DATA AND KNOWLEDGE DUAL-DRIVEN ARCHITECTURE FOR AUTONOMOUS NETWORKS

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Abstract – *The vision of autonomous network has become an industry consensus. Leading operators have moved from network automation to network intelligence, and the deep integration of network and AI technology as the main technical method enters the scale adoption in production networks. At the same time, the third-generation AI technology has ushered in a research and development boom driven by both data and knowledge. To build an architectural consensus to further guide technical standards for accelerating industrial cooperation, a data and knowledge dual-driven autonomous network architecture, as well as its design principles, functional modules and deployment options, are given to unleash the power of technology innovation and industry transformation.*

Keywords – Autonomous network, knowledge management, network intelligence, operation management

NOTE: This work is a position paper.

1. INTRODUCTION

An autonomous network is the goal of digital intelligent transformation of communication network operation management, aiming to build automated and intelligent operation and maintenance capabilities for the whole life cycle of the network, providing new network and ICT services to consumers and vertical industry customers with **Zero-Wait, Zero-Failure, Zero-Touch** experiences, via in-built digital and intelligent operation and maintenance capabilities for **Self-configuring, Self-healing, Self-optimizing** [1].

On one hand, from the perspective of customers in terms of their digital experience [1]:

•**Zero-Wait provisioning** means that through the precise control of network resources, real-time service provisioning and immediate use are enabled;

•**Zero-Failure maintenance** means through end-to-end monitoring of the network, hidden risks are identified before customer complaints, and faults are recovered before customers perceive them; and

•**Zero-Touch service** means through the exposure of network data and capabilities, customer self-service is supported, and online digital techniques are used to quickly responds to customer needs.

On the other hand, from the perspective of OAM practice in terms of digital transformation [1]:

•**Self-configuring** means that network expansion, upgrade and configuration are automated, along with automatic dialing and testing and machine on-duty inspection after network changes are made;

•**Self-healing** means that the network failure and semi-healthy state (which might lead to later failures) are keenly sensed, and services are guaranteed based on technologies such as dynamic load balancing and multilevel disaster recovery;

•**Self-optimizing** accurate perception and identification of poor service quality, dynamic generation of optimization policies, and closed-loop control are provided based on big data and AI technologies, so as to ensure high-quality user experience.

To this end, autonomous networks deeply integrate AI technology with the hardware, software, and systems of communication networks to help intelligent network operations, enable agile business innovation, and build intelligent endogenous networks.

At the same time, the development of AI technology has ushered in a new stage. The first generation of modern artificial intelligence, first originated at the Dartmouth Conference in 1956, was knowledge-driven symbolic artificial intelligence [2][3]. The second generation since then is perceptual artificial intelligence, which relies on a large number of data-driven statistical learning methods to implement the perception and recognition of information such as text, pictures, and speech [4][5].

According to the comparison in [6], in the knowledge-driven artificial intelligence framework, large-scale knowledge base and common sense base could be built which allows the machine to describe all the knowledge of human beings. However, this method cannot change dynamically, so it cannot adapt to large-scale data and flexible knowledge. while in the data-driven perceptual AI framework, ML models cannot solve cognitive problems, nor can they reason.

With the pervasive application of model AI and the vision for its enablement to support digitalization transformation, a new trend of development direction for the third-generation artificial intelligence, which integrates knowledge and data to build a dual-driven framework, has emerged to combine the advantages of knowledge-driven and data-driven to improve the explainability and robustness of the model [7][8].

In the context of digital and intelligent transformation, with the improvement of network autonomy, dynamically updated networks/systems bring complex and dynamic knowledge management requirements, and automatic and intelligent management and operation of knowledge have also become a new trend.
Knowledge is concept, notion, or skill acquired through study, practice, or exploration. Knowledge management is the life cycle management of knowledge, including knowledge construction, knowledge processing, knowledge sharing, knowledge application, knowledge update, etc.
An automated and intelligent knowledge management system can improve the quality of knowledge generation and promote the efficient operation of the knowledge life cycle, so as to achieve a timely update and accurate application of knowledge. Especially when manpower cannot meet the current situation of huge knowledge management requirements, redundant processes can be further streamlined, automated management processes fulfilled, operational management efficiency improved, and management costs reduced.
However, implementing automated, intelligent iterations of knowledge management in the context of autonomous networks introduces the following new challenges and opportunities that need to be addressed:

•**Data acquisition** is the starting point of knowledge construction. In practical applications, the diversity of data sources results in inconsistent data standards and poor data quality, resulting in multi-source data ambiguity, high noise, and an unclear relationship between data. From the perspective of source form, knowledge is contained in structured (e.g. alarms, indicators, etc.), semi-structured (e.g. configuration, log, standardized product documentation), unstructured (e.g. practice manual, failure case, experience sharing, packet capture data on production network for an alarm failure diagnosis, etc.) data, even in the minds of experts. Correspondingly, we need to match the tools to obtain this data and provide "clear and unambiguous" specifications to allow interoperability. At present, both the tools for non-institutionalized data acquisition and industry standards need improvements, which could be accelerated by collaborative efforts via an archietectual blueprint.
•**Practical approach:** due to the systematic characteristics of the communication network itself, the integration of AI and the network is bound to become systematic. However, it is not trivial to introduce artificial intelligence technology into the communication network and finally achieve the goal of systematic transformation. One needs firstly to start from single-point algorithm innovation, then integrating into the production operation and maintenance process, and then building platform-based hosting and sharing of common capabilities to finally form a complete intelligent system, achieving standard interoperability in both an efficient and economic manner.
•**Deployment method** for knowledge collaborative management: an autonomous network involves multiple business fields and hetergeneous networks. It is necessary to manage knowledge at different layers through cross-field knowledge creation, integration, sharing and collaboration. Considering the hierarchical characteristics of the network and management system, and the differences in IT resource requirements at each stage of AI-driven knowledge generation (knowledge acquisition, training, reasoning, etc.), it is necessary to build distributed AI capabilities in the network to support an automatic closed-loop at each layer, as well as knowledge sharing and collaboration between different layers.
In order to address the above issues and promote industrial cooperation, an autonomous network architecture, dual-driven by data and knowledge, deeply integrated and coordinated, with advanced technologies, is given.

2. BASIC CONCEPTS

Applying the Data, Information, Knowledge, Wisdom (DIKW) pyramid[9] into the context of autonomous network, the following basic terms are used in this paper.
•**Data** are symbols that represent the properties of objects and events, as a collection of facts in a raw or unstructured form. In autonomous networks, the raw data about the managed objects obtained by the corresponding management system through measurement, such as Performance Monitor (PM) data, Measurement Report (MR) data, service status data, etc.
•**Information** consists of processed data, contained in descriptions, answers to questions that begin with such words as who, what, when, where, and how many, that can be interpreted in a specific context. In autonomous networks, it corresponds to the data content that can reflect the logical relationship and meaning of the network status after being processed by the network management system, such as traffic statistics indicators, complaint work orders, and alarm data.
•**Knowledge** conveyed by instructions, answers to how-to questions, as filtered, refined, and processed information associated with a specific context that guides action. Concepts, rules and experiences applied to autonomous networks to achieve system automation and autonomy, such as exceptions, intents, static rules, dynamic policies, classification/prediction models, etc.
•**Wisdom** or **Meta-knowledge** conveyed by explanations, answers to why questions, which in the context of autonomous networks, means the ability to effectively manage knowledge according to the environmental context, through correct judgment of the environmental context, updating iterative knowledge as needed, and realizing the correct application of knowledge.

3. RELATED WORK

At present, TM Forum and ETSI have carried out preliminary research on knowledge management of communication networks. The current research areas mainly focus on knowledge management and application requirements, challenges, basic architectural reference points and preliminary concept definitions.

The Knowledge Management sub-domain in the eTOM [10] and TAM [11] standard projects of the TM Forum has made a preliminary review of knowledge management from the perspective of business and application. The ODA project team released IG1130F [12] in June 2019, where requirements of knowledge management applications, and suggestions for knowledge management applications in TAM were given. The AIOps project team released IG1190E [13] in May 2020, which studied the challenges and opportunities faced by knowledge management practices after the introduction of AI, with new proposed process principles, etc. The Autonomous Network project team released IG1251 [14] in July 2021 to study the autonomous network reference architecture. The knowledge base and intelligence cross-domain module and domain intelligence single-domain module are mentioned in the architecture, which is expected to provide knowledge management functions.

ETSI GS ENI 005 [15] gives the definition of the knowledge management function block of the ENI system, and introduced the driving force, function, operation process, etc. of the knowledge management module. In the draft of ETSI GR ENI 015 [16], the knowledge management of intent policies is studied, and the intent policies are managed by means of a knowledge graph. ETSI GR ENI 031 [17], which recently kicked off in March 2022, plans to study the construction and application of network knowledge graphs into fault maintenance applications.

4. ARCHITECTURAL PRINCIPLES

This section provides several basic princples for guiding the architecture design later.

4.1 Principle of layered operations

The autonomous network architecture should follow a layered architecture model, which reduces the complexity of the overall system and enables the independent evolution of each layer, which can operate autonomously and hide domain implementation technology, intra-domain operations, and intra-domain functional details from its consuming layer.

4.2 Principle of closed-loop automation

In autonomous networks, automation is based on a closed-loop mechanism and works as a feedback-driven process. The closed loop seeks to either achieve and maintain the explicit set of intents or automatically execute the determined instructions from pre-configured static rules or programmable dynamic policies, that drive the four-phase "closed loop", consisting of perception, analysis, decision-making and execution. Depending on the timeliness requirements to closed-loop processing in different application scenarios in autonomous networks, both the fast closed loop inside an autonomous domain and the slow closed loop involving cross-layer interaction and collaboration can be applied, respectively. The rules/policies/intents driving the closed loops as well as the closed loops themselves become the managed objects in the autonomous network.

4.3 Principle of model-driven open interface

An open architecture based on a model-driven approach defines service interfaces and resource management interfaces by using information models that specify the attributes of managed entities and the operations they support. The definitions of the interface and related models can thus be partially decoupled and independent of the implementation of managed entities, which can promote portability, reusability of interfaces, and allow vendor-neutral management of resources and services. For example, for closed-loop management automation requirements, for different operation layers of the autonomous network can define a unified model-driven standardized interface with a common model for the rules/policies/intents that drive the closed loops in different layers of operation.

5. TARGETED SYSTEM ARCHITECTURE

As shown in Fig. 1, the autonomous network architecture follows the layered architecture model, dividing into four layers of operations and management, with open interfaces for inter-layer interactions and closed loops [18].

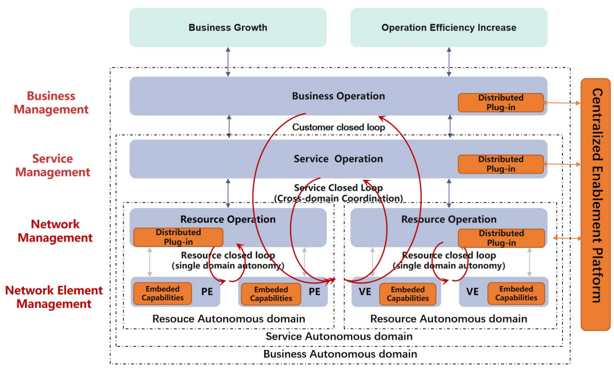

Fig. 1 – Targeted architecture for autonomous networks [18].

5.1 Four layers of operation management

•**Business management layer** provides customers, ecosystems and partners with business enablement and operation capabilities for the network business.

•**Service management layer** implements cross-vendor and cross-domain service layer autonomy in the end-to-end process of planning, construction, maintenance, and optimization.

•**Network management layer** fulfills the SLA commitment of network connections or behaviors, through the closed-loop capabilities of perception/analysis/decision-making/execution within a single network domain.

•**Element management layer** dynamically senses and automatically loptimizes equipment components and operating states, and opens up automated operation capabilities.

5.2 Three closed-loops of automation

The autonomous network consists of three closed loops to implement the full life cycle interaction between layers, including:

•**Resource closed loop** for single-domain resource management to achieve single-domain autonomy;

•**Service closed loop** for service-oriented, end-to-end management to achieve cross-domain collaboration; and

•**Customer closed loop** for customer and business management, including user information, business, billing, customer service, etc.

5.3 Autonomous domain

An autonomous domain is the smallest unit of an autonomous network. It is coordinated by the upper-layer OAM system through a closed loop management interface. Corresponding to the four-layer architecture of the autonomous network, building on top of the basic infrastrucure facilities in the form of collections of network elements and corresponding management systems, the autonomous domains form a three-layer hierachy based on their autonomous boundaries:

•**resource autonomous domain** corresponding to the network element management and network management layer of the architecture, includes the management and control system and the network elements, implements the autonomous closed loop of a single-domain network, supporting the upper-layer OAM systems to achieve collaborative autonomous closed loops across multiple resource operation autonomous domains.

•**service autonomous domain** corresponding to the business management layer of the architecture and each subordinate resource operation autonomous domain, includes the service operation layer software system on the basis of each resource operation autonomous domain, and provides the upper-level business operation layer with the autonomous capability of service closed loop autonomy, by driving the resource operation autonomous domain(s) to implement the internal closed loop capability within its governance scope. In other words, the service operation autonomous domain and the resource operation autonomous domain are cascaded.

•**business autonomous domain** corresponding to the business operation layer of the architecture and each subordinate service operation autonomous domain, includes the business operation layer software system in each service operation autonomous domain, and provides E2E business closed loop operation capabilities to customers/tenants, by triggering correspondent closed loops inside the resource operation autonomous domain(s) and the service operation autonomous domain(s).

5.4 Evolving interfaces

As specified in [19], there are different types of interfaces between the layers (i.e. the boundaries between autonomous domains) in various levels of autonomous networks, including:

•**rules**, specifications for how managed entities use data and interact within a defined environment, is the featured interface for Level-2 autonomous networks.

•**policies**, sets of rules that govern and control the states and state transitions of managed objects, is the featured interface for Level-3 autonomous networks.

•**intents**, normative definitions of expectations, including requirements, goals, and constraints for the system [20], is the featured interface for Level-4 autonomous networks.

Higher-order autonomy means that business, service, and resource operations can dynamically adjust decisions and actions to adapt to changing goals and needs and cover a wide range of situations without human intervention. In this new environment, the business objectives of operators and the expectations of customers need to be communicated to the software systems that make up the autonomous network.

For this reason, the interfaces between autonomous domains have to gradually evolve from being based on statically-scripted rules, to dynamically programmable policies to allow human-involved knowledge updates, and further to declarative intents (i.e. descriptions of the desired status or features without dictating the methods or commands to achieve them) to allow full-automatic adaptation of system behavior without human engagement.

5.5 Distribution of intelligence

Due to the widespread existence of closed loops in autonomous networks (autonomous domains), the application scenarios of intelligence are scattered at various layers in the network. To realize systematic data-knowledge management, in an autonomous network, cognitive intelligent capabilities (i.e. abilities to generate knowledge by using existing information) will be deployed in a distributed manner and fall into one of the following categories.

•**Embedded** capabilities, built into the network elements, as part of fast closed loops.

•**Plug-in** capabilities, bulit as an external supplement to the devices or systems, which can be further classified into the following two sub-classes.

•**Centralized plug-in** capabilities, in the form of data lakes, training platforms, knowledge centers, providing model training services, digitizing knowledge, which embodies the *Centralized enablement platform* in Fig.1.

•**Distributed plug-in** capabilities, in the form of specific domain models and reasoning applications, local knowledge optimization, as part of fast or slow closed loops in various autonomous domains.

6. LOGICAL ARCHITECTURE

In this section, a general data and knowledge driven architecture for autonomous networks is proposed, which could be applied to various autonomous domains as either *Centralized* or *Distributed Plug-in Capabilities* in autonomous networks, for data collection, information extraction, knowledge generation, knowledge fusion, knowledge application, and knowledge update, etc.

6.1 Functional components

The knowledge management system includes a knowledge management module and a knowledge management application domain. The former provides knowledge management services for the latter, and the latter is the application domain of the former. External systems can exchange data and knowledge with the knowledge management system through the external interfaces via format conversion, if needed.
The knowledge management module is composed of the data domain, information domain, and knowledge domain. Each domain has specific functional sub-modules, which cooperate to complete the transformation from data to information to knowledge, and through the knowledge management application domain, external system interaction, collaboratively complete the processes of knowledge generation, sharing, application, and iteration.

6.1.1 Data processing/collection

The data processing sub-module preprocesses the data provided by the data source (incl. data cleaning, data filtering, etc.), and sends the processed and available data to the information extraction sub-module of the information domain. Its data sources include:

•**Raw data** from knowledge management application domains (for example, various network management data, business data, environmental data, etc.) in the basic architecture, and knowledge application monitoring report (for example, rule/policy/model application frequency, success rate, performance statistics, etc.) in the extended architecture;

•**External data** from outside the system, including structured data, semi-structured data, unstructured data, etc. For data with inconsistent formats, format conversion should be performed before acquisition and processing.
This module can apply the technology, rules, strategies and other knowledge provided by the knowledge storage in data processing.

6.1.2 Information extraction

The information extraction sub-module extracts basic knowledge elements such as entities, attributes and relationships from the data, and sends them to the knowledge generation sub-module. The above process may apply knowledge such as extraction algorithms and models provided by the knowledge storage sub-module.

6.1.3 Knowledge generation

Based on the basic elements of knowledge, the knowledge generation sub-module completes the correct correspondence with the existing knowledge in the knowledge storage through technologies such as entity linking, generates knowledge, and sends the generated knowledge to the knowledge fusion sub-module. The above process can apply knowledge such as generation algorithms and models provided by the knowledge storage.

6.1.4 Knowledge fusion

The knowledge fusion sub-module compares and merges the input knowledge with the existing knowledge in the knowledge storage to eliminate potential conflicts and inconsistencies. Further, based on knowledge storage, original knowledge combined with new input knowledge, by applying knowledge reasoning, knowledge mining and other technologies, combined, reasoned, and derivative new knowledge is created to improve the completeness of the knowledge base.
The input to the knowledge fusion sub-module includes:

•**Internal knowledge** from the knowledge generation sub-module; and
•**External knowledge** from experts or knowledge storage from external systems.

6.1.5 Knowledge storage

The knowledge storage sub-module implements the storage and query functions of knowledge, which include:

•responding to the knowledge application request of each sub-module within the knowledge management, and providing the corresponding knowledge in return;
•responding to the knowledge application requests of the knowledge management application domain, and providing the corresponding knowledge in return; and
•providing corresponding knowledge in response to knowledge sharing requests of external systems.

6.1.6 Knowledge recommendation

The knowledge recommendation sub-module recommends and provides knowledge based on the knowledge requirements of the knowledge management application domain. When the knowledge recommendation sub-module receives the knowledge application request from the knowledge management application domain, it queries the corresponding knowledge in the knowledge storage according to the application requirements.

•If the corresponding knowledge is found, the knowledge is sent to the knowledge management application domain.

•Otherwise, the query does not return with an exact match, knowledge recommendation calculation is performed and the recommended knowledge is sent to the knowledge management application domain.

6.2 Functional variations

There are three types of knowledge management modules, depending on the combination of internal functional components and the characteristics of external presentation. The basic variation provides the fundamental elements for a minimal applicable combination (where the knowledge is imported externally), the extended meta-knowledge variation monitors the knowledge in application and provides support for independent and automatic knowledge generation locally, and the active variation provides further knowledge recommendation if no exact match is found from the existing knowledge base.

6.2.1 Basic knowledge management

As shown in Fig. 2, the basic functional architecture supports the import, application, mining and updating of knowledge. Specifically, it includes five sub-modules: data processing, information extraction, knowledge generation, knowledge fusion, and knowledge storage. Through the cooperative closed loop of each module, the functions of knowledge import, generation, processing, update and application are completed.

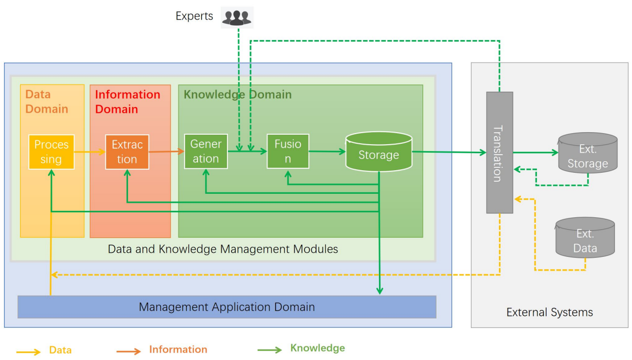

Fig. 2 – Architecture for basic knowledge management.

6.2.2 Extended meta-knowledge management

On the basis of the basic architecture, the extended architecture further supports the status monitoring, effectiveness evaluation and on-demand active iterative updates of applied knowledge, as shown in Fig. 3, by superimposing the management functions and interfaces corresponding to the knowledge application, meta-knowledge on each module of the knowledge management basic function architecture. Specifically, it includes five steps of monitoring data processing (knowledge application report), state information extraction, effectiveness evaluation, updated knowledge generation, and updated knowledge storage.

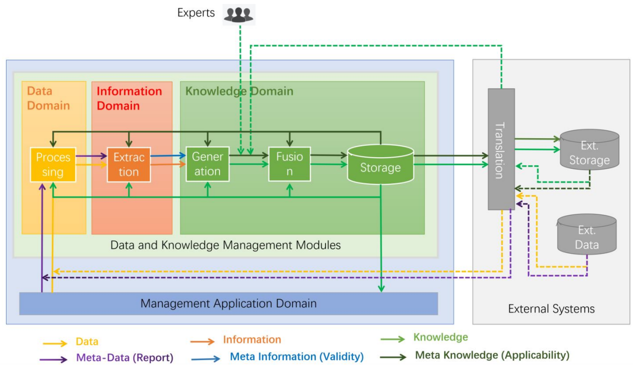

Fig. 3 – Architecture for extended knowledge management.

6.2.3 Active knowledge exploration

As shown in Fig. 4, active management functional architecture introduces a new knowledge recommendation sub-module to further support the knowledge requirements based on the knowledge management application domain, which actively excavates and recommends new knowledge if no exact match is found in the existing knowledge base, based on status monitoring, effectiveness evaluation and an active iterative updates on demand for the application of previously applied/recommended knowledge.

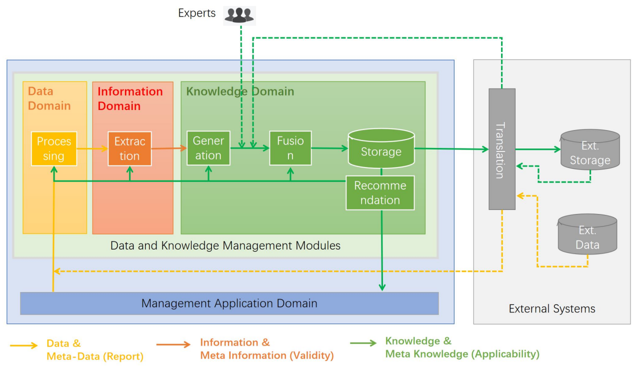

Fig. 4 – Architecture for active knowledge exploration.

6.3 Illustrative applications

This sections provides two illustrative applications enabled by the proposed architecture.

6.3.1 Policy management application

As shown in Fig. 5, the basic functional architecture for knowledge-driven policy management supports the static import, application, and update of policies. Specifically, it includes two sub-modules, conflict resolution (knowledge fusion) and policy storage (knowledge storage), to support policy knowledge import, application and passive update of OAM experts and external systems. As shown in Fig. 6, the extended functional architecture for knowledge-driven policy management further realizes the status monitoring, effectiveness evaluation, and on-demand active iterative updates of policy application

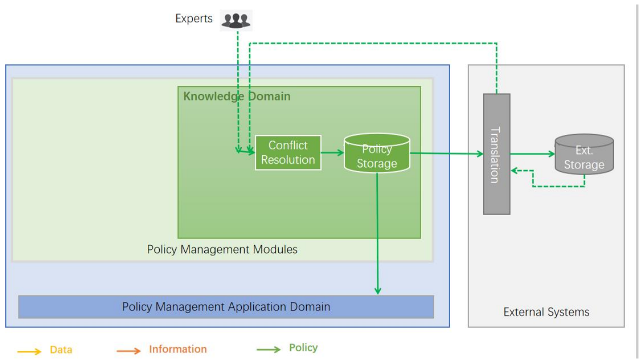

Fig. 5 – Basic knowledge-driven policy management.

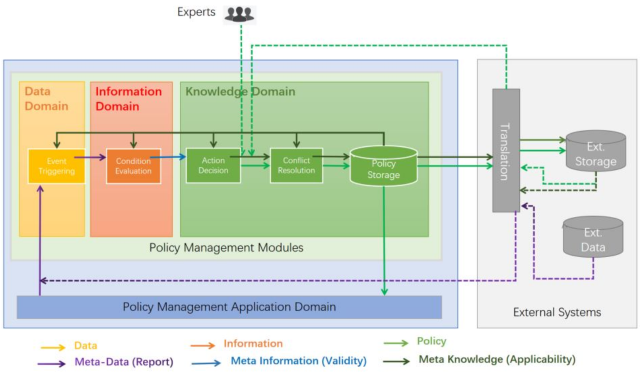

Fig. 6 – Extended knowledge-driven policy management.

by defining and supporting "meta-policies" in the policy management domain based on its basic functional architecture (supporting static import, application, and passive update of policies). By superimposing the management functions corresponding to the policy application meta-knowledge on the basic function architecture of policy management, including meta-policy event triggering (corresponding to policy monitoring report processing), meta-policy condition evaluation (corresponding to policy application effectiveness evaluation), and meta-policy action decision-making (corresponding to policy update and optimization), it cooperates with the existing conflict resolution and policy storage modules to complete the import, generation, processing, update, application and other functions of managing the corresponding meta-policies. In addition, policy-driven logic can be further introduced into the execution of each module of the original policy application domain and the conflict resolution function module, and the relevant policies are uniformly stored. As shown in Fig. 7, the active functional architecture for knowledge-driven policy management adds a new policy recommendation sub-module based on the extended functional architecture of policy management (supporting static import, application, monitoring, analysis, and dynamic update of policies) to further support policy requirements based on policy management application domains, actively mine and recommend new policies, and perform status monitoring, effectiveness evaluation, and on-demand active iterative updates of recommended policy applications.

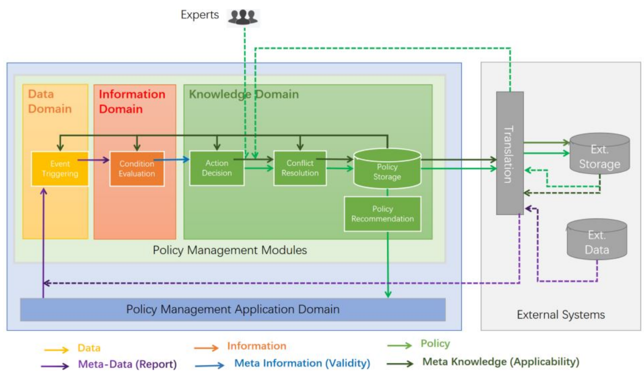

Fig. 7 – Active knowledge-driven policy management.

6.3.2 *AI/ML model management application*

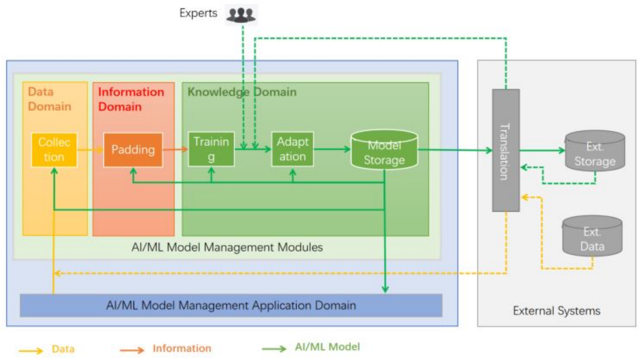

Fig. 8 – Basic for knowledge-driven AI/ML model management.

As shown in Fig. 8, the basic functional architecture for knowledge-driven AI/ML model management supports model training, external model import, model processing, model inference (application), and update, by including five sub-modules: data collection, data padding and preprocessing (information extraction), model training (knowledge generation), model processing (knowledge fusion), and model storage (knowledge storage). As

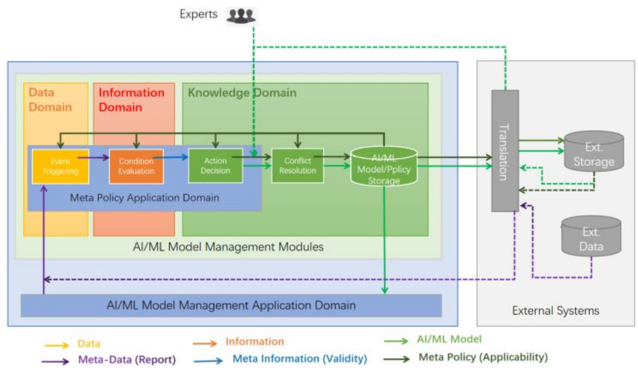

Fig. 9 – Extended knowledge-driven AI/ML model management.

shown in Fig. 9, based on its basic functional architecture, the extended functional architecture for knowledge-driven AI/ML model management further realizes the status monitoring, effectiveness evaluation and on-demand active iterative updates of AI /ML model applications by defining and supporting meta-policies in the AI/ML model knowledge management domain. As shown in

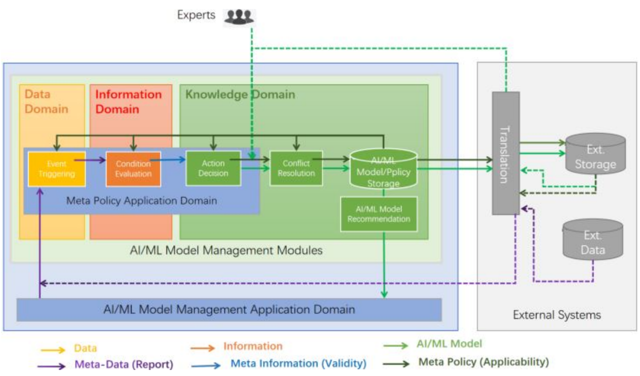

Fig. 10 – Active knowledge-driven AI/ML model management.

Fig. 10, on the basis of the extended functional architecture of AI/ML model management (supporting static import, application, monitoring, analysis and dynamic update of AI/ML models), the active management function architecture adds an AI/ML model recommendation submodule to further support the knowledge requirements of the AI/ML model knowledge management application domain, by actively mining and recommending AI/ML models, and conducting status monitoring, effectiveness evaluation and on-demand updates of the recommended AI/ML models in application.

6.4 Summary

In summary, the functional architecture described above addressed two key issues for autonomous network evolution:

•**Provision of a collaborative framework for data and knowledge.** Traditional knowledge-driven methods based on mathematical/physical models often have the characteristics of relatively complete theoretical support, but when the data-driven model is integrated, robustness and adaptiveness of the entire collaborative framework is considerably improved.

•**Enablement of an iterative evolution between data and knowledge.** Using knowledge to guide the generation of data models, inducting and generating new knowledge from data models, and forming alternate iterations of knowledge and data is an important path to enable the autonomous evolution of intelligent systems, and it is also an important way to implement the knowledge system that can be understood by people but surpasses the human knowledge system.

7. PHYSICAL ARCHITECTURE

This section provides an illustration of how to apply the above-mentioned logical architectures into realistic deployment scenarios for the OAM of production networks. Driven by the vision of autonomous networks, China Mobile strengthens the automatic operation and maintenance capabilities of network elements, network domain OAM, and service management systems, in realizing end-to-end service provisioning, automatic operation guarantee, and automatic quality optimization. In particular, two platforms are introduced in the company's network OAM blueprint, as shown in Fig. 11 [18], for cross-domain data sharing and intelligence enablement, respectively. In such context, an application architecture for the above funtional architecture is composed of two main parts, one for the data plane evolution and the other for knowledge plane integration.

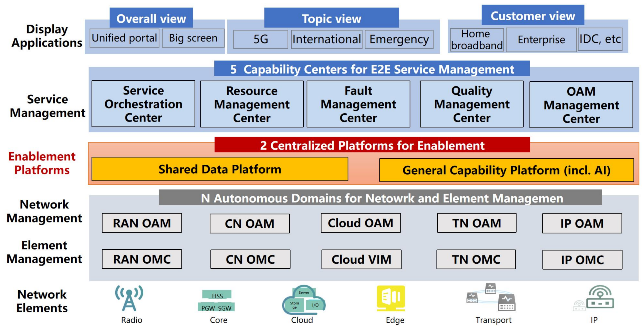

Fig. 11 – China Mobile's network OAM blueprint [18].

7.1 Data plane for evolving automation

•**Network element layer** has dynamic perception and automatic optimization of equipment components and operating status, and open automatic operation capabilities;

•**Element management layer** has opening equipment auto-configuration interfaces, and supporting cross-manufacturer collaborative management; and

•**Shared data platform** serves as the centralized data pool for various applications/systems in different layers.

•**Network management layer** realizing process integration, data sharing, and capability opening from the shared data platform to five operation and maintenance capability centers, and multiple domain OAM subsystems.

7.2 Knowledge plane for evolving intelligence

In terms of intelligence, the general capability platform is introduced to serve as the AI platform, which provides four types of AI capabilities, namely perception intelligence, diagnostic intelligence, predictive intelligence, and control intelligence, are built around the three scenarios of "image recognition for field operations, complex calculation of network strategies, and network big data analysis", energy saving and other fields for large-scale application.

There are three deployment options to implement the knowledge plane into the distributed intelligence ecosystem inside autonomous network architecture:

•**Centralized deployment**, where all the funtional submodules are integrated inside the central AI platform, which is applicable for "offline learning and offline application" slow-loop scenarios.

•**Distributed deployment**, where all the functional submodules are deployed aside to their application domain, with only initial configuration needed from the remote centralized platform, which is applicable for ”online learning and online application” quick-loop scenarios.

•**Hybrid deployment**, where the knowledge management sub-modules are deployed near to their application domain, while the meta-knowledge management sub-modules (as in extended architecture) are deployed in a centralized fashion, with unified monitoring and iteration on-demand triggered from remote center, which could be used in ”static/closed context” scenarios, when knowledge needs to be involved in a quick-loop application while its iteration could suffice with a slow-loop interation.

8. CONCLUSION AND NEXT STEPS

A data and knowledge collaborative architecture framework for the evolution of autonomous networks is given to accelerate the introduction of advanced technologies, efficiently promote industrial cooperation, and deepen network capacity building.

At present, the research on knowledge management standards for autonomous networks is in its infancy, leading the formulation of knowledge management standards in the context of autonomous networks, helping to guide the industry to reach a consensus on knowledge management, cross-domain knowledge-sharing and network intelligent applications; enabling knowledge management to facilitate the hierarchical evolution of network autonomy capacity building, and further promotes the standardization of existing network operation and maintenance processes.

In particular, three parties would be playing essential roles in the way forward:

•**Standards** for data collection, ontology models, knowledge representation, as well as general functional architecture to establish a unified mindset around collaborative endeavors of integrating knowledge management into autonomous networks.

•**Practice** in production from service providers by introducing into the existing network an operation and maintenance process to guide the application of and feedback into further research and development of systems or tooling for knowledge introduction, life cycle management, and cross-domain knowledge sharing.

•**Implementation** from network element/network management manufacturers to decouple domain knowledge management and business logic implementation, hence providing flexibility in reference implementation for centralized and cross-vendor knowledge sharing and applications.

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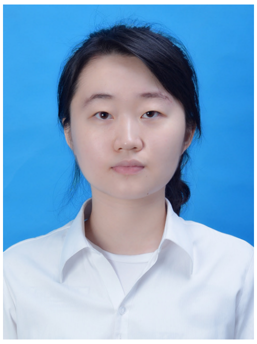

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