Integrating Network Digital Twinning into Future AI-based 6G Systems

D2.3

Functional models (initial)

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Authors and institutions	Inès El Korbi (UBOU), Paola Soto Arenas (IMEC), Ayat Zaki-Hindi (LIST), Wasim A. Ali (POLIBA), Burkhard Hensel (TUD), Gaetano Volpe (POLIBA), Andrey Beogalev (IMEC)
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Executive Summary

Network Digital Twins (NDTs) are critical enablers for the success of 6G systems, supporting real-time optimisation, per-user Quality of Experience (QoE), and full network automation through zero-touch management.

The SNS JU Stream B 6G-TWIN project focuses on embedding digital twinning into AI-driven 6G networks. One of its core objectives is the design of a federated, graph-based NDT that accurately reflects dynamic and complex network scenarios, enabling advanced planning, management, and control strategies. As part of this objective, a series of Key Performance Indicators (KPIs) have been defined to guide and assess progress. Among them, KPI 2.3 specifically targets the completeness of functional models - ensuring that they cover all necessary functions to emulate the physical behaviour of systems involved in selected use cases.

This deliverable, **D2.3 "Functional Models (Initial)"**, part of Work Package 2 (WP2), addresses KPI 2.3 by laying the groundwork for the definition, classification, and lifecycle integration of functional models within the 6G-TWIN NDT framework. It introduces model types (analytical, AI-based, probabilistic, etc.), proposes a taxonomy based on several classification criteria, and outlines how these models fit within a layered 6G architecture.

The document is structured into seven chapters. It begins with an introduction to the deliverable's scope and objectives, followed by a recap of the 6G-TWIN NDT architecture and the placement of functional models within its layers. Subsequent chapters define the main types of functional models and their characteristics, present a detailed taxonomy and its alignment with the 6G architecture, and describe the integration process through key stages such as data preparation, training, and evaluation. The penultimate chapter focuses on the creation of functional models and their interaction with simulation tools, while the final chapter concludes the document.

This is the initial version of the work on functional models; a final, consolidated version will be provided in Deliverable D2.5 at Month 36, incorporating further developments and validation.

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Abbreviations and acronyms

Abbreviations and acronyms	
AI/ML	Artificial Intelligence/Machine Learning
AMF	Access and Mobility Management
CN	Core Network
CSMF	Communications Service Management Function
DNN	Deep Neural Network
DQL	Deep Q-learning
DRL	deep reinforcement learning
E2E	End to End
eMBB	Enhanced Mobile Broadband
ETSI	European Telecommunications Standards Institute
GNN	Graph Neural Networks
HDLLC	High Data rate and Low Latency Communications
HMTC	High performance machine type communications
IBN	Intent-based networking
IoT	Internet of Things
ITU	International Telecommunication Union
KPI	Key Performance Indicator
M2M	Machine to machine
MAC	Medium Access Layer
MANO	Management and Network Orchestration
MDP	Markov Decision Process
mMTC	massive Machine-Type Comms
NDT	Network Digital Twin
NE	Network Element
NF	Network Function
NFMF	Network Function Management Function
NFV	Network Function Virtualization
NFVO	NFV Orchestrator
NLSE	Nonlinear Schrödinger equation
NS	Network Service
NSMF	Network Slice Management Function
NSSMF	Network Slice Subnet Management Function
ONAP	Open Network Automation Platform
OPEX	OPerating EXpense
OSM	Open-Source MANO
PCI	Physical Cell Identity
PDCP	Packet Data Convergence Protocol
PMD	Polarisation mode dispersion
QoS	Quality of Service
RAN	Radio Access Network
RF	Radio Frequency
RIC	Radio Intelligent Controller
RIS	Reconfigurable intelligent surface
RL	Reinforcement Learning
RLC	Radio Link Control
RRC	Radio Resource Control
RRM	Radio Resource Management
RU	Radio Unit

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SDAP	Service Data Adaptation Protocol
SDN	Software Defined Network
SFC	Service function chaining
SMF	Session Management Function
SMO	Service Management and Orchestration
UDM	Unified Data Models
UDR	Unified Data Repository
UE	User Equipment
UPF	User Plane Function
URLLC	(Ultra-Reliable Low-Latency):
V2X	Vehicle to everything
VIM	Virtualized Infrastructure Manager
VNF	Virtual Network Function
VNFM	Virtualized Infrastructure Function Manager
WP	Work Package

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1. Introduction

The rapid digitization of industries necessitates advancements in network technologies, particularly as we transition towards 6G systems. The 6G-TWIN project addresses this need by proposing an AI-native reference architecture that incorporates Network Digital Twins (NDTs).

We first outline the objectives of 6G-TWIN, emphasizing its core mission to develop a sophisticated network framework, before specifically focusing on the key targets of this deliverable, presenting its structure and the contribution of the project's partners.

1.1. Aims and objectives

1.1.1. 6G-TWIN objectives

In response to the accelerating digitization across industries, the 6G-TWIN project emerges with a singular mission: to pioneer an AI-native reference architecture for the forthcoming 6G systems. At its core lies an ambitious vision to seamlessly integrate Network Digital Twins (NDTs) into the fabric of future networks, revolutionizing their optimization, management, and control in real-time.
To achieve its ambition, the 6G-TWIN has been built around several specific objectives:

- Specific Objective 1 (SO1) is central to the project's ambition, promising to design an open, federated and AI-native network architecture for the imminent 6G landscape. This architectural blueprint is designed to leverage NDTs, empowering intelligent data analytics and real-time decision-making, thereby laying the groundwork for unprecedented network efficiency and performance.
- Moreover, Specific Objective 2 (SO2) underscores the project's commitment to constructing a federated, graph-based NDT capable of accurately representing the intricate dynamics of highly dynamic and complex network scenarios. By establishing this digital sandbox for network planning, management, and control, 6G-TWIN paves the way for enhanced operational agility and adaptability.
- Simultaneously, Specific Objective 3 (SO3) drives the project's efforts towards implementing a robust modelling and simulation framework. This framework serves as a cornerstone for accurately portraying networked environments and rigorously testing the functionalities of the envisioned 6G architecture.
- Ultimately, as the culmination of its efforts, 6G-TWIN aims to materialize Specific Objective 4 (SO4) by testing, validating, and demonstrating the transferability of its solutions. Through the development of dynamic demonstrators catering to tele driving and energy efficiency use cases, the project aims to showcase the practical impact of its architectural foundation on real-world network scenarios, heralding a new era of connectivity and innovation.

Embedded within the core of the 6G-TWIN project lies a foundational framework driven by specific objectives aimed at revolutionizing the architecture of future 6G systems.

1.1.2. Deliverable objectives

This deliverable corresponds to the initial version of the functional models developed within Task 2.3 of the 6G-TWIN project. It focuses on the creation of models capable of simulating or predicting the behaviour and dynamics of the network, based on the representations

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developed in Task 2.2. These functional models, which include analytical, AI-based and probabilistic approaches, are essential to enabling both predictive (for planning) and reactive (for management and control) functionalities in the 6G NDT framework. A final version of this deliverable will be provided at the end of the project, consolidating the work initiated here.

This initial version aims to:

1. Identify and classify relevant functional model types applicable to 6G NDTs;
2. Outline their role within the model lifecycle and 6G-TWIN architecture;
3. Set the basis for their integration and future implementation within the simulation framework of WP3.

1.2. Relation to other activities in the project

As represented in Figure 1 below, the work presented in this deliverable is closely linked to several other tasks and work packages within the 6G-TWIN project. It builds directly on the outcomes of Task 2.1 (data sources and requirements) and Task 2.2 (basic models and system representation), which provide the foundation upon which the functional models are developed. The models designed here are also intended to be integrated into the open simulation framework developed in WP3, and to contribute to the low-TRL prototypes interfaced with the network management and control mechanisms explored in that work package.

Furthermore, this deliverable provides early input to Task 1.4, particularly regarding the system-level architecture and functional requirements of the 6G-TWIN platform. The functional models proposed here are therefore not only technical building blocks but also contribute to the project's scientific positioning and alignment with standardisation efforts.

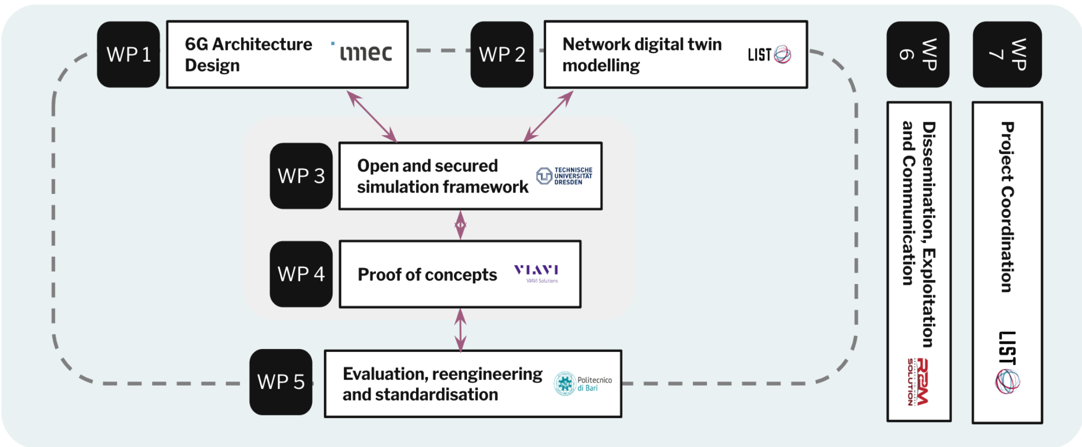

Figure 1 6G-TWIN PERT chart.

1.3. Report structure

This deliverable is structured into seven chapters, each addressing a key component of the initial development of functional models within the 6G-TWIN Network Digital Twin architecture.

- **Chapter 1** introduces the deliverable, outlining its objectives, scope, and positioning within the overall structure of Work Package 2 (WP2) and Task 2.3.

- **Chapter 2** defines the concept of functional models in the context of 6G-TWIN and presents their main types: analytical, AI-based, probabilistic, deterministic, and hybrid. The chapter also discusses the respective advantages and limitations of each model type.
- **Chapter 3** focuses on the taxonomy of functional models. It first identifies classification criteria - such as functionality, computing element, deployment domain, and use-case relevance - before mapping the models within a broader 6G architecture to support end-to-end Quality of Service (QoS). The proposed taxonomy is presented at the end of the chapter.
- **Chapter 4** considers the initial 6G-TWIN architecture introduced earlier (cf. Figure 2), with a focus on the NDT layer. It details how functional models are structured across different stages, including data preparation, model/data selection, initial training, and evaluation/fine-tuning.
- **Chapter 5** addresses the creation of functional models, explaining how they are trained using available data, how their parameters are optimised, and how they interact with the simulation toolbox to evaluate network performance.
- **Chapter 6** offers further insights into the nature of functional models, distinguishing them from simulation models and emphasising the importance of simulation-generated training data in enabling models to generalise beyond past network conditions.
- **Chapter 7** concludes the document.

1.4. Contribution of partners

The following table present the contributions from all the partners into the deliverable.

Table 1 Partners contributions to the D2.3 deliverable.

Partner	Section(s)	Contributions
LIST	**1, 5**, 4, 7	LIST led the work in Section 1 (Introduction), Sections 5 (Integration of functional models in the 6G-TWIN functional architecture). Supported the content in Section 4 on the alignment with 6G-TWIN use-cases, and Section 7 (Conclusion). Document review and content harmonization.
IMEC	**4,** 3	IMEC led the work in Section 4 (6G-TWIN NDT functional models taxonomy) and contributed to Section 3 (Functional Model: Definitions and Types). Document review and content harmonization.
POLIBA	3	Poliba contributed to Section 3 (Functional Model: Definitions and Types)
UBOU	**2, 3**, 4, 5, 6, **7**	Lead editor on the document; UBOU contributed across the deliverable and led the work in Section 2 (Background on NDT architecture) and Section 3 (Functional Model: Definitions and Types).
TUD	**6**	TUD led the work in Section 6 (Functional models and simulation models).
VIAVI	-	Contributions to follow in the final version of the deliverable.

Bold *numbers represent section technical leaders*

1.5. Deviations from the GA

Not applicable.

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2. Background on NDT architecture

A Digital Twin (DT) architecture is a conceptual framework that integrates physical systems with their digital counterparts to create a tightly synchronised, intelligent, and responsive communication ecosystem. It enables real-time monitoring, control, and decision-making across both physical and virtual environments. In the context of 6G mobile networks, the DT will support autonomous and efficient monitoring and management of the physical network and its main components - user equipment (UE), the radio access network (RAN), and the core network - thanks to trained and accurate models that operate on the network's digital replica before being applied to the real system.

Hence, this will first require the digitalisation of the physical network components through "basic models" to capture their main behaviour. Then, the creation of "functional models" to model higher functionality in the network such as optimization, management and monitoring. This will be achievable thanks to several system models (analytical, AI-basic or probabilistic models) to learn about the network behaviour. This step will then allow a more efficient service operation in the real network such as automation, real-time decision and behaviour prediction. Hence, analogically to the deliverable D2.2 [1] where the basic models were identified in the 6G-TWIN NDT, we propose in the current deliverable D2.3 a study of the 6G network functional models and how these models will be integrated with the NDT to later fit the 6G-TWIN project use cases requirements.

For instance, to briefly recall the context of Deliverable D2.3, it aims to address KPI 2.3, which states: *"to ensure the completeness of the functional models, covering at least all the necessary functions to emulate use case physical system behaviour"*. This KPI is part of WP2, which contributes to SO2: *"the design of a federated, graph-based NDT that accurately represents highly dynamic and complex network scenarios and serves as a sandbox for optimising network planning, management and control applications."*

To support the fulfilment of KPI 2.3, this chapter first recalls the layered 6G-TWIN NDT architecture initially proposed in the project. We explain the role of each layer - namely, the physical layer, the digital twin (DT) layer, and the application/human layer - with a particular focus on the DT layer, where the functional models are located and interact with other NDT components.

As illustrated in Figure 2, we provide an overview of the initial 6G-TWIN NDT architecture, in alignment with Deliverable D1.1 [2], which outlines the "Architecture and Technical Foundations" of the 6G-TWIN project.

This architecture is structured into three layers:

- the human layer, where applications reside;
- the digital network layer, which includes the DT components;
- and the physical network layer, representing the real-world infrastructure**.**

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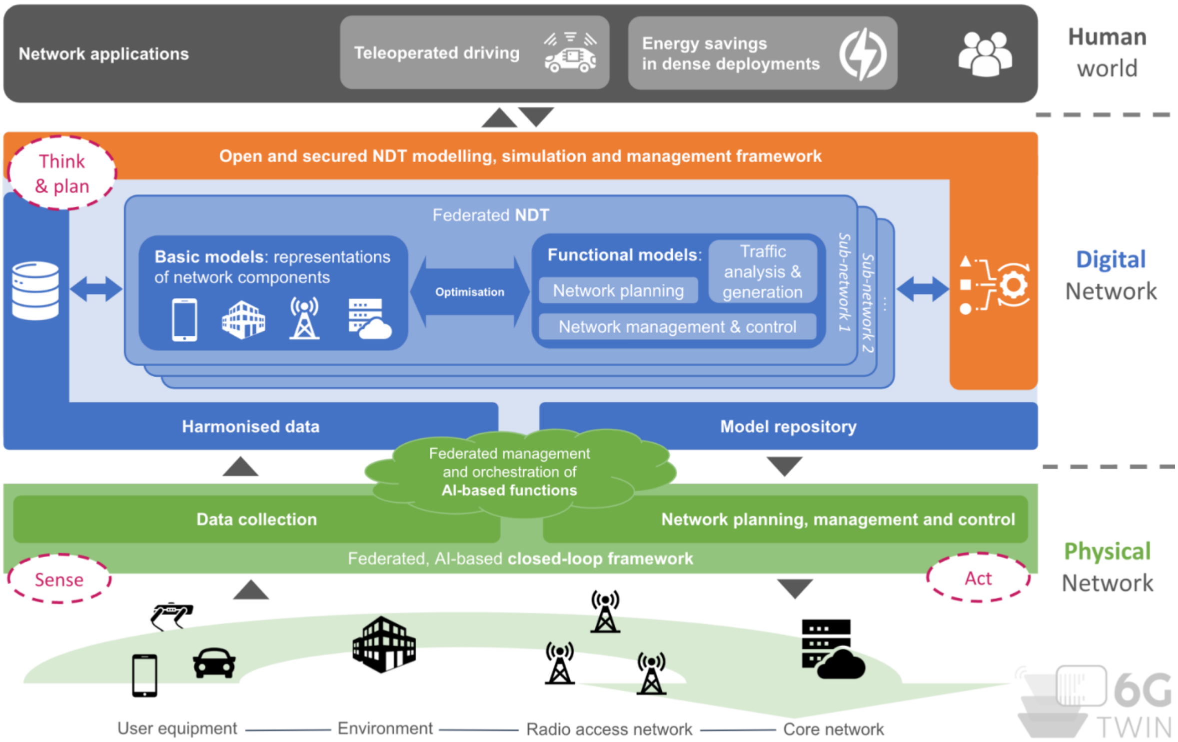

Figure 2 The 6G-TWIN NDT architecture

a. The physical network

This layer represents the physical world from which data should be collected from the different network elements (NEs)/components (UE, RAN and core network) to be transmitted to the digital network layer in a way to allow the digital network to create a carbon copy of the real world by capturing its main behaviour (propagation, mobility, transport, medium access, etc.). The way how data is collected from the different network elements through diverse traffic patterns, protocols, and data formats is thoroughly described in the deliverable D1.2 [3] related to the data collection in the NDT. Data collection aims to gather accurate, real-time, and historical data from the real network to feed the digital twin so it can mirror, simulate, and predict the network's behaviour.

b. The digital network

The digital network is a replica of the real world, mainly built on the data collected from the physical network. Each component of the real world will then have a copy in the digital network. The digital network is composed of two main blocks: The basic models and the functional models.

- *The basic models* are digital representations of the elementary network elements (UE, network channel, Network function (NF), Network service (NS), etc.). These models are built based on the data collected from the physical network. They also capture the interconnections between these elements and form a graph-based model that represents the network topology and logical links.
  As detailed in the deliverable D2.2 **[1]** of the 6G-TWIN project **[4]**, the basic models can be classified by the network domain, i.e., UE, RAN, Transport, core network and Edge computing network elements. Metamodels examples of each category of basic models are described in the same deliverable D2.2.

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- *The functional models* refer to the set of models that while making an abstraction of the real world, can predict the behaviour of the network within the digital world (the twin), then make the decision applicable within the real world.

The Functional models generally interact with basic models through specific interfaces [5] to derive network parameters and to achieve the optimization purpose for which they were conceived.

Moreover, they both basic and functional models will interact with other components of the digital network (simulation and management frameworks) to evaluate the networks dynamics, behaviours in the context of complex scenarios that are evaluated in a proactive way. In addition to the proactive evaluation, the digital twin also interacts with the application layer in a real time manner. How functional models can interact with the rest of the NDT components is detailed in chapters 4 and 5.

c. The application/human world

The digital twin will also interact with the end user (human world) through application specific scenarios. In this context, two major use cases have been identified in the project: the teleoperated driving and the energy saving use cases.

To satisfy the user requirements within these 2 use cases, several KPI have been identified with specific targeted values [6].

In the next chapter, we focus on the definition of the functional models and their different types. A comparison between the functional models' types is given at the end of chapter 2.

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3. Functional models: definition and types

In this chapter, we present the functional models' definition and their different types. We conclude the chapter by dressing the advantages/limitations of each model.

3.1. Functional models definition

3.1.1. What is a functional model?

As mentioned in the introduction, functional models refer to the set of models that can predict the network behaviour in the digital world while abstracting the real world.

Hence, in DTs, functional models can be defined as high-level formal representations of network patterns (NS, network management and controlling mechanisms, etc.) that aim by collecting data from digital replica of the physical components to analyse, optimize, and control the performance of the physical systems either in a real-time or in a proactive way.

In the context of 6G networks, functional models play an important role in network optimization, resource allocation, and performance enhancement [7]. DTs have numerous significant qualities that make functional models useful in modelling and managing physical systems.

3.1.2. How does a functional model work?

NDTs expand the concept of DTs by including real-time data from network components, which enables more precise and dynamic representations of network activity [8]. NDTs are critical for predicting and optimizing network performance in complex environments like 6G networks [9]. A key function is their ability to simulate and predict outcomes by replicating how systems behave under various conditions in a controlled environment. NDTs also provide real-time data on network performance and can integrate live data from multiple sensors and IoT devices, which enables proactive decision-making. Moreover, NDTs leverage AI and machine learning to optimize network resource allocation and improve network efficiency, which helps ensuring network services to meet stringent performance requirements [10]. In NDTs, functional models are crucial because they facilitate proactive decision-making. Indeed, combined with the simulation framework (cf. chapter 4), functional models can be used to predict the network behaviour for complex scenarios and mitigating potential issues before they effectively affect network operations. From a modelling perspective, functional models in NDTs can be of different types: analytical models, AI-based models, probabilistic models, deterministic and hybrid models. This will discuss in the next section [11], [12], [13]. Moreover, functional models can also be categorised into general and special-purpose models, and multiple models can be combined to create a model for more specific application scenarios [14].

3.2. Functional model's types

Building a functional model depends on different factors (the primary function for which the model is proposed, its complexity and the technology on which it will be embedded). Thus, functional models can be of different types: analytical models, AI-based models, probabilistic models, deterministic and hybrid models. The categorization helps to understand how different models can be applied to specific network tasks, each with varying degrees of complexity, scalability, and adaptability [15]. By categorizing them into following types we can more effectively match the appropriate approach to the unique characteristics of the problem at hand.

3.2.1. Analytical Models

Analytical models are created with basic mathematical equations and physical rules. They are used to simulate and forecast the behaviour of physical systems [16]. They also use closed-form solutions and provide accurate predictions for well-understood network scenarios. Analytical models are particularly useful for network performance analysis and capacity planning, where precise calculations are required. These are some examples of analytical models:

Mathematical models that explain the behaviour of an optical signal propagation system including equations. For example, Queueing models are frequently used in RAN to model network traffic behaviour at base stations (waiting time and buffer management). These models are critical for predicting network congestion and meeting quality of service (QoS) criteria for various forms of traffic in 6G context [17].

Physical models consider physical phenomena such as radio wave propagation, signal attenuation, and mobility in wireless networks. These models are crucial for simulating how signals travel through the environment and interact with network components like base stations, user equipment, and network infrastructure.

3.2.2. AI-based models

AI-based models leverage machine learning and deep learning approaches to detect complicated patterns and correlations in datasets. These models are designed to handle non-linear relationships and high-dimensional data, making them ideal for dynamic and developing systems such as 6G networks [18]. AI-based models may predict network behaviour, optimize resource allocation, and automate decision-making processes by learning from historical data. The key AI-based models are:

Deep Neural Networks (DNNs): Used for complex and high-dimensional data representation, such as deep Q-learning (DQL) for resource allocation. DNNs excel in detecting patterns and correlations in large datasets, making them ideal for tasks such as predicting traffic demand and optimizing resource allocation in real-time networks.

Reinforcement Learning (RL): A technique for making dynamic decisions, such as deep reinforcement learning (DRL), and optimizing network resource allocation. RL models constantly adapt their strategies through trial and error, enabling real-time decision-making that improves network performance and user experience.

Graph Neural Networks (GNNs) are used to represent complicated network topologies and interactions, such as QoS measures in network slicing. GNNs provide effective modelling of network relationships, enabling better resource optimisation and increased network stability.

3.2.3. Probabilistic Models

Probabilistic models incorporate statistical methods to handle uncertainty and variability in the system. These models are particularly useful in scenarios where data is incomplete or

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uncertain, thus allowing more accurate predictions and decision-making based on probabilities rather than certainties [19]. For example:

Bayesian Networks: Used for probabilistic reasoning and decision-making. Bayesian networks offer a flexible framework for reasoning under uncertainty and updating beliefs as new data becomes available.

Markov Decision Processes (MDPs): Used for sequential decision-making under uncertainty. It optimises decisions over time by modelling the system as a series of states and actions, hence maximising cumulative rewards while considering future implications.

Monte Carlo Methods: Used for simulating and analysing complex systems, such as network traffic patterns. These methods use repeated random sampling to estimate solutions, making them useful in evaluating network behaviour under a wide variety of conditions and scenarios.

3.2.4. Deterministic models

Deterministic models use algorithms to model network behaviour that give always the same output for the same input (Example: Finite State Machines (FSM) to model a network protocol) [20]. These models are useful for simplifying complex network processes by providing clear, predictable outcomes, especially when the system follows strict and predefined rules. When the algorithms include closed-form equations they can also be analytical.

3.2.5. Hybrid Functional Models

Hybrid Functional models combine several types of functional models: deterministic, probabilistic, AI-based and analytical approaches. They are much prone to be implemented in the simulation environment where multiple models can be combined to create a model for a specific application scenario [21]. This will ensure an efficient capture of the behaviour in the real world.

3.3. Advantages/limitations of the functional models' types

Below we summarize in Table 2 the different types of functional models, by listing their characteristics and comparing the advantages and drawbacks of each model.

Table 2 Functional models' types Summary

Model Type	Characteristics	Advantages	Limitations	Examples
Analytical models	-Built using fundamental mathematical equations and physical laws and employ differential	- Provide precise solutions for theoretical problems	- Cannot model complex, nonlinear systems effectively	- Queuing models in RAN for network congestion prediction and QoS estimation - Radio wave propagation

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	equations and linear algebra - Closed-form solutions for latency/throughput - Fixed parameters	- Fully transparent and verifiable - Excellent for fundamental analysis - Require minimal training data	- Inflexible to real-time network changes	- Signal attenuation
AI-based models	Data-driven approach using machine learning - Utilize neural networks for slicing (CNNs, RNNs, GNNs), and Deep reinforcement learning for resource allocation (DRL) - Capable of automatic feature extraction - Continuously learn from new data - Handle high-dimensional inputs	- Model complex nonlinear systems - Adapt to changing conditions - Process raw data directly Scale to large systems - Discover hidden patterns	-Require massive training data - High compute costs for edge deployment	- Coverage Prediction - Resource Allocation in RAN and MEC
Probabilistic models	- Incorporate statistical methods to handle uncertainty - Use Bayesian inference methods - Model random variables and stochastic processes - Implement Monte Carlo techniques	Provide uncertainty measurements - Handle noisy/incomplete data - Enable evidence-based reasoning - Support risk assessment - Combine prior knowledge with observations	Computationally intensive - May need approximations for complex systems	- Line-of-sight (LOS) probability models for coverage planning - Probability-based latency forecasting

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Deterministic models	-Use fixed rules and predefined parameters - Apply discrete equations (Boolean logic)	- Predictable, repeatable outputs (no probabilities). - Easy to implement	- Cannot adapt to changes. - Oversimplify real-world dynamics	- Network protocol emulation via FSM
Hybrid models	Combine multiple modelling approaches - Apply AI with analytical constraints - Support multi-scale modelling	- Balance accuracy (analytical) and adaptability (AI) - Proactive-reactive decision fusion - Handle complex scenarios	- Increased complexity - Require careful integration of different methods - Validation challenges across domains	- Combination of different models in simulation environments

Functional models in a network digital twin are designed to be AI-based, analytical, probabilistic, deterministic, or hybrid in nature, depending on the complexity and purpose of the network environment. These models are built to either predict network behaviour in real time or operate within simulation frameworks to optimize performance under complex scenarios. AI-based models leverage machine learning to detect patterns and forecast outcomes, while analytical and deterministic models rely on strict mathematical and logical formulations. Probabilistic models capture uncertainty and variability in network behaviour, and hybrid approaches combine multiple techniques to maximize accuracy and adaptability. Critically, these functional models are continuously refined and adjusted using live data collected from the real-world network, ensuring that the digital twin remains synchronized, responsive, and able to support both operational decision-making and strategic planning. Details on the functional model lifecycle and its interaction with other NDT blocks as the simulation toolbox will be discussed in chapters 4 and 5.

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4. 6G-TWIN NDT functional models taxonomy

In the previous chapter, we provided a definition of functional models and presented their different types. The type of each functional models will clearly specify how this latter will be built within the whole NDT architecture. In this chapter, we present a classification of these models based on various criteria as described in the following section. We then explore how these functional models can be integrated within an extended 6G architecture. Finally, we review and organize related work from the literature according to the proposed classification, offering a comprehensive taxonomy of functional models that highlights the major research directions of the 6G-TWIN project.

4.1. Functional models classification

According to the international telecommunication union (ITU) recommendation Y.3090 related to the “Digital twin network – Requirements and architecture” [22], functional models can be constructed by multiple dimensions: by network type (single or multiple domain model); by function (traffic analysis, security, fault diagnosis, etc.) or by generality (general purpose or specific purpose model).
Below, we provide a detailed classification of the functional models based on different aspects: the functionality, the operational mode, the network deployment domain, the computing element and the use cases.

4.1.1. Classification based on the functionality

In this category, the functional models are grouped according to the function -role- for which they are designed.

a. **Network planning and design:** These models are used prior to network operation. Their focus is to plan and design the network infrastructure and capacity according to a known demand. They are involved in operations like coverage, resource allocation, and the creation of network topology scenarios.

b. **Network Management and Control:** Functional models in this category are deployed during network operation to ensure compliance with agreed service levels. Operating in real-time, these models dynamically optimize network performance, adapting to changing conditions and demands. Due to their runtime nature, they are inherently more complex, incorporating policies, rules, and decision-making mechanisms that continuously adjust to evolving network dynamics.

c. **Network Diagnosis and Security:** The functional models in this category are focused on identifying anomalous patterns in networks that require the triggering of higher-level decisions, e.g., re-route the traffic flow, deny admission, or denial of service. For instance, in a 6G NDT, functional model security refers to the modelling, simulation, and protection of security functions (authentication, encryption, threat detection, etc.) as part of the digital twin's operation. In the same context, functional models for network diagnosis are self-learning and predictive systems that monitor, detect, and resolve faults and anomalies across extremely heterogeneous and dynamic networks.

d. **Network Monitoring:** The functional models in this category focus on mechanisms that continuously observe network performance, traffic, and status. They are

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foundational for enabling the other functional model types since they can aggregate the data from the network to build an initial network model, ensuring that its behaviour is as expected. The network model represents the operational status of the network. Otherwise, troubleshooting mechanisms are triggered, e.g., functional models for diagnosis and security or management and control.

4.1.2. Classification based on the operation mode

In this paragraph, we classify functional models according to their mode of operation. Depending on whether the models react to events, predict future behaviours, or combine both strategies, they can be categorized into reactive, proactive, and hybrid functional models.

a. **Reactive functional models:** These models respond to network events as they occur, used for real-time monitoring and troubleshooting.

b. **Proactive functional models:** They predict and prevent potential issues using AI/ML, enabling predictive maintenance and optimization.

c. **Hybrid functional models:** They Combine reactive and proactive approaches for both real-time response and long-term network planning.

4.1.3. Classification based on the network deployment domain

Functional models can also be classified based on their deployment across different network domains. Depending on their specific role and operational context, functional models can be categorized according to whether they are deployed in the RAN, transport network, or core network. Each domain has unique requirements and responsibilities, shaping the design and functionality of the models accordingly.

a. **Deployment in the RAN domain:** In the RAN, the functional models are related to Radio Resource Management, the admission and the power control and the handover decision. They are also involved in the packet scheduling and the QoS mapping operations.

b. **Deployment in the transport domain:** In the transport domain, functional models encompass all the functions related the path computation, load balancing, traffic isolation and forwarding per network slice, telemetry analysis, QoS Enforcement, traffic engineering, software-defined networking (SDN) controlling and data confidentiality and integrity.

c. **Deployment in the core network:** In the core network, the functional models oversee the management of the Virtual Network Function (VNF) through the Management and Network Orchestration (MANO) which aim to provide an automated deployment of 5G services, the monitoring of network functions and an efficient use of virtualized infrastructure. The main virtualized NFs however, like access and mobility management (AMF) and the session Management Function (SMF) in the control plane and the user Plane Function (UPF) in the user plane will be implemented within the NDT as basic models.

4.1.4. Classification based on the computing element

Another key classification of functional models relates to the computing infrastructure where they are deployed. Depending on latency requirements, processing needs, and scalability considerations, functional models may be implemented on edge nodes, in centralized cloud environments, or in a federated manner that bridges both. This deployment strategy directly influences the performance, responsiveness, and efficiency of the network digital twin.

a. **Deployment on edge nodes:** Functional models are deployed at the edge computing nodes for low-latency applications. This is useful for real-time processing in artificial intelligence/machine learning (AI/ML) models.

b. **Deployment in the cloud:** These models can be used for non-real time scenarios to predict the network behaviour and taking profit from the high computational resources in the cloud to achieve the prediction. They are hosted in centralized cloud infrastructure.

c. **Federated deployment**: It supports the integration of cloud and edge models and can ensure efficient data sharing across network domains.

4.1.5. Classification based on the use cases

Functional models play a crucial role in supporting a wide array of advanced applications. They help tailor network infrastructures to meet specific KPIs in various fields, such as transportation, industry, healthcare, and immersive experiences.

Below, we explore key categories where these models are deployed, with a focus on their alignment with the two main use cases of 6G-TWIN project: teleoperated driving and energy efficiency.

a. **Autonomous Vehicles and Smart Transportation**: This category regroups the models of vehicle-to-everything (V2X) communication and traffic patterns.

b. **Industrial IoT (IIoT) and Smart Factories:** The models here simulate machine-to-machine (M2M) communications and predictive maintenance.

c. **Smart Cities and Urban Management:** The models are intended to enable real-time monitoring of urban infrastructure, energy grids, and public services.

d. **Healthcare and Remote Surgery:** The aim here is to provide ultra-reliable, low-latency simulations for telesurgery and remote patient monitoring.

e. **Extended Reality:** In this category, models are proposed to support immersive digital experiences by synchronizing virtual environments with real-world network conditions.

Alignment with 6G-TWIN use cases

The relevance of functional models is exemplified in the two main use cases of 6G-TWIN:

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- **Teleoperated driving**: Functional models are trained to replicate and predict network behaviour under variable mobility patterns, allowing pre-deployment validation of ultra-reliable low-latency services along the vehicle path.

- **Energy efficiency**: Models predict optimal configurations (e.g., gNB sleep schedules, reconfigurable intelligent surface (RIS) activations) to meet load demands with minimal energy usage, driven by AI agents trained in simulated environments.

Both use cases highlight the role of functional models as enablers of advanced decision support and as validation mechanisms for real-world deployments.

In Figure 3, we summarize the classification of the functional models in 6G-Twin NDT as described above.

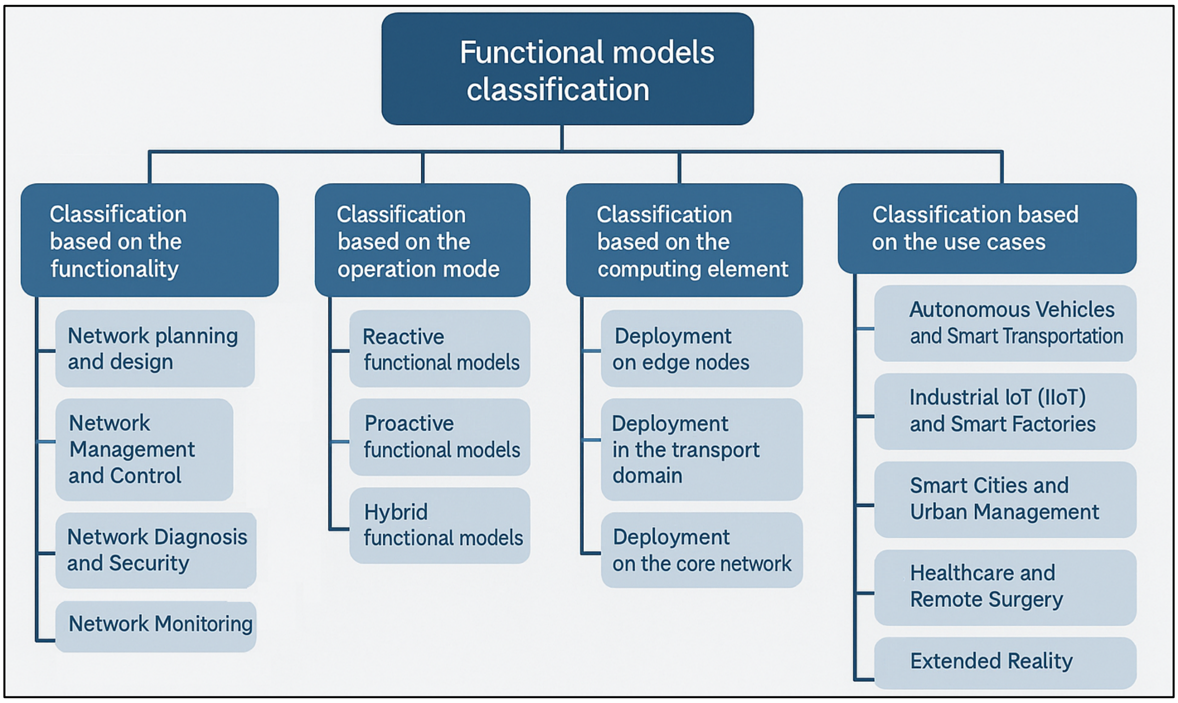

Figure 3 6G-TWIN NDT Functional models' classification

4.2. Proposed NDT functional models' taxonomy

This section aims to identify and describe the key functional models shaping the 6G network architecture. To achieve full interoperability and service orchestration across multi-vendor environments, 6G networks incorporate advanced elements such as Radio Intelligent Controllers (RICs), Software-Defined Networking (SDN)-enabled transport slicing, Virtual Network Function (VNF) management frameworks, and multi-domain Service Management and Orchestration (SMO) architectures. The following sections will revisit the fundamental 5G/6G architecture, explore the roles of RICs, slicing, VNFs, and SMO frameworks. The last section of this chapter aims to categorize the functional models identified in the literature based on the classification criteria described in the previous section.

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4.2.1. Functional models identification within 6G network architecture

a. Brief reminder of the 5G/6G architecture

The 6G networks deployment architecture depicted in Figure 4 is mainly based on the native 5G network infrastructure [23].

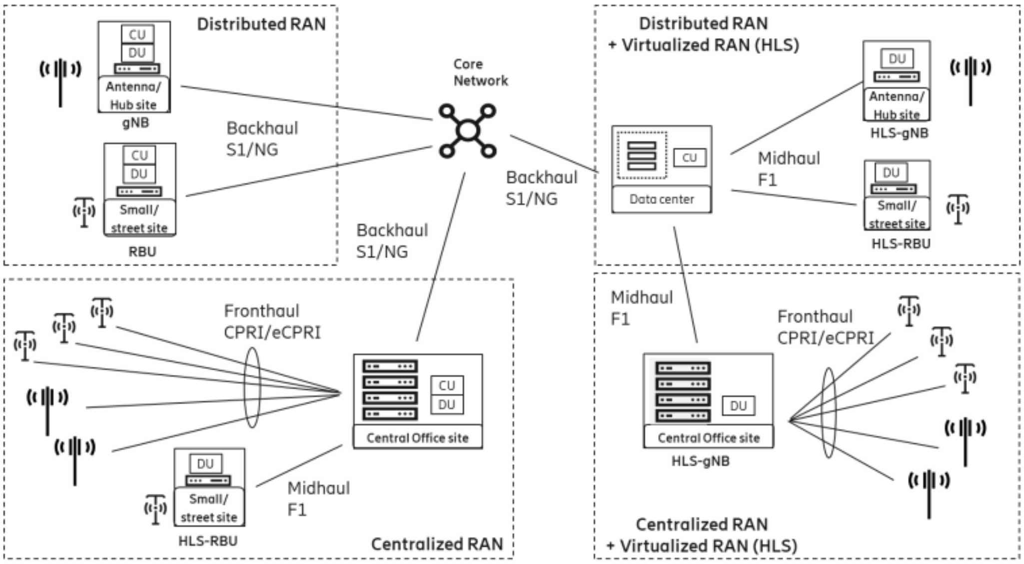

Figure 4 Deployment of 5G network infrastructure [23]

In this architecture gNB refers to the base station where the radio unit (RU) implements the lower physical layer and the radio frequency (RF) functions. RU is directly connected through fronthaul to the distributed unit (DU) that implements the higher functions of the physical layer, the MAC layer and the radio link control (RLC) layers. Centralized Unit is connected through the midhaul to the DU and supports protocols like RRC[1], SDAP[2] and PDCP[3] for QoS flow handling and header compression and security. The centralized unit (CU) can be implemented as a virtualized Edge that connects different DUs. RU/DU/CU represent the RAN that is connected through the Backhaul to the core network (CN). The transport network encompasses the fronthaul, the midhaul and the backhaul. SDN controllers are used to separate the data plane from the control plane at the transport layer. In the core network, network functions related either to the control or data plane are virtualized using Virtual Network Functions (VNFs).

Compared to the 5G, 6G aims to integrate multi-vendor networks using the Open RAN technology and integrating it thanks to AI/ML highly automation capabilities. To achieve this interoperability between the different vendors using open RAN and massive AI/ML techniques for automation, service management and orchestration (SMO) should be achieved within the three domains RAN, Transport and core domains.

[1] Radio Resource Control
[2] Service Data Adaptation Protocol
[3] Packet Data Convergence Protocol

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b. Radio Intelligent Controller

In the 6G networks, the Open RAN (O-RAN) alliance[4] will transform radio access networks into open, intelligent, virtualized and fully interoperable RANs. Then, the Radio Intelligent Controller (RIC) will be a software-based platform that enables programmability and automation of the RAN through real-time and non-real-time control functions. It leverages AI/ML and policy-based decision-making to optimize radio network performance, resource management, and user experience.

Figure 5 depicts the logical architecture of O-RAN [24] and illustrates how the RIC interacts with the RAN components including RU, DU and CU.

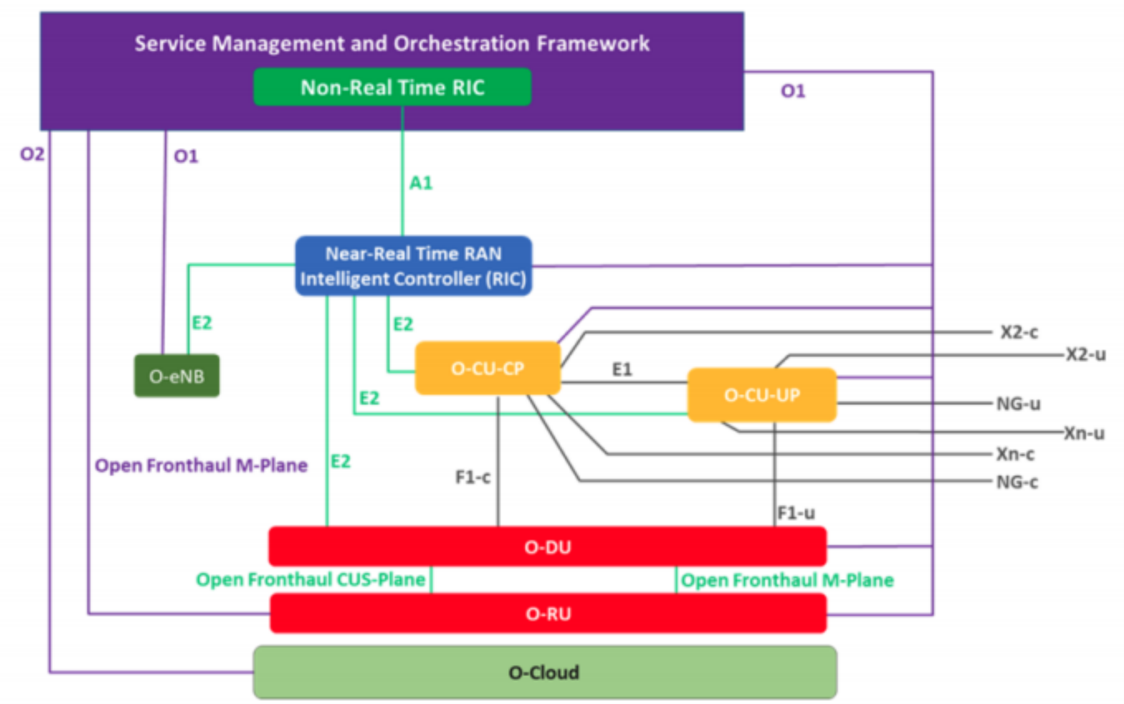

Figure 5 Logical architecture of O-RAN [24]

Different functionalities are supported within the RIC to manage/orchestrate operations within the RAN. The RIC splits in two main components:

- *The Non-Real-Time RIC*: it runs in the SMO layer, operates at time scales >1 s and focuses on policy management and Long-term optimization. It achieves the training of machine learning models that will be used by the near-real-time RIC.
- *The Near-Real-Time RIC:* It operates at time scales from 10 ms to 1 s, runs closer to the RAN (often at the edge). It handles scheduling decisions (Interference management, Handover optimization, QoS enforcement, Mobility management).

[4] The O-RAN Alliance is a global community of mobile network operators, manufacturers, research and academic organizations working in the telecommunications space around the world. It defines the specifications for all Open RAN components and the interfaces between them.

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c. Network slicing

At the transport domain, SDN controllers will be in charge of the separation between the control plane and the data plane hence ensuring an efficient network slicing. Thus, routing and security functions will be completely separated from the data forwarding process and QoS fulfilment hence ensuring that each 3GPP service type could be implemented as a standalone slice/service. Each slice is tailored for a specific service or customer requirement. In 3GPP, we identify 6 service types [25] as described in Table 3.

Table 3 Types of the slices and their characteristics

Slice type	Characteristics
eMBB (Enhanced Mobile Broadband)	High throughput (e.g., video streaming)
URLLC (Ultra-Reliable Low-Latency)	Low latency, high reliability (e.g., IoT, automation).
mMTC (Massive Machine-Type Comms)	Huge number of devices (e.g., sensors)
V2x (Vehicle to everything)	Suitable for handling V2x services
HMTC (High performance machine type communications).	Low-latency, high-availability, and high-data-rate services without the need for any mobility or auxiliary links
HDLLC (High Data rate and Low Latency Communications)	Suitable to QoS demands of extended reality and multi-modality (XRM) streams.

The high-level network slice management framework published by the European telecommunications standards institute (ETSI) [26] outlines four key management functions for network slicing:

a) the communications service management function (CSMF),
b) the network slice management function (NSMF),
c) the network slice subnet management function (NSSMF) and
d) the network function management function (NFMF).

The CSMF converts a network service into a network slice thanks to the slice requirement descriptor. The NSMF is responsible for decomposing the requirements of the slice into the requirements for each sub-domain. In each domain, the NSSMF manage and orchestrate the resources allocated for each slice.

d. VNF management and orchestration

Virtual Network Function (VNF) management and orchestration (MANO) is a critical aspect of network function virtualization (NFV) that ensures the efficient deployment, scaling, and operation of VNFs in cloud environments. Mathematically speaking, the VNF orchestration problem is an optimization problem, typically modelled as NP-hard, where the objective is to minimize the overall network operating expense (OPEX) and physical resource fragmentation

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by (i) provisioning an optimal number of VNFs, (ii) placing them at the optimal locations, and (iii) finding the optimal routing paths for each traffic request, while respecting the capacity constraints (e.g., physical servers, links, and VNFs) and ensuring that traffic passes through the proper VNF sequence [27]. Finally, the VNF lifecycle should also be managed.

The most commonly used techniques in VNF include policy-based automation, machine learning (ML)-driven optimization, and intent-based networking (IBN), following a cloud-native microservices architecture. Policy-based automation leverages predefined rules and policies to automate VNF lifecycle management, including instantiation, scaling, and termination. ML-driven optimization enhances resource allocation and fault prediction by analyzing historical data and optimizing VNF placement and scaling decisions. Intent-based networking abstracts low-level configurations by allowing operators to define high-level intents, which are then translated into specific orchestration actions. Additionally, the adoption of cloud-native principles, including microservices-based VNFs and containerized orchestration using Kubernetes, has gained significant traction to improve agility and scalability.

The ETSI NFV MANO framework [28] is a widely adopted standard for managing and orchestrating VNFs. It consists of three main components:

- **NFV Orchestrator (NFVO):** Responsible for the lifecycle management of network services and VNFs.
- **VNF Manager (VNFM):** Manages the lifecycle of individual VNF instances.
- **Virtualized Infrastructure Manager (VIM):** Oversees the management of virtualized infrastructure resources.

The MANO framework provides a structured approach to VNF management, enabling dynamic service provisioning and resource orchestration. It is particularly effective in container-based virtualization environments, which are gaining traction in 5G networks

Open-source implementations of the ETSI NFV MANO frameworks such as Open-Source MANO (OSM), Open Network Automation Platform (ONAP), and Cloudify integrate these techniques to enhance automation and interoperability. AI-powered closed-loop automation further enhances orchestration by enabling self-healing and predictive/proactive scaling mechanisms. Moreover, service function chaining (SFC) is used to define traffic flow through multiple VNFs efficiently, ensuring network performance and security. These techniques collectively contribute to reducing operational complexity, optimizing resource utilization, and improving service reliability in NFV environments.

f. Multidomain service management and orchestration (SMO)

Based on the above description of the different network domains where functional models are most likely to be called, we depict in Figure 6 a multidomain SMO architecture as proposed by Juniper [29] or in the new release of 3GPP [30] that presents an example of the deployment scenario for the management of a mobile network using multidomain orchestration for efficient slicing.

The multidomain orchestration will then result in federating, monitoring and optimizing services and network functions emanating from the different network domains (RAN, Transport or Core network) hence ensuring end to end service provisioning.

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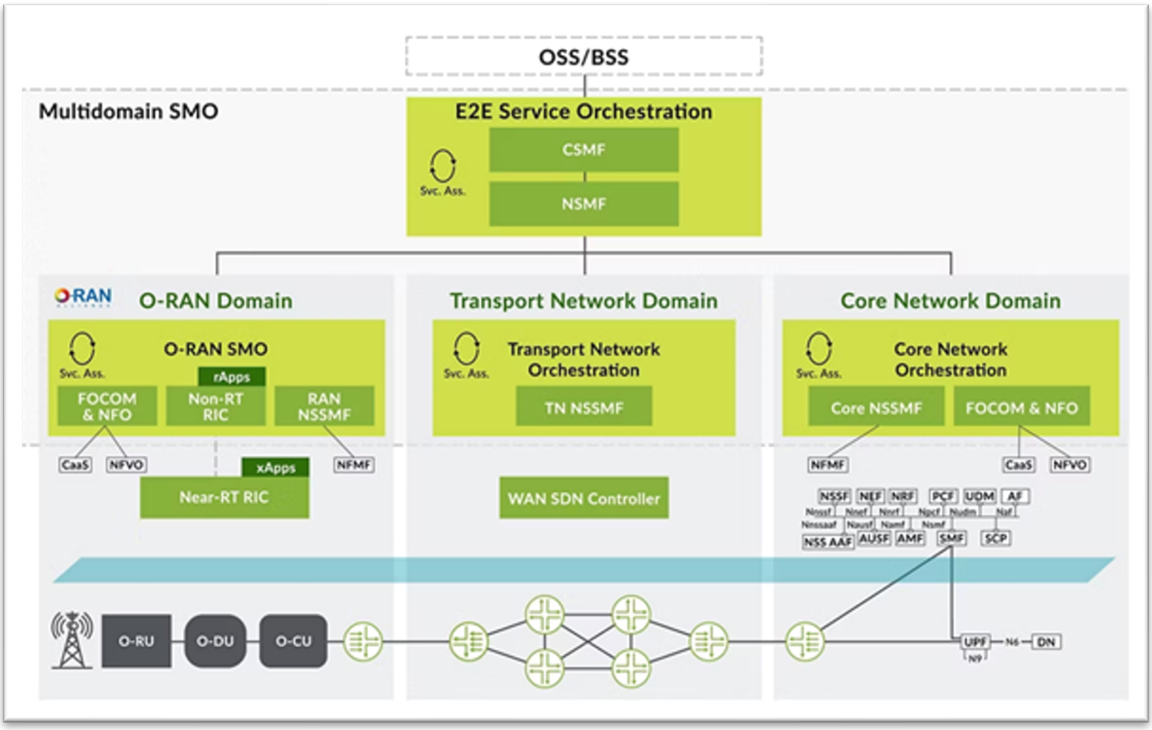

Figure 6 Multi-domain Service Management and Orchestration [24]

4.2.2. Functional models taxonomy

This section is dedicated to the presentation of Table 4 that aims to classify the functional models identified in the literature that are most likely to be included in the 6G-TWIN NDT architecture according to functional models' types (cf. section 2.2) and the classification criteria described in the previous in section 3.1.

Hence, in Table 4, functional models will first be classified based on their main functionality that identifies the category to which the functional model belongs (Network Management and Control, Network Planning, Network monitoring and Network diagnosis and security). The second column presents the specific purpose/problem aimed to be solved by the functional model (e.g. RIC function, VNF Mano, slicing, scheduling, multidomain orchestration, etc.). The subsequent columns refer to the model type (analytical, deterministic, probabilistic, AI-based and hybrid) as identified in section 2.2, the operation mode (reactive, proactive and hybrid), the operation deployment domain (RAN, transport, core) and the computing element (edge, cloud and federated). The last column refers to the works related to each functional model category.

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Table 4 6G-TWIN Functional models taxonomy

Functionality	Specific focus / Problem to solve	Model type	Operation Mode	Computing element	Network domain	Bibliographic reference
Network Management and Control	VNF MANO	Analytical	Reactive	Edge, Cloud/	Core	[27]
	VNF MANO	Deterministic	Hybrid	Cloud	Core	[31]
	VNF MANO	AI-based	Proactive	Edge, Cloud	Core	[32], [33, 33], [34], [35], [36]
	VNF MANO	Hybrid	Proactive	Edge, Cloud	Core	[37]
	Federated VNF MANO	AI-based	Proactive	Edge, Cloud	Multidomain	[38]
	Federated VNF MANO	Deterministic	Reactive	Edge, cloud	Multidomain	[39], [40]
	Beam management	Analytical	Proactive	Edge	RAN	[41], [42]
	Beam management	AI-based	Proactive	Edge	RAN	[43], [44], [45]
	BS sleep management	AI-based	Proactive	Edge, Cloud	RAN	[46]
	BS sleep management	AI-based	Reactive	Edge, Cloud	RAN	[46]
	Frequency (RAT) mapping Positioning	AI-based	Proactive	Edge	RAN	[47]
	Traffic steering/ Near-real time RIC	AI-based	Reactive	Edge, Cloud	RAN	[5]
	SLA assurance/Near-real time RIC	AI-based	Proactive	Edge, Cloud	RAN	[48]
	VNF/CNF/ SFC Placement	Hybrid /Deterministic/ Analytical	Reactive	Edge, Cloud	RAN, Core, Transport, Multidomain	[14], [49], [50], [51]
		AI-based	Proactive	Edge, Cloud		[52], [53], [54], [55]
	SFC composition	Analytical	Reactive	Edge, Cloud	RAN, Core, Transport, Multidomain	[56]

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Network Planning	SFC/ Service Composition	AI-based	Proactive	Cloud	RAN, Core, Transport,	[57], [58]
	Slice Design /Creation	AI-based	Proactive	Cloud	RAN, Core	[59], [60]
		AI-based	Proactive	Edge, Cloud	RAN, Core, Transport	[61]
	PCI planning	Analytical	Proactive	Edge, Cloud	RAN	[62],
	Slice monitoring/ Visualization	Analytical/ Deterministic	Proactive/ Reactive	Edge, Cloud	RAN, Core	[63]
		AI-based/Hybrid	Proactive	Edge, Cloud	RAN, Core	[64]
Network diagnosis and security	Anomaly / Intrusion detection / Attacks prevention	AI-based, Hybrid	Proactiv, reactive	Cloud	Core	[65]
		AI-based/ Analytical	Proactive	Edge, Cloud, Federated	RAN, Core	[66]
		AI-based	Proactive	Cloud	Core	[67]
		AI-based	Proactive	Edge, Cloud	RAN, Core, Transport	[61]
	Encryption Authentication	Analytical	Reactive	Cloud	Core/RAN	[68]
		AI-based	Proactive, reactive	Cloud	Core	[69]

In summary, the taxonomy of 6G-TWIN functional models described above offers a structured understanding of how different types of models contribute to the realization of intelligent, flexible, and service-oriented 6G digital twin networks. By classifying these models according to their functionality, operation mode, deployment domain, computing environment, and targeted use cases, we established a comprehensive foundation for their integration within the broader 6G ecosystem. This classification not only clarifies their role within the NDT architecture but also sets the stage for identifying concrete implementation. The next chapter will describe the lifecycle of the functional model within the NDT and how it interacts with the other components of the 6G-TWIN NDT framework.

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5. Integration of functional models in the 6G-TWIN functional architecture

Functional models are core components in the 6G-TWIN NDT framework, enabling predictive intelligence, adaptive control, and closed-loop automation. As introduced earlier in this deliverable, NDT functional models span a broad taxonomy including different model types: analytical, probabilistic, deterministic, AI-based, and hybrid types. The 6G-TWIN functional architecture, illustrated below and detailed in [70], is designed to natively support this diversity of models, offering mechanisms for their deployment, execution, orchestration, and continuous adaptation based on real-time data and simulation feedback.

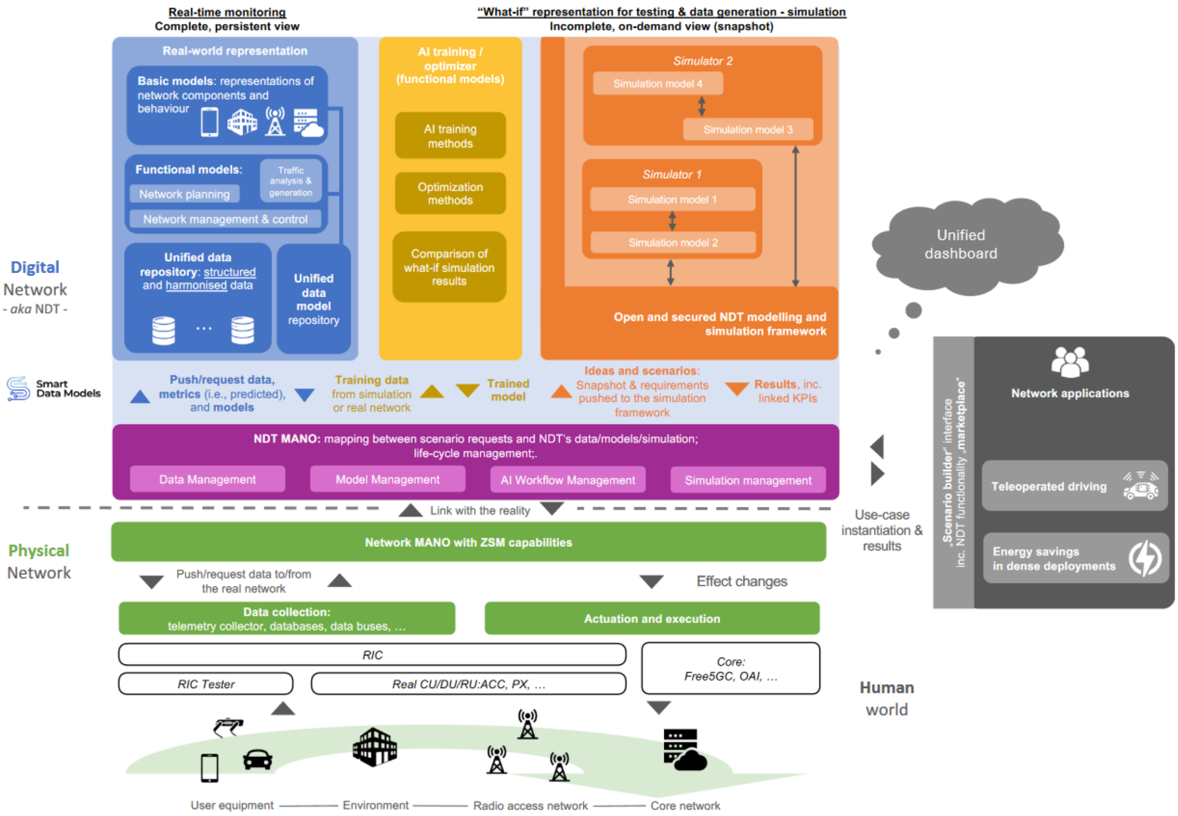

Figure 7 6G-TWIN's functional architecture.

In the following, we describe how the 6G-TWIN architecture manages the lifecycle of functional models, covering aspects such as instantiation, training, validation, update, and interaction with other architectural components.

5.1. Model lifecycle management (purple layer)

Functional models are inherently task-specific, designed to address application's goals within the network. Their lifecycle is governed by the NDT MANO component, which oversees the E2E process, starting from selecting appropriate training datasets (blue layer, derived from basic models) and choosing suitable training environments (yellow layer), to align these layers with application-specific requirements (grey layer). NDT MANO is also responsible for instantiating the models within the simulation framework (orange layer), managing their evaluation and refinement, storing validated versions with appropriate scenario labels (blue layer), and ultimately orchestrating their deployment in the physical network (green layer).

In addition to deployment, the NDT MANO manages the continuous updating and retirement of functional models throughout their lifecycle. As network conditions evolve, models may need to be retrained, re-parameterized, or entirely replaced to maintain alignment with operational requirements. The NDT MANO handles the versioning of models, ensuring that new iterations are properly validated before deployment and that previous versions remain traceable for rollback if needed. Deletion policies are also enforced at this layer, allowing obsolete, underperforming, or redundant models to be safely retired without disrupting service continuity or operational integrity.

Traditionally, this lifecycle, especially the selection and instantiation phases, has relied on expert-driven decisions. However, the 6G-TWIN vision anticipates a shift toward partial or full automation of this process through intelligent orchestration mechanisms embedded in the NDT MANO, enabling scalable, adaptive, and self-optimizing model management.

Emerging research trends also suggest a future direction based on network foundation models, large-scale, general-purpose AI models trained on heterogeneous datasets and capable of supporting many downstream network tasks [71]. Analogous to Large Language Models (LLMs) in Natural Language Processing (NLP), these models could support knowledge transfer across use cases, tasks, and domains. NDT MANO automation will be further studied in D1.3.

A key principle of the 6G-TWIN architecture is that functional models do not interact directly with either the unified dashboard (used by network applications and end users) or the physical network infrastructure (e.g., RAN, core, or edge nodes). Instead, all communication and orchestration are handled through the NDT MANO layer, which acts as the central control and abstraction point. This layer ensures that configuration inputs from the dashboard are translated into appropriate model parameters, that outputs from functional models are validated before being applied to the physical network via actuation interfaces, and that the entire model lifecycle remains tightly integrated with data streams and simulation workflows. This design ensures modularity, security, and traceability by decoupling inference processes from operational infrastructure, a key requirement for scalable, AI-native, and trustworthy network automation.

5.2. Functional models creation and storage (blue box)

Functional models are logically situated within the "real-world representation" layer of the 6G-TWIN architecture, alongside basic models and the Unified Data Repository (UDR). Non-trained functional models, along with their trained or optimized versions are stored in the Unified Data Models (UDM), where they are labelled according to the taxonomy proposed in this deliverable, for easier management of these models.

The development of functional models in the 6G-TWIN architecture is grounded in a structured approach to data acquisition, processing, and modelling. It begins with the data pipeline detailed in D1.2 [3], that ensures the efficient collection, transmission, and transformation of telemetry from the physical network into the NDT. This pipeline harmonizes data from diverse sources, enabling it to flow seamlessly across network layers and domains. A critical part of this process is the definition of data requirements and structures that ensure semantic alignment and interoperability, notably using Smart Data Models and interfaces standardized by 3GPP (e.g., 3GPP TS 28.552, TS 28.541 [72], [73] and other relevant bodies. These models are defined in D2.1 [74] and provide a common language for describing network elements, metrics, and configurations, which is essential for scalable and reusable workflows.

At the core of this data ecosystem are basic models, persistent, graph-based representations that capture the static and historical states of network entities, including their configurations, relationships, and time-evolving behaviours (cf. D2.2). Functional models are dynamically constructed and specialized based on these basic models, enabling predictive intelligence, adaptive control, and closed-loop automation within the NDT. Specific implementations of functional models from specific basic ones will follow in the final version of this deliverable.

While AI-based functional models rely heavily on structured training datasets, other model types: analytical, deterministic, probabilistic, and hybrid, also require parameterization and calibration using real-world or synthetic data to ensure their operational relevance. The training and optimization of all functional models is handled by dedicated components in the architecture and is further detailed in Section 4.3.

5.3. Functional model training and optimization (yellow box)

The 6G-TWIN architecture provides dedicated mechanisms for the training and optimization of all functional models prior to their deployment. This process applies to all model types, including AI-based, analytical, deterministic, probabilistic, and hybrid models, each following tailored methodologies based on their nature.

For AI-based functional models are trained using a variety of ML paradigms, notably supervised learning for tasks like traffic classification or anomaly detection; unsupervised learning: for clustering, segmentation, and dimensionality reduction; reinforcement learning: for decision-making in dynamic environments (e.g., mobility, resource allocation); and semi-supervised and self-supervised learning: for tasks where labelled data is scarce.

Training typically starts with small, high-quality datasets and is gradually expanded to include broader samples to improve generalization. In 6G-TWIN, training may occur on data collected from the live network (reactive models) or in tandem with simulated environments that generate training scenarios (proactive models).

Other functional model types also require optimization before deployment. Analytical models are parameterized to align theoretical behaviour with empirical network measurements. Deterministic models undergo calibration to ensure precision and reproducibility based on observed conditions. Probabilistic models involve statistical fitting to empirical distributions derived from historical datasets. Hybrid models combine both data-driven and theoretical approaches, requiring integrated optimization strategies.

The outputs of training and optimization processes—whether trained AI models or optimized parameter sets for other model types, are systematically stored in the UDM. Each model instance is labelled with relevant metadata (e.g., functionality, model type, operation mode, network domain), enabling traceable reuse, adaptation, and orchestration within the digital twin environment.

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5.4. Simulation, evaluation, and pre-deployment testing (orange box)

Simulation is a core feature of the 6G-TWIN architecture and in the functional models' lifecycle. In a sense, NDTs are seen as expansions of classic network simulators [21]. Some authors even use digital twin and simulation synonymously, but digital twins should be closer coupled to a real system [75] [76] [77]. Nevertheless, in the context of NDTs, simulations are mainly needed to analyse what-if scenarios [78], i.e., it can be checked how the KPIs of a network would change if parameters of that network are altered. For instance, it can be checked what happens to the latencies and energy consumption if several UEs are associated in a different order to the available gNBs.

In line with the taxonomy in Section 4.2, AI-based models benefit from scenario generation to improve training (especially in RL setups); analytical and probabilistic models may be evaluated against real traffic traces for precision and performance comparison; and hybrid models may leverage simulation to test rule-based decision logic alongside ML-based prediction. Validated models are then stored persistently and pushed to the physical network as needed by the NDT MANO.

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6. Functional models and simulation models

Functional models of networks have the purpose to optimize the network regarding defined criteria like quality of service or energy consumption. Therefore, functional models are not simulation models, but more than that. Some functional models might even work only with the real network, without the need for any simulations. Functional models contain optimization strategies (usually called training methods in the context of AI models) that adapt structurally simple models like neural networks to fulfil tasks that normally require complex simulation models. For example, an AI model (neural network) might have the goal to compute the best resource allocation based on input data like number of current UEs and their positions, energy characteristics, and current communication requirements. To fulfil this task, the AI model must be trained. This training data might be real measured data, what is the best case for getting a realistic model. However, in most practical situations real measurement data will only be available for a limited number of scenarios, namely these that already happened in the past in the real network. Therefore, in order make decisions, the AI model must also learn from data that represents situations that did not happen in reality yet, and it should know the effect of decisions that have never been tried in reality. Otherwise, it would be limited to selecting one of the already occurred configurations instead of selecting a better one. Therefore, model training usually requires a lot of simulations to create such training data. Different simulation configurations might result in different KPIs like throughput, packet loss rate, and energy consumption. After learning from that simulated data, the functional model can select the best configuration depending on the performance criterion of the optimization strategy (that might use only one of these KPIs or a multicriteria approach).

It follows that a functional model consists of at least three components (see Figure 8):

- a model that can be trained or optimized (e.g., an AI model or analytic model),
- an optimization algorithm (training method in the context of AI models),
- a simulation model for testing the AI model and for generating training data based on “what-if” scenarios.

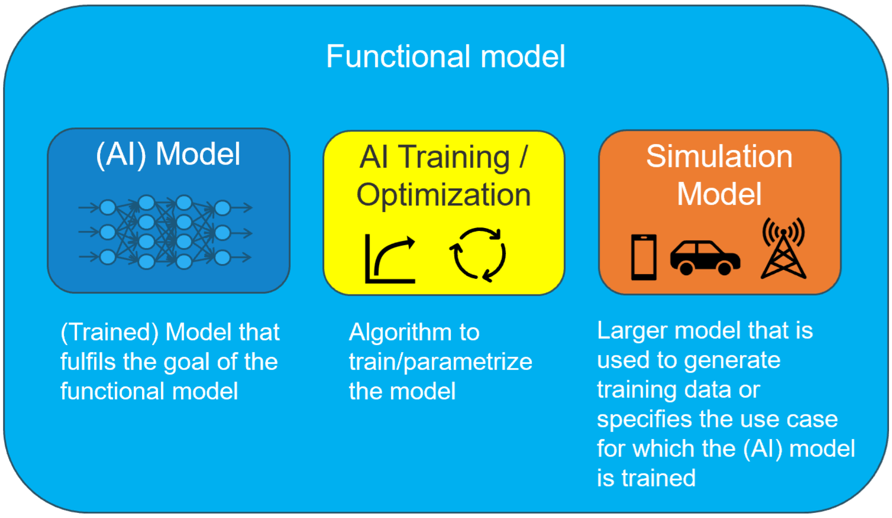

Figure 8 Components of a functional model

Since functional models and simulation models are closely related, but not the same, a clearer definition is necessary:

- **Simulation model:** a machine-readable description of a scenario that can be read and run by a simulator

- **Simulator**: software that reads a simulation model, runs the simulation, and stores the results
- **Simulation**: Execution of a simulation model in a simulator
- **Functional model**: entity necessary for analysing or optimizing a network, consisting of an analytic, stochastic, or AI model, an optimization or training algorithm, and a simulation model defining the use case of the model

So, a functional model both contains a simulation model, but the trained part of it can also be run within a simulation.

The creation and usage of functional models should be realized in the following steps, also visualized in Figure 9:

1. **Data collection**: Before the creation of a functional model, data is collected in the physical network. This contains structural data as the number and position of UEs and gNBs and the topology including wired and wireless connections. Furthermore, relevant capabilities and energy consumption information of all devices and connections are collected. Also, runtime data like measured latencies and packet loss rates might be measured. All this data is sent to the NDT management which harmonizes the data and stores it in the data repository. This is planned to be done in the form of basic models.

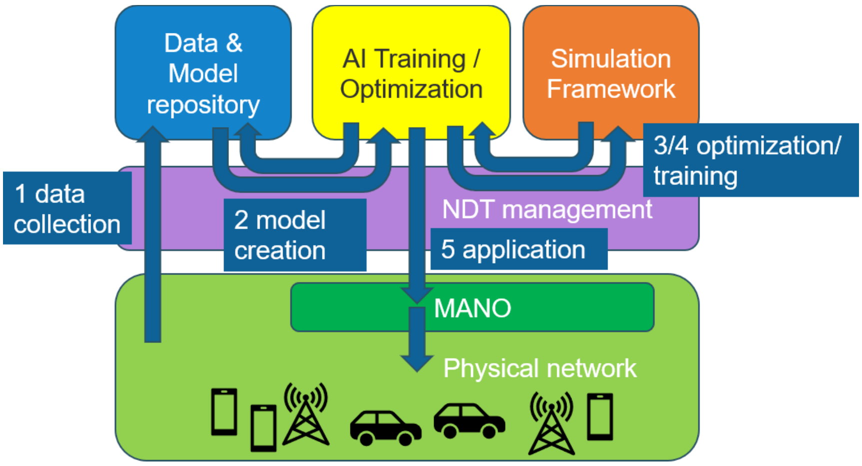

Figure 9 Steps of functional model creation and application, shown in a simplified version of the 6G-TWIN functional architecture (cf. previous Chapter)

2. **Model creation**: In the next step, a functional model is created. As functional models have the purpose of optimizing a network, this requires an optimization goal that is set by the application layer. Fitting to that optimization goal, necessary data from the basic model is selected and used to generate a simulation model from that data. This step is described later in more detail. Besides the simulation model, also a model type (e.g., neural network, polynomial, differential equation etc.) and an optimization algorithm (training method) are selected.
3. **Fitting simulation model to real network**: Before optimizing or training the (AI, analytic, or stochastic) model, the simulation model should be fitted to the real data. Like the training itself, this usually requires an optimization procedure. In that procedure the simulation model is run by the simulation framework, the simulation results are compared to the stored real data, and the simulation model parameters (these that are

not known from the real data) are adjusted until the simulation results match the real data as closely as possible. The model is now stored in the model repository as a part of the functional model.

4. **Training**: Now, the training of the (AI or analytic) functional model can be started. Also, this is an optimization procedure containing a lot of simulation runs with changed simulation model parameters. But different to the optimization before, not the best simulation parameters for matching the real-world data are searched. Instead, the simulations generate training data that is used by the (AI or analytic) model to learn about "what-if" scenarios, i.e., it learns how the outputs of the (simulated) network changes if certain input parameters are adjusted. This also means that only model parameters have to be changed that either can be adjusted later by the trained model in the real network (e.g., resource allocation for each UE) or might change in the real network due to the environment (e.g., number and position of UEs). The learning is realized by adjusting (AI or analytic) model parameters (e.g., neuronal network weights or coefficients of differential equations). Ideally, simulation results of the prior step can be reused here for reducing the computational time (or increasing the amount of training data within a given amount of time). This trained model is then stored in the model repository via the NDT management.
5. **Application**: After finishing the training process, the trained (AI or analytic) model can be sent via the NDT management to the management and orchestration layer (MANO) of the real network. There, the trained model can be used to efficiently make decisions based on the current network state (channel load, number of UEs, etc.) and the beforehand learnt relation between these parameters and the best actions. This step does not require simulations and can therefore be executed in real-time.

One important aspect mentioned in Step 2 is the creation of simulation models based on the information contained in the basic model. This process is not straightforward, as a simulation may involve multiple simulators (i.e., simulation software) that must be coordinated via the simulation framework. For example, a given simulation might combine a RAN simulator (e.g., OMNeT++ with Simu5G, or ns-3) with a mobility simulator (e.g., SUMO), both of which are synchronised by the framework. If the basic model of each network element (e.g., a UE or gNB) includes both mobility information (such as position or trajectory) and network-related parameters (such as communication capabilities), then these aspects must be correctly transferred to the appropriate simulators: mobility data to the configuration files of the mobility simulator, and network parameters to those of the RAN simulator. As such, basic models cannot be simulated directly - they must first be translated into simulator-specific formats.

As written above, it is expected that functional models contain simulation models as one of their components. However, it might also be the case that they only contain a basic model and the simulation model must be generated from that information in the same way as described before. This simulation model creation must be initiated by the NDT management layer when a simulation must run (cf. Figure 10).

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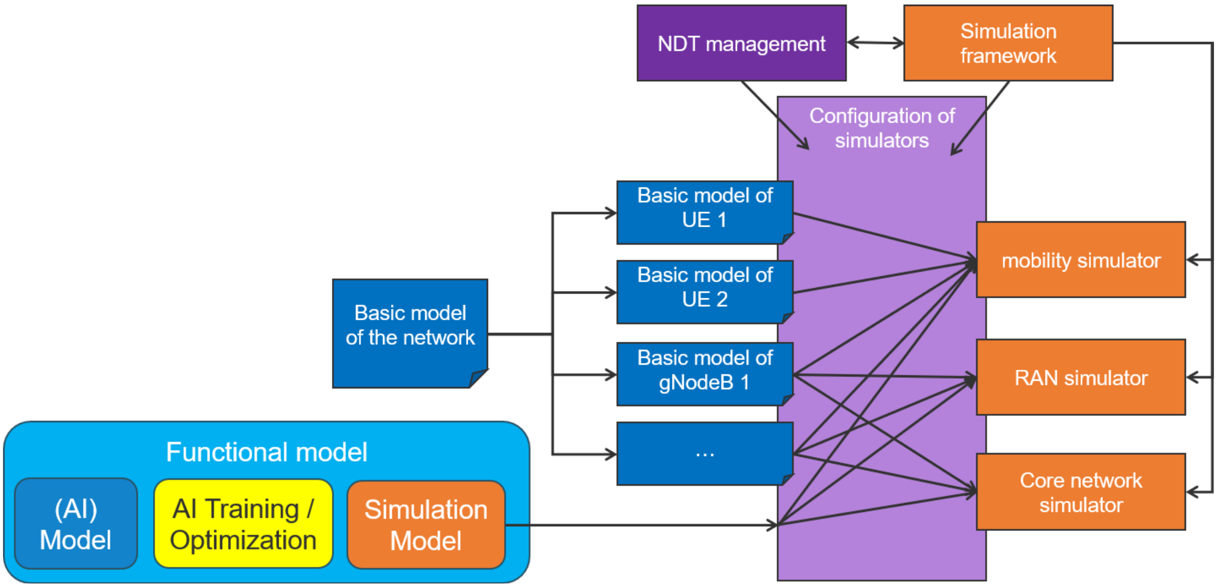

Figure 10 Creation of simulation models from basic and functional models

7. Conclusion

In this deliverable, we presented the fundamental concepts related to functional models within the 6G-TWIN Network Digital Twin (NDT) framework. As this is the initial version, the content and contributions outlined here will be further developed and consolidated in the final version to be provided in Deliverable D2.5 at Month 36 of the project. The key contributions of this document can be summarised as follows:

- We provide a **definition of functional models** and **categorise** them into various types, including analytical, AI-based, probabilistic, deterministic, and hybrid models. For each type, we highlight the main advantages and limitations.
- As a major contribution of this deliverable, we propose a **detailed taxonomy of functional models**, including a classification of related works based on several criteria: functionality, operation mode, network deployment domain, computing elements, and use cases - particularly the two project use cases of teleoperated driving and energy saving. Within the broader 6G-TWIN architecture, we identify how functional models operate across different network domains (RAN, transport, and core) and within a multi-domain architecture involving end-to-end service and management orchestration.
- We describe the functional model architecture, which consists of three main components:
    - the trained model that fulfils the objective of the functional model,
    - the algorithm used to train or parameterise the model, and
    - a large simulation model used to generate training data or define the use case for which the model is designed.

The analysis and classification of functional models presented in this deliverable aim to support the future specification of these models in relation to the project's two use cases. Moreover, this work can contribute to standardisation activities, particularly those pursued in WP5.

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