network, regulating information flow based on local and global objectives. The paper proposes a connectionist-inspired methodology for capturing communication, interaction, and synergy among interdependent, potentially autonomous DTs. While connectionism is often associated with deep learning models, this paper draws inspiration from the fundamental principles and mechanisms studied in this theory and cognitive neuroscience to study interrelationships in FDTs. As a proof of concept, a precision agriculture use case within Smart Connected Farming (SCF) systems [25] is considered, wherein a network of cooperative Farm DTs are deployed as an FDT, virtually representing a community of real-world smart farms in an agri-food production region.

The contributions of the paper are as follows:

1. Conceptualization of FDTs as Networks of Interconnected DTs: The paper proposes a new perspective of Federated Digital Twins (FDTs) as a network of interconnected, cooperative DTs facilitating dynamic information flow across a federated ecosystem. This framework enables coordination and resource exchange while maintaining the autonomy of individual DTs.
2. Development of a Connectionist-Inspired Methodology for Federated Digital Twins (FDTs): This paper introduces a novel methodology inspired by connectionism theory to study and model the interrelationships between Digital Twins (DTs) within a federated system. The approach captures communication, interaction, and synergy among autonomous, interdependent DTs, enhancing their collaboration and decision-making.
3. Application to Smart Connected Farming (SCF): The paper demonstrates the practical applicability of the proposed FDT framework through a Smart Connected Farming (SCF) use case. This case study explores how a network of Farm DTs can be deployed in an agri-food production region, serving as a proof of concept for the potential of FDTs in large-scale, complex systems like precision agriculture.

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The remainder of the paper is organized as follows: Section 2 presents an overview of an FDT and current frameworks addressing federated ecosystems for DTs. Section 3 provides a detailed exploration of the connectionism theory, focusing on its application to FDTs. Section 4 outlines a proof-of-concept use case within the context of Smart Connected Farm, while Section 5 presents an experimental evaluation of the system. Section 6 concludes the paper by outlining potential areas for future work.

2 Federated Digital Twins

A network of connected DTs representing multiple interconnected physical assets, encompassing a wide range of complexities, has been analyzed by the Alan Turing Institute within the UK's national DT programme [13]. An ecosystem of connected DTs representing the highest level of integration for homogeneous and heterogeneous DTs, capable of capturing the intricacies of interconnected real-world systems across various spatiotemporal scales, leveraging shared resources and combined insights within federated environments [3]. Considering four potential architectural styles, FDTs have been conceptualized as a virtual medium for connecting autonomous DTs [32,33]. Security, standardization, and interoperability are crucial aspects that enable collaboration, informed decision-making, and systems optimization through advanced data analytics and simulations.

FDTs have also been proposed as part of an evolutionary development model for DTs, consisting of five layers to address their inherent complexity [19]. This model incorporates replication, intra-twin synchronization, modeling, and simulation with FDTs, enabling advanced services in the fourth stage via an intelligent platform. In urban and smart cities, the Internet of FDTs framework [36] is being developed as a unified platform for coordinating DT networks within the context of Society 5.0. A hierarchical architecture facilitates both horizontal and vertical interactions between local DTs, accounting for crucial factors such as inter-twin synchronization, dynamic resource allocation, and scalability. Similarly, the MATISSE project [6] envisions an FDT framework to enhance operations in industrial systems, reduce costs, and accelerate time-to-market by promoting the adoption of DTs in this domain. Model-driven engineering (MDE) techniques, general-purpose and domain-specific languages, the Functional Mockup Interface (FMI), and model transformations support federation across various large-scale industrial systems.

3 Connectionist Federated Digital Twins

3.1 Connectionism Theory

Connectionism, a concept from cognitive science, is a theory of information processing that emphasizes the parallel nature of cognition. It draws inspiration from the brain's neurophysiology to explain human cognitive abilities through mathematical and statistical principles in Artificial Neural Networks (ANNs) [27]. In

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contrast to the classical symbolic theory, connectionism posits that complex cognitive processes and mental phenomena *emerge* from the dynamic interactions of simpler processing units, similar to biological neurons. Neurocognition refers to modelling cognitive neuroarchitectures based on modern neuroscientific evidence [20]. The connectionist paradigm, also known as the Parallel Distributed Processing (PDP) framework, was extensively developed by the PDP Research Group, drawing on earlier connectionist ideas and neuroarchitectures [24]. This framework has profoundly influenced modern AI development, especially in Deep Learning [4]. However, its origins trace back to Aristotle's ideas on mental associations, later expanded by psychologists and neuropsychologists to explain complex cognitive functions associated with brain processes [21].

Connectionist models focus on the communication between presynaptic and postsynaptic neurons through activation states, with information flowing through synaptic links modulated by Hebbian learning principles [15]. Nonetheless, most computational models in ANNs are time-agnostic, overlooking the essential dynamism inherent in neural systems and cognitive processes, which prioritise time over order [28]. Contemporary neuroscience emphasises that biological intelligence involves cognition as an internal physical process unfolding through time [22]. From the perspective of dynamical systems in cognitive science, philosophy of mind, and neuroscience, cognition is viewed as the simultaneous, mutually influencing unfolding of complex temporal structures. Thus, *temporal dynamics* are crucial for understanding how neural connections organize and interrelate in dynamical spiking neural network models [31].

3.2 Connectionist-inspired FDT Model

This paper leverages principles from connecitonism theory, synaptic communication (including synaptic weights), and Hebbian learning rules to conceptualize an FDT as a connectionist network of interconnected processing units (DTs) where synaptic weights modulate interrelationships and potential synergies between them based on *neural activity*. Relevant similarities between FDTs and connectionism (Table 1) motivate this study according to the fundamental properties outlined in the PDP framework [24]. Moreover, biologically plausible Spiking neuron models over ANNs are used to model dynamic DT state activation and information propagation across the federated environment.

In this paradigm, each DT is treated as a processing unit within a connectionist network (federation) utilizing Leaky-Integrate and Fire (LIF) neuron models [12]. Each processing unit accounts for two types of LIF models: (1) *Intra-twin LIF*, which produces neural spikes to propagate events and stimulate interconnected DTs, and (2) *Inter-twin LIF* which trigger operations and interactions in the receiving DT upon continuous input stimulation, as illustrated in Figure 1. LIF models are used due to their biological plausibility, simplicity, low computational cost, and capability to compute temporal dynamics.

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Table 1. Connectionist PDP properties applied to Federated Digital Twins

Connectionist (PDP) property	**Federated Digital Twins**
Set of processing units	Each processing unit in a connectionist network models activation states propagating through the network. Thus, in this study, each DT acts as a node within the federation, utilizing LIF spiking neuron models (intra and inter-twin) to capture its dynamics.
States of activation	Activation states reflect the incoming stimuli. In an FDT, the internal state of each DT is determined by real-time inputs from its physical counterpart. When active, a DT emits an event (spike) to signal its state. Inter-twin activation triggers DT operations and interactions, modulating synaptic weights across interconnected DTs in the federation.
Patterns of connectivity	Connectivity matrices represent the relationships between units. In the FDT, these matrices determine inter-twin connectivity, capturing aspects such as geographical distance, similarity, or communication relevance.
Propagation and activation rules	Determines how DT outputs are transmitted across the network, modulated by the connection weights within the connectivity matrices (synaptic weights). This study considers two modes: (1) When DTs are directly connected, stimulation is based on the weight and output from external DT, emitting spikes; (2) when DTs are not directly connected, a probabilistic sigmoid function in the receiver is used to notify about potential connections on its connected nodes, enabling the emergence of new synaptic links.
Algorithm for modifying patterns of connectivity	The algorithm that adjusts synaptic weights based on experience is crucial in connectionism. This study applies the *Spike Timing-Dependent Plasticity (STDP)* rule, a form of Hebbian learning, which modifies connectivity due to interactions between DTs.
Representation of the environment	DTs are situated within a virtual environment that replicates the real world. For instance, in agricultural applications, the environment is represented by data on weather and soil conditions, which influence the behaviour of DTs.

The threshold for each LIF model depends on the specific application, typically indicating a level of interest or saturation. For instance, intra-twin thresh-

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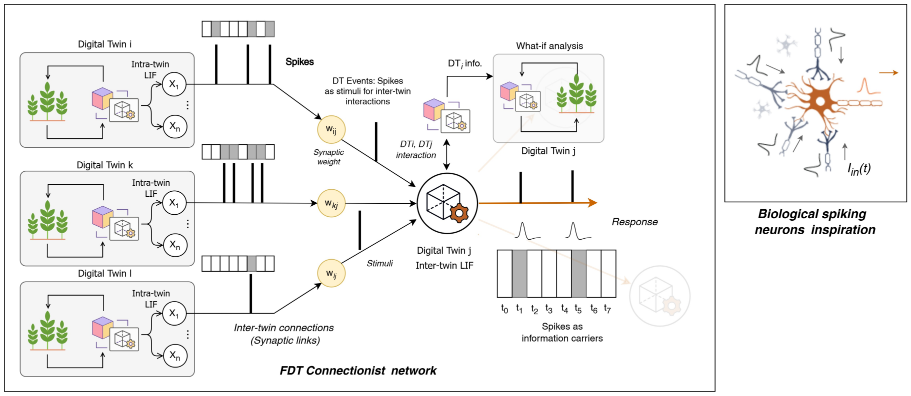

Fig. 1. FDT conceptualized as a connectionist network

olds might denote the productivity levels of a smart farm in agriculture, the operational state of a machine on a manufacturing shop floor, or the traffic flow limit in a cross intersection in transportation systems. Inter-twin LIF activation depends on the level of connectivity between two DTs. Connections between them are modeled as synapses, with the relevance of communication encoded in the synaptic weights that flow through the synaptic links. Over time, connectivity can adapt based on interaction and the significance of information (plasticity in neuroscience), influenced by parameters such as similarity, frequency, or trust, using a Hebbian Learning rule.

The Leaky-Integrate and Fire neuron [10] describes the evolution of a neuron's membrane potential in response to input stimuli, and is modeled as:

$$\tau \frac{dU(t)}{dt} = -U(t) + I_{in}(t)R \tag{1}$$

Where $U(t)$ is the membrane potential at time t, in volts (V) and τ is the membrane time constant (s), which determines how quickly $U(t)$ decays without input current. τ is calculated as $\tau = RC$, with R being the membrane resistance (ohms, Ω) and C the membrane capacitance (Farads, F). The term $dU(t)/dt$ represents the rate of change of membrane potential, while $I_{\text{in}}(t)$ is the input current in amperes (A), influencing the neuron's charge. Larger values of I_{in} promote significant changes in the membrane potential, towards its firing threshold ϑ. Equation 2 describes the discrete version of LIF used in this paper [10].

$$U(t + \Delta t) = U(t) + \frac{\Delta t}{\tau} \left(-U(t) + RI_{\text{in}}(t)\right) \tag{2}$$

The membrane potential $U(t)$ is interpreted as the evolving internal state of a DT at time t, where observations are treated as input currents $I_{in}(t)$, encoding information as charge in the LIF model. Two types of LIF neuron models, based on the two communication modes in DT networks [35], have been considered in this study:

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- *Intra-twin LIF:* Models the internal state of a DT using the LIF neuron model, where the input current $I_{in}(t)$ represents local data sourced from sensors or generated by simulation models. This data is structured as a vector of characteristics $X = [x_1, x_2, ..., x_n]$, with each element x_i corresponding to a specific attribute of the DT. For example, in a smart farming context, attributes related to biomass productivity, influenced by irrigation and crop nutritional strategies, contribute to the internal activity level of a DT-Farm. The DT may emit an outgoing event (spike) if the accumulated input exceeds a threshold, indicating significant internal change.
- *Inter-twin LIF:* Captures inter-twin communication within the federation using the Leaky Integrate-and-Fire (LIF) neuron model, where each DT integrates incoming spikes modulated by synaptic weights. These spikes trigger internal processes in the receiving DT, which may include: (1) initiating interactions to request additional information from connected DTs, or (2) directly processing the content encoded in the event (spike), which includes performance metrics, model parameters, or predictive outputs. This model facilitates interoperability between DTs, which is a fundamental aspect of FDT systems.

The rationale for using two separate LIF models in each DT (processing unit) lies in the distinct nature of the information they handle. The proposed approach integrates intra-twin LIF (outgoing) spikes into external inter-twin LIF from connected DTs, influencing their behaviour (See Figure 1).

3.3 Spike Generation and DT Events

When an intra-twin LIF fires due to accumulated input current (observations within the DT), it emits an event, represented as a spike, which is propagated to connected units in the network. Modeled as a $\delta - Dirac$ function, these "instant pulses" occur at a specific time t when a threshold ϑ is reached [12]. The temporal nature of spikes is suitable for encoding information and generating temporal dynamics across the network.

In this paper, each DT event carries information about the emitting DT in the form of $< P, Sp, t(s) >$, where P contains the current properties of the DT (static and dynamic attributes), Sp is the spiking state ($True$ or $False$) and t is the time when the spike is generated. Inter-twin spikes enable interactions between connected DTs across the federation. Successive spikes and the time between them may encode information, forming *spike trains* that represent the intensity of *neural activity*. The stimulation between two DTs is influenced by the temporal correlation and the synaptic weight in their connectivity, reflecting principles of neural plasticity.

3.4 Spike Timing-Dependent Plasticity

Spike Timing-Dependent Plasticity (STDP) is an unsupervised Hebbian learning mechanism that adjusts synaptic weights (w) based on the temporal relationships between pre- and postsynaptic spikes [26]. This mechanism embodies a

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core property in the PDP connectionist framework [24]. The weight between two processing units is reinforced if a presynaptic spike precedes a postsynaptic spike ($\Delta t > 0$), a process known as Long-Term Potentiation (LTP), indicating a potential causal relationship. In this paper, such stimulation initiates a process of interaction between DTs. If this interaction is beneficial, the synaptic weight between them is strengthened, fostering synergy. Conversely, synaptic weights are weakened if a presynaptic spike follows postsynaptic activity ($\Delta t < 0$) or if no meaningful interaction among DTs occurs. This process is known as Long-Term Depression (LTD). Following the STDP rule, the synaptic weight w at time t between DTs is updated as:

$$w_t = w_{t-1} + \Delta w_t. \tag{3}$$

$$\Delta w_t = \begin{cases} A_+ e^{-\frac{\Delta t}{\tau_+}}, & \text{if } \Delta t > 0 \quad \text{(post after pre)} \\ -A_- e^{\frac{\Delta t}{\tau_-}}, & \text{if } \Delta t < 0 \quad \text{(pre after post)} \end{cases} \tag{4}$$

Here, A_+ and A_- are the learning rate amplitudes for potentiation and depression, respectively, which determine the magnitude of the synaptic change. Parameters τ_+ and τ_- are the time constants that control the decay rate of potentiation and depression. $\Delta t = t_{\text{post}} - t_{\text{pre}}$ captures the time difference between postsynaptic and presynaptic spike events.

4 A Pilot Case

To demonstrate the proposed approach, this section applies the concepts presented in Section 3 to scenarios involving sustainable irrigation practices and cooperation in smart farming systems. In smart agriculture, DTs are increasingly being considered to enhance agri-food production through cyber-physical systems, thereby improving food security, sustainability, and waste management. By visualizing farming systems, DTs optimize resource efficiency and biodiversity conservation [2]. Reinforcement learning agents, utilizing synthetic data, minimize resource consumption while maximizing crop yields. *What-if* simulations can explore strategies to enhance carbon sequestration in croplands and pastures, including agroforestry [29].

On a larger scale, Smart Connected Farms (SCF) are transforming agriculture by leveraging high-precision sensors, Big Data, and AI for crop and climate monitoring. This promotes precision agriculture while providing socio-economic benefits and a framework for studying the impacts of climate change on agri-food systems [25]. Therefore, SCFs operating within federated environments utilizing DTs have the potential to optimize natural resources across vast agri-food production regions.

4.1 The Connectionist Model

A federation of DTs, conceptualized as a connectionist FDT, operates within a network of independent farms in the context of a Smart Connected Farming system, as illustrated in Figure 2.

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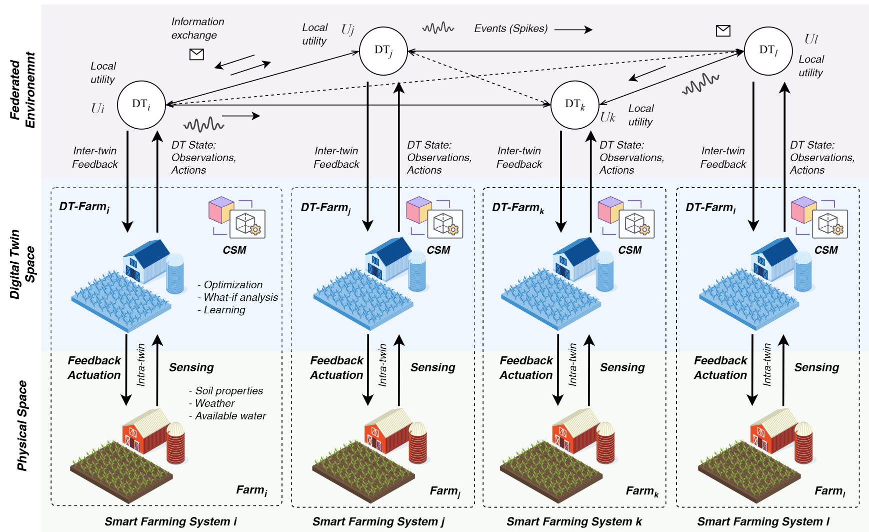

Fig. 2. Smart Connected DT-Farms as a Connectionist FDT

Given the complexities in agriculture and the daily challenges farmers face, interconnected DTs share information to optimize water resources in a decentralized, online manner within the federated ecosystem. An Agent-Based Modelling (ABM) approach enables autonomous decision-making based on local observations and utilities while integrating external influences from connected peers. Information is transmitted through events (spikes) that reflect productivity levels, facilitating communication within the federation and exchanging efficient strategies.

4.2 The Digital Twins Federation

At the core of each DT is a Crop Simulation Model (CSM) that simulates crop growth and abstracts biological processes. Developed by agronomists and biologists, CSMs enhance understanding of crop responses to varying conditions [8]. This study considers the WOrld FOod STudies (WOFOST) model [30], a dynamic, mechanistic CSM that simulates crop growth based on environmental factors (e.g., weather, soil, water, etc.). WOFOST operates on a daily time basis, modelling various crops and enabling annual production analysis. The simulated crop is a potato, with physical soil parameters provided by WOFOST in the Python Crop Simulation Environment (PCSE) [34].

In this scenario, each DT-Farm acts as a processing unit in a connectionist network, where intra-twin states and inter-twin communications are modeled using LIF neuron models. WOFOST defines various crop performance metrics, such as Total Above-Ground Production (TAGP), Leaf Area Index (LAI), and

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Total Weight of Storage Organs (TWSO), which are computed and retrieved through its implementation in the PCSE.

At the end of the growing season, TWSO $\left(\text{kg ha}^{-1}\right)$ is a key performance metric used to evaluate crop productivity and estimate potential profits [34]. Throughout the simulation, each DT-Farm monitors the daily biomass evolution, quantified by the changes in TWSO calculated as:

$$\Delta TWSO_t = TWSO_{t-1} - TWSO_t \tag{5}$$

Daily changes $\Delta TWSO$ are normalized relative to their yearly average (simulated), indicating productivity levels. This value is then transformed into the current inputs I_{in} to charge the intra-twin LIF model. When the neuron's membrane potential reaches a threshold (indicating an increase in productivity), a *spike* event is fired and transmitted to connected DTs to stimulate their inter-twin LIF model, triggering a what-if analysis. Both intra- and inter-twin LIF model parameters were calibrated using WOFOST outputs, with the following configuration: threshold $\vartheta = 0.2$, time step $\Delta t = 2\,\text{ms}$, resistance $R = 1\Omega$, and capacitance $C = 5F$.

Six irrigation regimes (1-6), adapted from [18], were used to assess crop response to varying irrigation strategies. These regimes were classified into two groups based on frequency: low-frequency (every 4-6 days) and high-frequency (every 1-3 days). Initially, all sites operated under low-frequency schedules. However, 30% of the sites had a 50% weekly probability of assessing implications to use high-frequency irrigation, potentially offering benefits for local and similar agroecosystems. Daily irrigation (depending on the strategy) is determined based on crop evapotranspiration ET_c (cm), computed as:

$$ET_c = K_c \times ET_0 \tag{6}$$

Where ET_0 is the daily reference evapotranspiration derived using the Penman-Monteith model [1], which incorporates weather effects. K_c, a crop coefficient specific to crop developmental stages, was set for potatoes at 0.5 (initial), 1.15 (mid-season), and 0.75 (late-season) [9].

Therefore, DT-Farms aims to optimize water consumption, considering initially low-frequency regimes while exploring potential strategies that lead to increased local productivity. The decision-making process determines the optimal irrigation strategy between DTs in the federation, considering shared resources and individual demands based on local conditions. The social interaction model [5] (Equation 7) serves as a local utility, capturing spillovers and network effects, and guides weekly choices.

$$U_i(\omega_i, \omega_{-i}) = \left(\gamma x_i + z_i + \delta \sum_j c_{ij}(t) x_j\right)\omega_i - \frac{1}{2}\omega_i^2 + \phi \sum_j a_{ij}\omega_i\omega_j \tag{7}$$

Each DT_i selects a strategy ω_i from irrigation regimes that maximizes its local utility while accounting for peers' actions and influence. The variable x_i denotes the weekly predicted local yield ($TWSO$) and z_i the Water Use

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Efficiency (WUE). WUE represents the ratio of yield to the amount of water applied, expressed as kilograms per cubic meter $\left(\mathrm{kg\ m^{-3}}\right)$ [7]. The term $\delta \sum_j c_{ij}(t) x_j$ captures *contextual effects* or direct influence from connected nodes while $\phi \sum_j a_{ij} \omega_i \omega_j$ reflects strategic complementarity [5]. A and C are weighted (normalized) sociomatrices, where a_{ij} and c_{ij} represent the peer and contextual effects. The middle term captures the convex costs of water consumption. Hence, farms with similar characteristics will most likely influence one another. For simplicity, parameters γ, δ and ϕ are set to 1.

A is derived using the *Haversine distance* based on geographical locations according to Equation 8.

$$a_{i,j} = 2 \cdot r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_j - \phi_i}{2}\right) + \cos(\phi_i) \cdot \cos(\phi_j) \cdot \sin^2\left(\frac{\lambda_j - \lambda_i}{2}\right)}\right) \tag{8}$$

Where a_{ij} is the distance in meters, and r is the Earth's radius $= 6371$ km. ϕ_j and ϕ_i are the latitudes of DT-Farms j, and i, respectively, while λ_j and λ_i are their longitudes.

C was obtained using the *Cosine distance* between connected farms as a metric of similarity according to Equation 9.

$$c_{i,j} = \frac{\boldsymbol{u}_i \cdot \boldsymbol{u}_j}{\|\boldsymbol{u}_i\| \|\boldsymbol{u}_j\|} \tag{9}$$

Where $\boldsymbol{u}_i$, $\boldsymbol{u}_j$ are normalized vectors encoding weather conditions and soil attributes between DT-Farms i and j, respectively. Weather features include average temperature, evapotranspiration, solar radiation, wind speed, vapour pressure, and total precipitation. Soil features comprise field capacity, wilting point, and saturation point.

An iterative message-passing process is done weekly to coordinate irrigation strategies among DT-Farms, using the CSM to predict the expected productivity (TWSO) that maximizes joint utility. The utility function considered is *topology-dependent*, capturing network effects on farm utilities. Successful strategies are identified and exchanged between connected nodes. In this connectionist approach, communication is modulated by local spiking activity and event-based transmission across synaptic links. If the cumulative stimulation exceeds the threshold in the inter-twin LIF model, an interaction process is initiated, enabling a what-if analysis based on shared data among DTs.

If information from one farm leads to notable improvements in another, the connectivity weight between them is strengthened according to the STDP rule (LTP), indicating similarities and potential synergies. If no meaningful gains or no activity is detected, the connectivity weight decays (LTD). The dynamic evolution of these synaptic weights influences social utility across the network, ultimately shaping decision-making processes. The objective is to study the impact of static and emergent dynamic topologies derived from connectionism. The STDP parameters used were $A_+ = 0.01$, $A_- = 0.005$ and $\tau = 5ms$. Δt is the time difference between the pre- and postsynaptic spikes obtained as $\Delta t = 0.001 \times (t_{post} - t_{pre})$.

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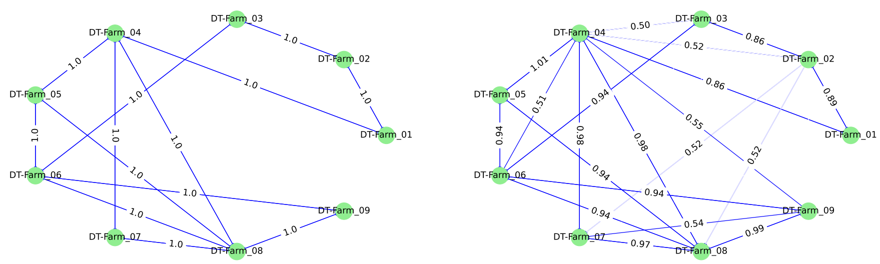
5 Experimental Results

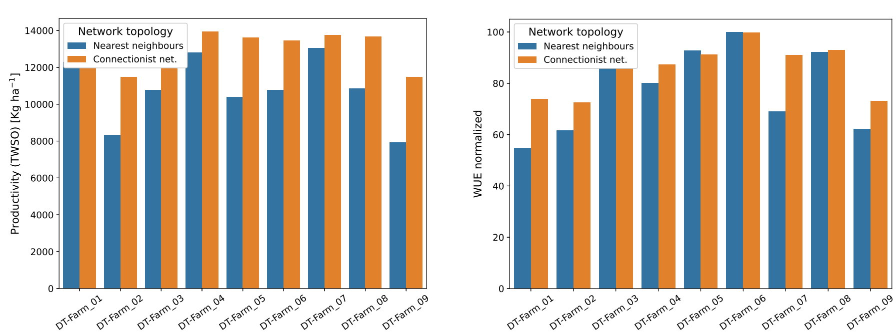
Experiments were conducted under two scenarios: a fixed nearest neighbours topology and a dynamic connectionist network. Fixed topologies constrain information exchange to predefined links, limiting the emergence of interactions among DT-Farms. In contrast, the dynamic connectionist approach enables adaptive links and synergies modulated by spiking neural activity. Figures 3(a) and 3(b) illustrate these structural differences.



(a) Nearest neighbours (b) Dynamic connectionist network

Fig. 3. FDT network topology for connected DT-Farms

Results revealed the emergence of *synaptic links* between synergistic DT-farms, such as DT-Farm 4 and DT-Farm 9 or DT-Farm 2 and DT-Farm 7 (Figure 3(b)), formed probabilistically through DTs intermediaries based on environmental conditions and soil similarities. These connections, enable productive DT-Farms to influence others through their intra- and inter-twin LIF models, fostering dynamic communication channels that promote interoperability and cooperative behavior within the federation.



(a) Final productivity (TWSO) (b) Water Use Efficiency (WUE)

Fig. 4. FDT performance comparison

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Figure 4(a) illustrates increased productivity across all connected DT-Farms, benefiting farmers with improved profits. Simultaneously, the integrated social model for irrigation decision-making penalises excessive water use, mitigating environmental impact. Therefore, synaptic links in a connectionist federation facilitate information diffusion among DTs, while fostering sustainable agricultural decisions based on the social model in Equation 7. Experimental results indicate a total productivity increase of up to 20.6% achieved by a connectionist network compared to the Nearest neighbours approach by the end of the 2023 growing season. Furthermore, Water Use Efficiency improved, ranging from 0.7% to 22.04% across all DT Farms, as illustrated in Figure 4(b), due to information exchange and decentralized decision-making considering the emergent network topology.

6 Conclusions

This paper proposes a novel framework based on connectionism theory to support Federated Digital Twins, modelling the dynamic interrelationships among interconnected DTs in a federated environment. Drawing on principles from cognitive neuroscience, the proposed approach captures collaborative patterns for communication and decision-making, enabling cooperation and resource exchange across autonomous DTs. By incorporating temporal dynamics and adaptive connectivity, this methodology enhances the capability of federated ecosystems to handle complex, large-scale systems.

The proof of concept in the context of precision agriculture demonstrates the potential of the proposed framework as an innovative solution to enhance computation for sustainability, by monitoring and analysing pending global challenges such as food security.

Future research will focus on evaluating the scalability and broader implications of this approach within more complex network topologies and federated ecosystems of Digital Twins in different domains. It will also refine the underlying architecture by incorporating new patterns and cognitive principles, and integrating human-in-the-loop modalities and expert knowledge, contributing to an extended suite of reference architectures for Federated Digital Twins [32,33].

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