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Digital Twin Design for Autonomous Drones

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***Abstract*—The rapid adoption of technology led to the rapid growth of various fields, including Unnamed Aerial Vehicles (UAV). Digital Twin (DT) became a popular concept to facilitate this progress, serving as a virtual replica of the physical drones to support run-time compliance checking, coordination, and analysis in trustworthy UAV design and operation. Nevertheless, the DT technology in UAV often lacks a precise specification and clear explanation of its characteristics, parameters, and functionalities. To address this gap, this paper investigates current research in DT applications for autonomous drones and compiles the findings towards the design of a DT to support the UAV sector. To this end, we extract the DT characteristics from existing papers and leverage these insights to propose a DT design for autonomous drones. The resulting DT is foundational in facilitating seamless collaboration and decision-making among collaborating autonomous drones in autonomous ecosystems to ensure safe and trustworthy operation, as demonstrated in a proof of concept, demonstrated through a case study of logistics shipment, showcasing the DT application for autonomous drones' collaboration in autonomous ecosystems.**

Keywords: Digital Twin, Digital Twin Design, Digital Twin Properties, Autonomous Drones, Trust, Autonomous Ecosystems.

I. Introduction

DURING the past decade, the Digital Twin (DT) concept has played an important role in integrating the physical and cyber worlds of critical infrastructures [1], attracting attention in an ongoing transformation to Industry 4.0 [2], [3], and later also the smart mobility [4], [5], including its applications in the growing sector of Unmanned Aerial Vehicles (UAVs) and autonomous drones [6], [7]. In UAV applications, the DT serves as a virtual replica of a physical drone, facilitating run-time compliance checking, coordination and analysis. This capability enhances the reliability of drone operation, builds trust among collaborating drones and safe operation, and provides a transparent DT framework for decision-making. consequently, the adoption of DT technology in the UAV sector is leveraging autonomous drones for trust-building during critical operations [7].

Unfortunately, DT technology often remains vaguely described, lacking a precise specification and clear explanation of its characteristics, parameters and functionalities [8], [9], [10]. Consequently, a gap exists between theoretical conceptualizations of DTs and their practical implementations for safe communication operation among collaborating autonomous agents in autonomous ecosystems.

To address this challenge, there is a need to understand the properties, characteristics and components that build up a DT. This involves moving beyond the generalized description towards specific methodologies and applications. Establishing clear parameters (i.e., navigation, environment perception, path planning, and control) of the DT can then support DT application in the critical operation of autonomous drones and promote the acceptance of autonomous drone ecosystems in general. Furthermore, it is foundational in facilitating seamless collaboration and decision-making among collaborating autonomous drones in autonomous ecosystems to ensure safe and trustworthy operation. DT can be a powerful tool for building trust in complex communication operations by thoroughly considering these factors.

Contribution. In this paper, we contribute to this research gap by identifying the characteristics and components of DTs for autonomous drones and proposing the process of DT design in the context of trustworthy drone collaboration in autonomous ecosystems. To this end, this work first systematically examines the application of Digital Twins (DTs) through a comprehensive review of existing literature across diverse scenarios and applications of autonomous drones and other vehicles in autonomous ecosystems. We focus on understanding how DTs act as virtual replicas and can help manage and control operations, particularly in Unmanned Aerial Vehicle (UAV) operations. We start this process with content analysis and specific search criteria to identify and analyze relevant papers on DTs applied in UAVs, particularly in autonomous drones. We then expanded our exploration to DT applications in autonomous vehicles due to the limited results identified among autonomous drones. Our aim is to gather insights from existing DT applications in autonomous vehicles to bridge existing knowledge gaps and leverage these insights to design and implement DTs for autonomous drones. The paper thoroughly examines existing literature, addressing relevant technical challenges and computational barriers reported in prior research.

Once the findings from the literature are collected, this work then analyses the findings to extract the characteristics and components of the DTs of autonomous drones, with the aim to provide a structure of the key enabling technologies towards a DT design, based on the parameters that compile a DT of an autonomous drone. As a context, we refer to a trust-building scenario where the DT is utilized in a trust-building process in drone communication [6]. Above all, the technologies used at the level of integration and the current description of DTs are a major focus of the investigation. This paper serves as an enabler for this direction and for further work in the field of the Digital Twin in communication [2].

Paper Structure. The remainder of the paper is structured as follows. Section II gives an overview of related work, followed by the methodology of the DT characteristics extraction and design in Section III. The findings of the study results are discussed in Section IV, and the drone DT conceptual design is presented in Section V. Section VI outlines the proof-of-concept of an autonomous drone DT, and the paper concludes in Section VII.

II. Related Work

Extensive research has been conducted to investigate the potential and enabler technologies of Digital Twins and to identify the key challenges encountered by practitioners during designing and implementing the Digital Twins [8], [9], [10]. Technical difficulties, computational barriers, and a shortage of well-founded frameworks and approaches have been reported as part of these challenges. The above research reviews existing literature exploring the utilization of DT design for the Unmanned Aerial Vehicle (UAV), employing Digital Twins as virtual replicas of physical objects to play a pivotal role in control and system management across various sectors, including technology, communication, and UAV operations [10].

DT in Simulation Environments. Within the state-of-the-art research, substantial attention is paid to simulation environments for DT application on shared infrastructure in future smart cities [11]. The linked approach [11] addresses safety and privacy concerns and facilitates pre-deployment testing and detection of real-time malfunctions. The research provides a simulation environment and DT support for shared drone infrastructure. It, however, lacks integration of essential functionalities for managing drone flights effectively and efficiently within airspace services. A novel DT-based intelligent collaboration framework of UAV swarms is proposed in [12]. The proposed framework establishes a high-fidelity DT model to mirror and reflect the complete life cycle of UAV swarm, integrating a machine learning algorithm to improve the decision-making and control behaviors. In [13], the authors outlined a DT-based cloud computing framework for large-scale military UAVs. The research explores factors such as business prediction, test cost, integrated perception, mission planning, and centralized control.

Data-Driven DT Concepts. A two-level data-driven DT concept for autonomous landing of aircraft is introduced in [14], featuring a DT instance for model predictive control and a real-time prototype for fluid-structure interaction and flight dynamics, though it lacks detailed construction and verification. A similar study [15] was proposed to characterize the dynamic environment of a commercial vertical take-off and landing convertible. The proposed method offers an estimation of aerodynamic forces and moments for various wind conditions but lacks realistic DT behavior due to limited functionality. Finally, a DT-based deep reinforcement learning training framework is proposed in [16] to enhance the effectiveness of a training model for UAVs by simulating complex environments that are difficult to replicate in physical testbeds. All these approaches focus on utilizing DT in specific scenarios rather than providing a comprehensive description or detailed design of the DT itself.

DT Frameworks for UAV. Several works have explored the utilization of Digital Twins to enhance the performance of wireless communication for applications such as computation offloading, content caching, and resource sharing. Proposed DT frameworks [9] optimize UAV-based MEC servers for IoT networks, ensuring efficient task offloading with low-latency communication. In [9], a DT framework is proposed for IoT networks using UAVs for on-the-fly task offloading MEC servers in industrial automation to meet the ultra-reliable low-latency communication link requirements. The proposed DT model optimizes the communication and computation parameters, such as power and processing rates, to make UAV-URLLC task offloading efficient. Additionally, the integration of DT technology with drone-assisted data collection offers precise ship maneuvering in smart seaports, enhancing operational efficiency and reducing environmental impact. Yoon et al. [17] proposes a seismic fragility analysis using a UAV-based updated DT. Their findings showed that the proposed approach can be applied to bridge condition assessment using UAV inspection to update the DT at an abstract level. Next, Sun et al. [18] explore dynamic DT and federated learning for air-ground networks, while other studies focus on DT-driven vehicular edge computing with UAV FlexEdge [19]. A DT-driven training framework was proposed in [20]. While these studies give invaluable insight into DT frameworks for UAV, they exclusively focus on the application of DT technology, without providing details on DT design itself.

Summary. While extensive research exists that explores the application of DT as a key enabling paradigm for improving the performance of smart mobility systems, very few works can be found that reveal the actual details of the DT description and design mechanism in the context of autonomous drones. Driven by these considerations, this paper presents a design process of a DT for autonomous drones, which is grounded in a comprehensive review of the existing literature identified through our systematic search.

III. Research Method

This study aims to systematically explore the recent development in the application and implementation of the DT concept in autonomous drones (from 2015 onwards). The goal is to comprehensively understand the trends, advancements, and challenges in applying DT technology and designing the DT for collaborating autonomous drones. Each step of our research method is described below and illustrated in Figure 1.

A. Search Process

The first step is to identify and review related work relevant to the design of the Digital Twin relevant to the context of autonomous drones. Our search initially starts with the focus on DT in UAV and autonomous drones, with inclusion criteria

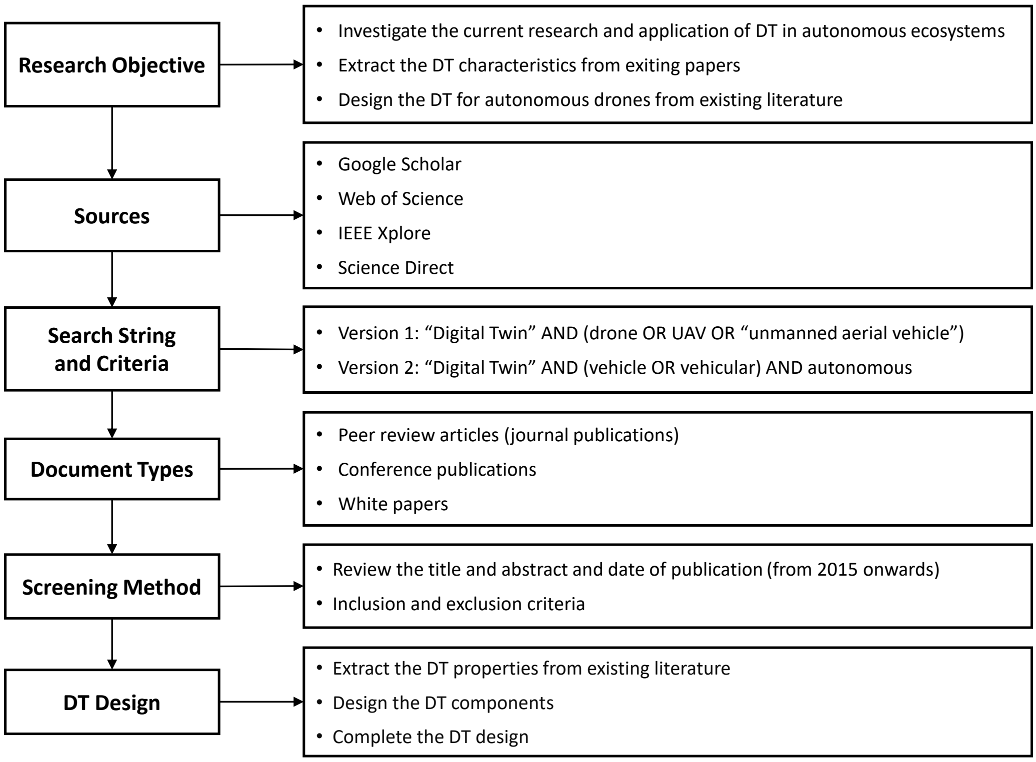

Fig. 1. Summary of Research Methodology

looking into the description of the design of a DT and its characteristics. The employed search term was:

- Version 1: "Digital Twin" AND (drone OR UAV OR "unmanned aerial vehicle")

Due to the limited results that resulted from filtering the search results with the inclusion and exclusion criteria below, the search was expanded to its second version, exploring Digital Twin design in a wider context of autonomous vehicles, but with transferability of the findings to the narrower scope of autonomous drones. The employed search term was:

- Version 2: "Digital Twin" AND (vehicle OR vehicular) AND autonomous

We have conducted both searches across multiple academic databases, including Google Scholar, Web of Science, IEEE Explore and Science Direct, focusing on the timeframe from 2015 onwards.

B. Inclusion and Exclusion Criteria

The following inclusion and exclusion criteria were used to filter the search results.

1) Inclusion criteria (IC) – for search version 1:

- IC1: The paper provides a detailed description of a DT of a drone, including an example.
- IC2: The paper describes the structure of the DT.

2) Inclusion criteria (IC) – for search version 2:

- IC1: The paper provides a detailed description of a DT of an autonomous vehicle, including an example.
- IC2: The paper describes the structure of the DT.
- IC3: The DT is relevant for autonomous drones.

3) Exclusion criteria (EC): – for search version 1 and 2

- EC1: Papers in languages other than English.
- EC2: Gray literature (e.g., editorials and keynotes).

C. Review Execution

Although each search version started with over 100 publications (after applying the exclusion criteria and removing duplicates), the inclusion criteria reduced the search results drastically. After the inclusion criteria were applied to titles, abstracts, and full-text, only 2 papers resulted from search version 1 [9], [10], and only 7 papers resulted from search version 2 [21], [22], [23], [24], [25], [26], [27].

D. Extraction of DT Properties

Following the identification and screening of publications regarding the DT of autonomous drone applications with details description [9], [10] and the publication describing the DT details for autonomous vehicles [21], [22], [23], [24], [25], [26], [27], DT analysis was chosen to extract the DT properties to be considered in the DT design. The DT properties were extracted by analyzing text to gather information useful for collaborating drones in autonomous ecosystems. This allows for the design and creation of patterns that autonomous drones use to exchange information during collaboration by linking predefined properties in the literature. To complement the findings resulting from this extraction, additional publications detailing autonomous drone behavior properties were considered [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38] despite not discussing them in the context of Digital Twins, to draw a more realistic and complete picture of the important properties that shall be considered in creating a virtual replica of a real autonomous drone.

E. DT Design Procedure

After extracting the properties from the literature, the design process clustered the properties to form DT components and complete the autonomous drone DT design. The workflow in the following sections details the results of this process, resulting in the DT design for autonomous drone communication in autonomous ecosystems. The DT design process is described and developed based on analyzing the selected papers to capture key concepts, trends, and hidden relationships in DT studies. The endpoint is a structured hierarchy of information and properties (the key components) of the DT for autonomous drones. The DT and its respective properties are described in Section V, based on the state-of-the-art Digital Twins properties extracted from the literature.

IV. Research Study Results

In this section, we discuss the observations and findings extracted from the reviewed papers. Besides, we look into further observations and insights we gained when reviewing the works and describe them as opportunities for in-depth knowledge of the design of Digital Twins in the area of autonomous drones (search version 1) and autonomous vehicles (search version 2).

A. Literature Search Findings

1) Search Version 1: Each of the papers that passed the search and inclusion/exclusion criteria for the search version 1 is described below, describing the context in which the DT is applied and what form it takes (e.g., a state diagram, a sequence diagram, a mathematical model).

The paper [9] proposed a DT framework for Internet-of-Things (IoT) networks focusing on Unmanned Aerial Vehicles (UAVs) acting as flying Mobile Edge Computing (MEC) servers. This framework supports on-the-fly task offloading, particularly suited for industrial automation with strict constraints on Ultra-Reliable Low-Latency Communication (URLLC) links. The study formulates the end-to-end latency minimization problem for DT-aided offloading UAV-URLLC, optimizing communication and computation parameters such as power, offloading factors, and processing rates of IoT devices and MEC-UAV servers. It further details the local and edge processing aspects, including the estimation of processing rates and latency gaps between real values and DT estimations. The research approach represented the DT as a transmission model based on a mathematical model formed by a set of equations.

The second study [10] proposed a three-layered approach to develop a comprehensive DT architecture for smart seaports, integrating physical-to-Virtual (P2V) and virtual-to-Virtual (V2V) communications. Aligned with the principle of emphasizing quality, evolution, and insight values, the architecture facilitates real-time data collection and transmission from physical entities, such as IoT devices, in the Data Layer. The Twin Layer provides digital replicas of physical entities, enabling effective monitoring and analysis of seaport operations, while the Service Layer offers insights and predictions on seaport operations, enhancing monitoring, analysis, and optimization of seaport performance. Overall, the proposed architecture enhances seaport efficiency and sustainability by providing practical insights into seaport processes and promoting sustainability in maritime logistics. The proposed study designs the DT as a state transition diagram to address the communication problem between ships and drones.

2) Search Version 2: Each of the papers that passed the search and inclusion/exclusion criteria for the search version 2 is described below, describing the context in which the DT is applied and what form it takes.

The study [21] presents a DT communication framework for DT-assisted Vehicular Edge Computing (VEC) networks, integrating edge computing into the vehicular network. It explores the application of DT in VEC, highlighting its benefits in real-time monitoring, adaptive network orchestration, and resource management. By integrating DT technology with Heterogeneous Information Networks (HINs), the paper presents a promising avenue for enhanced network modeling and management, ensuring resilience and adaptability to unpredictable changes in the VEC environment. Through intra-twin and inter-twin communication channels, DT-enabled VEC frameworks facilitate real-time data alignment and exchange between virtual and physical entities, thereby enhancing network performance and reliability in dynamic vehicular environments. The proposed DT is represented in the study in the form of a behavioral model that consists of network topology, channel condition and vehicle power level.

The study [22] delves into the structure and communication model of a DT, outlining its typical concept model consisting of four main components: the Physical Entity (PE), Digital Representative (DR), Intra-twin Communications, and Communications to the Outside World. In real space, the PE encompasses various infrastructures like sensors and cameras responsible for collecting real-time data of physical measurements. In the cyber domain, the DR is the application software that creates a current-model PE and takes the data it ingests and processes to render the current state and make future operation estimates. Intra-twin Communications meet the need to facilitate the interaction between the persistent execution and DR to allow the secure transport of raw data and processed information within the twin. It further discusses communications with the outside world pertaining to inter-twin communications among DRs and between DRs and the cloud.

In this way, the DR can make itself harmonic with its PEs or the sharing of information with other DRs or the cloud to maximize simulation or prediction ability and feedback loop within the DT system. As a key component of the study, the DT is represented as a digital representative model that can take part in the communication operation.

The study [23] reveals a framework of DTs in communicating vehicles based on the physical and cyber layers. The first module that is very critical in enabling communication between the two layers is using cellular technology. The physical layer incorporates vehicles, drivers, infrastructures, and sensors, while the cyber layer processes data, performs predictive analyses, and gives directives for the best maneuvers a car should take. The framework aims to improve safety, mobility, environmental sustainability and performance through integrated advanced computational techniques and seamless connectivity. The study represents the DT as a behavioral model of human motion planning and a digital replica of vehicle properties such as speed position and motion planning.

The paper [24] developed a DT framework to estimate tram position using virtual models whenever the information regarding the position is unavailable. The DT model comprises physical twin elements, which obtain sensor data from tram localization sensors and wireless routers to Digital Twins. This data is then used for virtual model training with a Long Short-Term Memory (LSTM) architecture in the Digital Twin to predict tram positions. The implementation framework includes sensor data transmission, virtual model training, data storage, and Human Machine Interface (HMI) for display integrated with the autonomous driving controller, which contains the Unscented Kalman Filter (UKF) with position estimation Stanley controller algorithm. This is done through various components embedded within the framework, such as sensors, network layers, a vehicle DT, data store, HMI, autonomous driving controller, and actuators, for its free movement and operations between physical and Digital Twins. The implementation framework of the proposed DT model is illustrated as an architecture that indicates the flow of data communication among different objects for autonomous tram localization.

The paper [25] introduces an Autonomous Vehicle Networks Digital Twin model to enable collaborative autonomous driving. Every Autonomous Vehicles (AVs) has a DT associated with an Edge Computing Device that connects it with the rest of the network. It offers a digital representation of an AV used to render support for the AV in both physical and virtual network environments. The system contains functional parameters in the AV and allows information and updates on transactions in the Autonomous Vehicular Networks (AVNs) to be made. As the AV switches between Edge Computing Devices (ECDs), its DT is passed in advance with pre-attached wired links to allow the DT to replace the AV and collaborate with other DTs on driving decisions. Collaborative driving is considered a service in the architecture of collaborative autonomous driving. The architecture is based on mapping between parameters into virtual networks of which ECDs at the intersection contribute to determining collaborative driving decisions. Time slots are interleaved for AV coordination, and ECDs use the DTs to map across the AV parameters and co-decide on driving. The paper presents the DT in the form of a DT-enabled architecture for autonomous driving. The architecture describes the driving behavior (like lane changes, map routing, and position changes) for driving decisions.

The paper [26] introduces a DT-based trajectory prediction scheme for real-time platoon operation. The structure consists of two layers: the physical entities layer and the DT layer. Intelligent vehicles with high-precision sensors monitor the traffic in the physical entity layers. The platoon tracks surrounding social vehicles based on Long Short-Term Memory (LSTM) neural networks to predict their trajectories. The platoon members are used to distribute the responsibility to offload their load for data sensing upon an LSTM neural network used simultaneously to train the network to reduce processing delay. The DT system is operated in the head vehicle to drive the updates of the LSTM network, in which a Deep Reinforcement Learning (DRL) agent maximizes the prediction accuracy while minimizing the processing delay. The operation of the DT-based prediction scheme includes real-time data collection, trajectory prediction, DT analysis, DRL-based optimization, and execution of optimal updating strategies by the platoon. This platooning strategy aims to achieve safe and efficient driving by continuously updating the prediction model in relation to the optimized strategy and en-route data. The paper presents a behavioral DT model for autonomous vehicle platooning. They deploy the DT at the head vehicle of the platoon to reduce the processing delay in the coordination of the platoon.

The paper [27] introduced a MEC-enabled framework that embeds two kinds of domains: the physical network represented in the real world by a large domain of MEC, while a small DT sub-domain represents a virtual replica of the network. The Connected Autonomous Vehicles (CAVs) in the MEC domain are equipped with sensors and computation devices that detect line-of-sight data for making on-the-fly safety decisions. This architecture allows CAVs to intelligently orchestrate and evaluate the strategy for changing a lane to improve overall safety and efficiency. The authors proposed the DT for connected autonomous vehicles resembling a behavior model of a traffic system. It takes the form of a collection of properties such as location and road traffic prediction.

B. Extraction of DT Properties and DT Design Mapping

In this phase of the study, the comprehensive literature review on autonomous drone technology is comprehensively categorized and analyzed, including the study of the DT technology, which allows an understanding of diversified applications of their highly dynamic nature for adaptation to diverse drone technologies and safety scenarios [39], [40]. This classification process enlarges toward the application areas of the collected works in drone technology, such as design and detailed description of the DT. Finally, the extracted DT characteristics are clustered into a hierarchy of

DT components, fitting the context of DT application for trustworthy drone communication in autonomous ecosystems. The part dealing with dynamic adaptation is emphasized, examining how Digital Twins enable such adaptation in real-time by drones in environments that are diverse and constantly changing. This phase further delves into how DT defines the social metrics that enable the drone industry to adhere to the highest regulatory standards and safety metrics. This ranges from practical research into using Digital Twins in simulated and real settings to their crucial role in enhancing drone functionality and how drone technologies are continuously developed based on feedback and existing research. The results of this phase are detailed in the next section.

V. Drone Digital Twin Conceptual Design

The classification of the DT characteristics (elements, properties, and metrics) and their mapping to a hierarchy of DT components for autonomous drones used in the context of trustworthy autonomous drone communication and collaboration is presented below.

A. Properties

Each DT is characterized by a static set of properties and by the characterization of its behavior (both past and future). This section lists the static properties that form the header of the DT (as visualized in the example in Figure 4).

1) Drone ID:

- The drone ID represents a unique identifier assigned to the drone from the regulatory authority according to the aviation regulations, for instance its registration number. It is then used for identification, tracking and accountability during the flying operations.

2) Reputation:

- The reputation property refers to the trust score provided by or verifiable by a central authority of the airspace system [28].

3) Physical Condition:

- The physical condition refers to the overall status of the drone (sometimes referred to as drone health), such as:
  - Battery Power Level: The battery power level represents the status and health condition of the battery.
  - Sensor Functionality: It describes the issues in the performance and reliability of sensors.
  - Data Quality [31], [32]: Accuracy of GPS and map data for precise navigation.

B. Behavior

The core component of the drone DT is the description of its behavior, which can be specified in terms of its guarantees with various metrics as well as in terms of dynamic behavioral models (such as a Petri Nets [6], Finite State Machines FSM [7], or Functional Behavior Models FBM [36]) preferably a combination of both. This way, the DT serves as a virtual representation of the expected drone behavior. In this regard, it is noteworthy to say that such a representation is future-directed, i.e. its examination gives clues about the declared future behavior of the autonomous drones. That is why it is useful to enrich this information in the DT with the past-behavior summary, to understand the dynamics of present-past behavioral changes of the drone, as well as past misbehavior and guarantee violations.

1) Past Behavior Summary: The representation and sharing of data about past behavior is the description of the combination of metrics and behavior patterns [32]. This allows autonomous drones to understand and interpret past behavior effectively.

- **Past Behavior Metrics:** Long-term trends in terms of safety, reliability, and response time, or trajectory sampling for selected past behavior are described for instance as:
  - Safety: Data on incidents, accidents, near-misses, and safety violations over a defined period.
  - Reliability: Data about past system uptime, failure rates, maintenance records, and mean time between failures (MTBF).
  - Response Time: Data on response times to incidents, customer service response times, and system performance response times.
- **Past Behavior Patterns:** Behavioral patterns of both wanted and unwanted past behavior, such as:
  - Lane Change Behavior [37]: Historical data on lane change decisions, frequency, and reactions to changing traffic conditions.
  - Emergency Braking Response [34]: Documenting and analyzing instances of emergency braking, understanding triggers and outcomes.
  - Consistency Tracking [32]: Monitoring how consistently autonomous drones responded to various traffic scenarios over time.
  - Violation of aviation regulations: Summary of the violations of given guarantees or the aviation traffic laws and regulations.

2) Declared Future Behavior: The representation and sharing of the expected drone behavior in the present and future interactions. This allows other drones to optimize mutual interaction and also to spot suspicious behavior that might be caused by malfunction or security attacks.

- **Declared Behavior Metrics:** The drone to declares its behavior and actions for collaboration with other drones during the operation in terms of a variety of guarantees, specified with the help of relevant metrics.
  - The summary of suggested metrics is given in Section V-C.
- **Declared Behavior Patterns:** Represented in terms of a behavioral graph such as Petri nets, FSM, or FBM. These graphical models capture the sequential and concurrent aspects of the behavior, allowing autonomous drones to understand and respond to the changes in environmental conditions. That is dynamically recalibrated by the source

drone (the DT is linked to) in case of changes in its intentions. Examples include:
- Planned Trajectory [29]: Communicating intended routes, including any upcoming turns, lane changes, or stops.
- Acceleration Pattern: The drone's expected acceleration patterns, parametrized by the surrounding objects and following the air traffic regulations.

C. Metrics

We have identified a variety of metrics relevant to autonomous drones that can be employed to support the DT design proposed in this section. The summary of the identified metrics is below. To a higher degree, these metrics are expected to detail the declared future behavior as discussed in the previous paragraph. However, the metrics can also be employed to concretize the past behavior summary.

- Quality of Service Metrics [29], [30]:
  - Dynamic Route Planning [31], [32]: The degree to which the drone plans the routes in real-time for efficiency, safety, and to avoid congestion.
  - Average velocity: The degree to which the drone follow the air traffic rules and average velocity.
  - Acceleration Smoothness [36]: The degree of smoothness of the drone acceleration under different conditions.
  - Response to Traffic Flow [36]: The degree to which the drone acceleration responds to the surrounding objects and traffic flow.
  - Emergency Response [37]: The ability to react in emergency situations, like sudden obstructions or system malfunctions is measured.
  - Sharing Data [38], [35]: The ability to share data from sensors (like LIDAR, radar, and cameras) to build a comprehensive understanding of the surrounding environment.
  - Obstacle Detection [38], [35]: The ability to communicate about detected obstacles, both static (like air traffic routes) and dynamic (like other drones and environmental risk).
- Safety Metrics [7]:
  - Distance with Front Objects: The ability to keep the distance for safety according to the rules and regulations.
  - Longitudinal Position: The ability to regulate vertical moments based on the position control (the up and down moments) according to the neighbor's drones and other object
  - Braking Patterns [34]: The quality of the breaking in terms of the frequency, intensity and duration of braking in various scenarios.
  - Predictive Braking [34]: The ability of the drone to anticipate the need to brake based on traffic and obstacles.
  - Safety Margin Analysis [36]: The ability to maintain safe distances from other drones, considering acceleration patterns, reaction times and stopping distances.
- Regulatory Metrics [7]:
  - Lane Following: The degree of following the lane properly during the task execution operation in the airspace.
  - Speed Regulation Compliance [37]: The degree of adherence to speed limits over time and across different positions.
  - Component Interaction Compliance: The compliance of the drone with other components, such as sensors and flight controllers, which is performed according to aviation regulations.
  - Airspace Safety Regulations: Compliance with civil aviation authority's airspace safety regulations during drone operation.
  - Licensing and Airworthiness Compliance: Compliance with civil aviation authority's license requirements and airworthiness standards.
- Interaction/Social Metrics [33]:
  - Relative Speed to Neighbors: The degree to which the relative speed to the neighbor drone is maintained so that their safe space is protected.
  - Location [35]: The willingness to share precise location data to maintain awareness of each other's positions.
  - Maneuver Plans [37]: The willingness to notify other drones of planned maneuvers, such as exiting air traffic or entering new zones.
  - Turn Signal [37]: The willingness to Indicate when a turn or lane change is about to occur.
  - Sharing Data [38], [35]: The willingness to share data from sensors (like LIDAR, radar, and cameras) to build a comprehensive understanding of the surrounding environment.
  - Obstacle Detection [38], [35]: The willingness to Communicate about detected obstacles, both static (like air traffic routes) and dynamic (like other drones and environmental risk).

VI. Proof of Concept

The proof of concept is formulated in terms of DT application in a concrete case study, relying on the employment of an autonomous drone DT for trustworthy drone communication in the scenario of UAV logistics.

A. Case Study

Technological advancements drastically changed the shopping concept as the retail industry adopted online shopping methods. This new way of shopping possesses enormous changes in the process of logistics companies and retailers to provide their goods to the customers without delays and mistakes. Thus, managing online shipment to the relevant

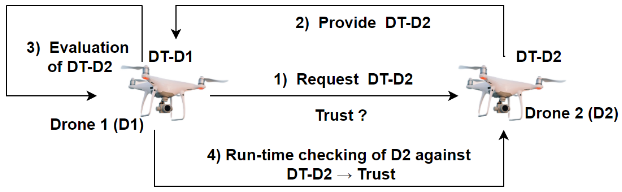

Fig. 2. How Drone 1 Decides to Trust Drone 2 [6]

customer to be operated with automated methods. In this regard, deploying an autonomous drone in logistics services requires an ecosystem where a large number of drones needs to coordinate with each other to avoid collisions, which might be caused by faulty (unintentionally harmful) or malicious (intentionally harmful) drone behaviour [6]. To address this issue, we propose utilizing the exchange of information between agents to communicate their mutual behavior, where the information is exchanged in form of their DTs.

The core idea of the approach is illustrated in Figure 2 with an interaction of two drones. The assessment of trust from the perspective of Drone 1 towards Drone 2 signifies a critical process employing a Digital Twin (DT) for evaluation. Drone 1 views Drone 2 as a black box that might be malicious. Now, Drone 1 requests Drone 2 to declare its behavior as a DT. Drone 1 checks this DT (declared behavior), and if it does not indicate any suspicious actions, it allows Drone 2 to enter its proximity while observing Drone 2 real-time behavior and its compliance with the declared behavior (communicated in form of Drone 2 DT). If Drone 2 actions align with the provided DT, trust is maintained during the operation; otherwise, trust is withdrawn. Subsequently, the incident is reported to the authority for the implementation of operational safeguards and further investigation.

B. Implementation Environment

Consider the following implementation setup, supporting the logistics scenario where the main function of the autonomous drone is to carry a shopping parcel from one place to another. As the foundation, the autonomous drone is equipped with an autonomous flight system. The autonomous drone is connected to the ground station through a communication data link and then assists with the exchange of information with other elements such as related personnel, and isolation space management [41]. Each autonomous drone utilizes the DT for the exchange of information and elements with other drones, according to the communication situation and environmental conditions. The physical space is equipped with an environment and virtual interaction platform in a real-time interaction state. In physical space, various sensors, agents, and actuators are used to rely on the perception of autonomous drones and uncertain environments and perceived information to provide feedback to a virtual data interaction center through communication. Finally, the control data interaction center sends the data to the physical terminal of the autonomous drone to make decisions. Hence, constructing an autonomous drone DT communication channel is very important. Figure 3 displays the composition and elements of the scenario. Through the DT communication channel, the autonomous drone can be controlled, and communication and transmission can be realized.

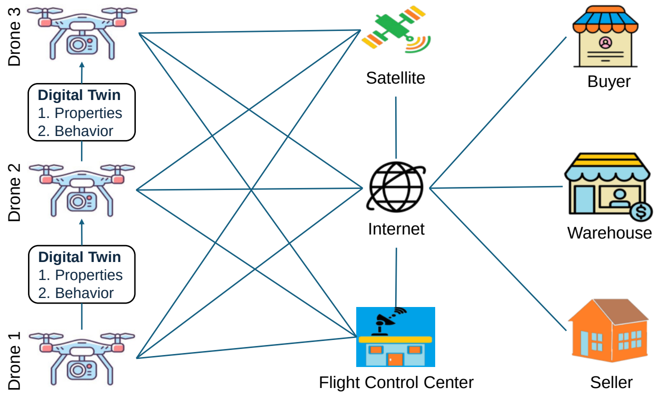

Fig. 3. Implementation Environment

C. Digital Twin Design of an Autonomous Drone

Based on the investigation of the case study and the DT characteristics (elements, properties, and metrics), this section gives a simple example of a DT to support the given scenario, i.e. to support trustworthy autonomous drone communication and collaboration in autonomous ecosystems. Note that while the design is simple, it is not unnecessarily too simple, as also in reality, the drones are expected to exchanged only a limited set of information (in an attempt to limit the level of information disclosure towards a potentially untrusted ecosystem member, and to optimize transmission speed). The DT design is presented below, with a structured presentation in Figure 4.

1) Properties:

- Drone ID:
  - Registration Number: X95804
- Reputation:
  - Trust Score: 0.94
- Physical Condition:
  - Battery Power Level: 100%
  - Sensor Functionality: 90%

2) Behavior:

- Past Behavior Summary:
  - Past Behavior Metrics:
    - Safety, i.e. percentage of safe operations, calculated as: (1 - (2 incidents + 1 accident + 1 near miss + 0 safety violations) / 57 total operations) = 93%.
    - Reliability, i.e. data about past system uptime (98%), failure rate (0.5%), maintenance records,

Digital Twin Design for Autonomous Drone			
A) Properties	1) Drone ID	Registration Number: X95804	
	2) Reputation	Trust Score: 0.94	
	3) Physical Condition	PC1: Battery Power Level: 100% PC2: Sensor Functionality: 90%	
B) Behavior			
1) Past Behavior Summary	• Past Behavior Metrics	PBM1: Safety: 93%	
		PBM2: Reliability: 90%	
	• Past Behavior Patterns	PBP1: Lane Change Behavior: data with snapshots of all unsuccessful lane changes.	
		PBP2: Emergency Braking Response: documenting and analyzing instances of emergency braking, understanding triggers and outcomes.	
		PBP3: Violation of Aviation Regulations: on 05/01/2024 violation of RegX125, on 07/03/2024 violation of RegX248, 08/06/2024 violation of RegX584.	
2) Declared Future Behavior	• Declared Behavior Metrics	Quality of Service Metrics	QSM1: Adaptive Route Planning: 93%
			QSM2: Acceleration Smoothness: 88%
		Interaction/Social Metrics	SIM1: Relative Speed to Neighbors: 97%
			SIM2: Location: 95%
			SIM3: Turn Signal: 98%
	• Declared Behavior Patterns	DBP1: Acceleration Pattern is described through FSM in Figure 5.	
		DBP2: Turn Strategy states are illustrated through FSM in Figure 5.	
		DBP3: Navigation and Mapping planning are described through FSM in Figure 5.	
		DBP4: Operation Pattern is presented through FSM in Figure 5.	

Fig. 4. Proposed Digital Twin Design for the Autonomous Drone Case Study

and MTBF, weighted and aggregated to a reliability level of 90%.
- Past Behavior Patterns:
  - Details are provided in Figure 4.

- Declared Future Behavior:
  - Declared Behavior Metrics:
    - Adaptive Route Planning, i.e. the declared ratio of effective adaptive route planning instances in a subsequent block of 100 instances, calculated as (93 effective planning instances / 100 total instances) = 93%.
    - Acceleration Smoothness, i.e. the declared ratio of smooth acceleration instances in a subsequent block of 100 instances, calculated as (88 smooth acceleration instances / 100 total instances) = 88%.
    - Relative Speed to Neighbors, i.e. the declared ratio of instances when the indicated relative speed to neighbours is maintained in a subsequent block of 100 instances, calculated as (97 successful relative speed instances / 100 total instances) = 97%.
    - Location, i.e. the declared ratio of instances where the precise location is successfully shared in a subsequent block of 100 instances, calculated as (95 instances of successful precise data sharing / 100 total instances) = 95%.
    - Turn Signal, i.e. the declared ratio of the instances where signal changes are successfully indicated in a subsequent block of 100 instances, calculated as (98 successfully indicated instances / 100 total instances) = 98%.
  - Declared Behavior Patterns:
    - Details are provided in Figure 4, together with the behavior patterns for the proposed scenario illustrated via FSM in Figure 5.

The designed DT can further be used in different scenarios of exchanging information during collaboration in autonomous ecosystems. For instance, when each autonomous drone enters the neighboring zone, it can start an exchange of information with another drone through the DT to perform safe operations, which are described in the next section. Every autonomous drone shares a set of properties or functionalities in the form of DT to achieve certain goals and designed objectives during the collaboration in autonomous ecosystems.

D. *Trust Assurance through Digital Twin Evaluation*

At this point, the autonomous drones are physically deployed and controlled by the central authority, each commu-

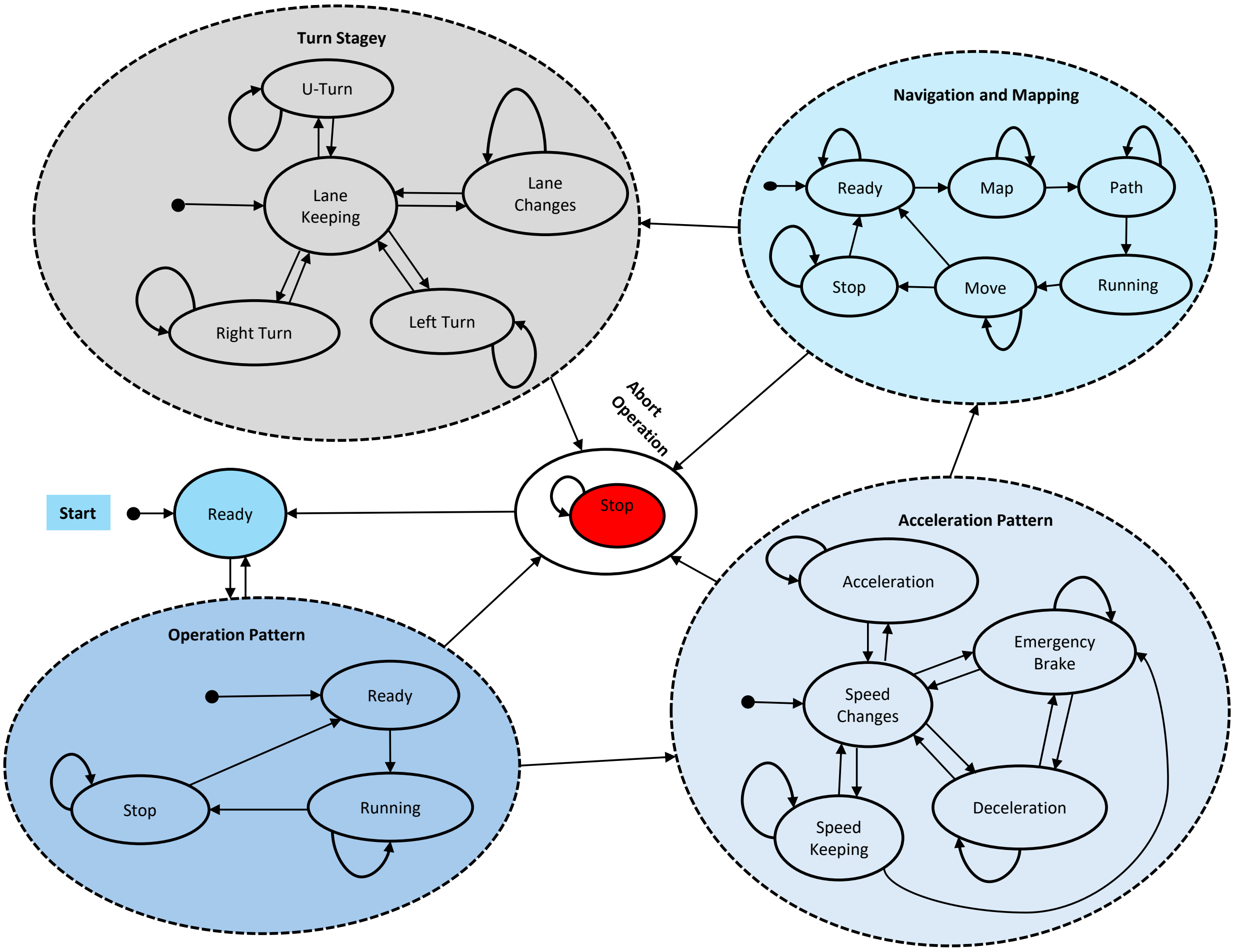

Fig. 5. Declared Behavior Patterns of an Autonomous Drone via FSM (Inspired from [42], [43])

nicating its DT as discussed above. After the deployment, the different number of drones will start to execute their own tasks. During the task execution, the collaboration is needed. During the operation, multiple drones pass each other in a space of autonomous ecosystems. To avoid collision and ensure safe operation, the autonomous drone requests its peer to declare the intended behavior for trust assessment and share it with in form of its DT.

Based on understanding their intended behavior, it can better plan the collaboration and ensure its safety. Furthermore, it can understand the deviations from the intended behavior to report the mismatch to the authorities that can take further action to protect the ecosystem from misbehaving drones. In this regard, reward and punishment strategy (upgrading or downgrading the Trust Score of the drone) can be employed in lighter cases, and direct drone isolation in the more serious ones.

VII. Conclusion

The primary contribution of this research is the investigation of existing literature on the DT design for autonomous drones. As also seen after the investigation of the existing literature, the details discretion of DT for an autonomous drone is still in infancy as literature mainly focuses on the application of DT at the abstract level rather than concrete details, description, and functionalities for an autonomous drone. After studying the relevant literature on properties, elements, and functionalities, we proposed a DT design for autonomous drones. In the end, we presented the DT design along with a detailed design characterization in a proof of concept with a simple example of an autonomous drone logistics shipment to illustrate the DT in a concrete scenario. The proposed DT design attempts to serve as a foundation for autonomous drones in facilitating seamless collaboration in decision-making to ensure safe and trustworthy operations of drones in autonomous ecosystems, and offers a stepping stone for further research in the domain. In the future, we want to use the DT design along with properties for the experimental exchange of information among collaborating autonomous drones, deployed in a realistic environment simulation.

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