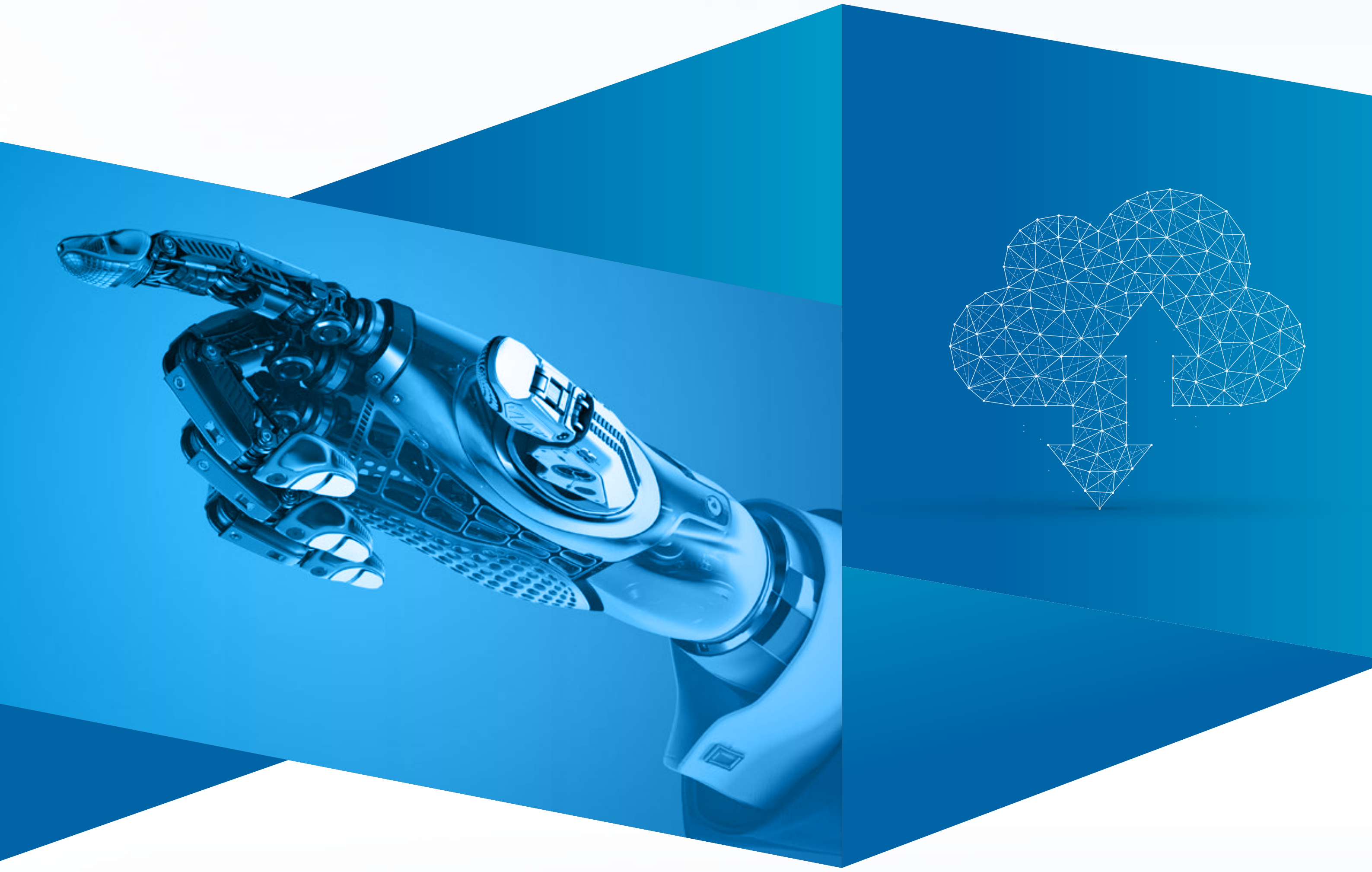

Enable Autonomous Driving Network

——Huawei Network AI Engine(NAIE) White Paper

Preface

Artificial intelligence has fluctuated through more than 60 years. With the development of computing power, innovation of algorithms, and accumulation of massive data , artificial intelligence (AI) will be rejuvenated in the next decade, become one of the most influential trends in science and technology.

As the infrastructure of information communication, telecommunication network has great space and potential for applying artificial intelligence technology. How to use the powerful analysis, judgment, and prediction capabilities provided by the AI algorithm to enable Network Elements, networks, and service systems, and combine them with the planning, construction, maintenance, operation, and optimization of telecom networks, become an important topic in the telecom industry.

Based on deep understanding , accumulated experience in telecom field, and long-term investment in the All Intelligence strategy, Huawei introduces the AI technology to the telecom network based on the full cloudification of the network and launches the iMaster NAIE solution. Based on the application scenarios in the telecom field, the network can be automatically deployed (automatic service deployment and automatic running), self-healing (automatic fault recovery), self-optimization (network self-optimization), and autonomous (network self-evolution), which improves the network efficiency and reduces the OPEX.

This white paper will explain Huawei's practice in Telecom AI field based on the background of the market trend of telecom networks. It includes the autonomous driving network strategy interpretation, NAIE(Network AI Engine) solution (including the communication intelligent platform, AI model service, and deployment solution), and typical application scenarios. It is highly expected to make values to all the colleagues who are engaged in the exploration of telecom AI.

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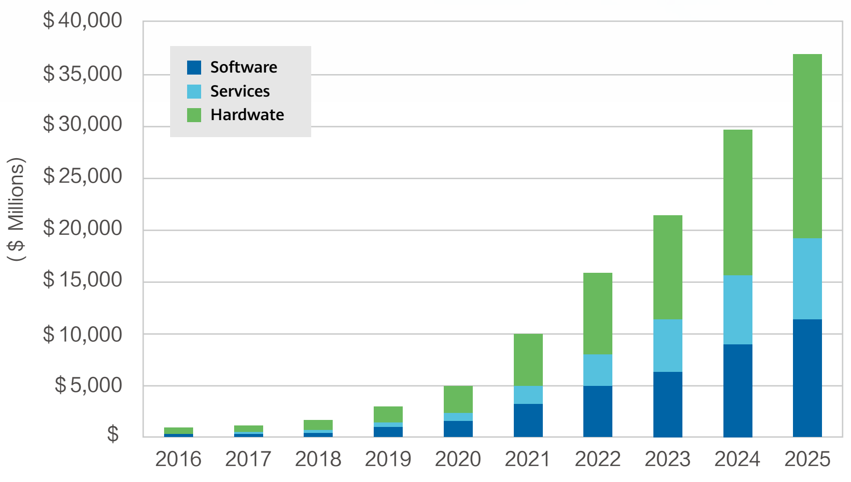
Telecom AI Market Overview

1）Telecom AI Market Trend

Telecom Industry Is Becoming the Largest AI Market—Network Automation Will Reach a Turning Point in 2021

Tractica/Ovum forecasts that global telecom industry investment in artificial intelligence (AI) software, hardware, and services will reach US$36.7 billion by 2025. The telecom industry is becoming the largest AI market. Telecom AI software revenue will grow from USD315.7 million in 2016 to USD11.3 billion in 2025, at a compound annual growth rate (CAGR) of 48.8%. Network automation will reach a turning point in 2021, as operators increasingly adopt SDN and NFV and deploy 5G networks.

Telecom AI Total Revenue by Segment, World Markets: 2016-2025



(Source:Tractica)

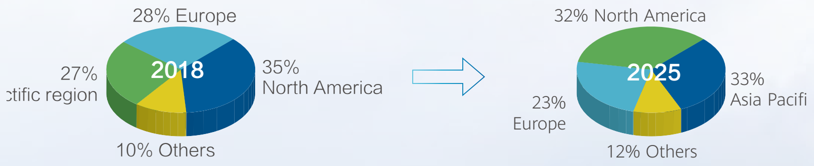
According to International Data Corporation (IDC), 63.5% of telecom organizations are investing in AI to improve their infrastructure construction, while the other 31.5% are focusing on utilizing existing investments or infrastructure.

63.5% of telecom organizations are investing in AI
36.5% of telecom organizations are focusing on tyilizing existing investments

Source：IDC

North America, Europe, and the Asia Pacific Region Will Account for 90% of Global Telecom AI Software Revenue

The key telecom AI markets will be North America, Europe, and the Asia Pacific region, in which AI software revenue will account for 90% of global revenue according to the forecast by Tractica/Ovum. The North American market will lead in telecom AI software revenue until 2025, at which point the Asia Pacific region is projected to take the top spot. Revenue in the Asia Pacific region will be significantly boosted after 2021.

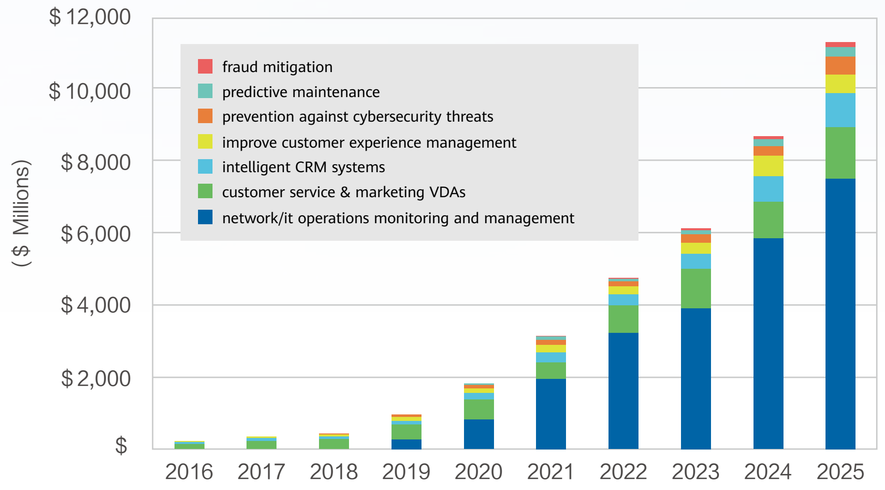


Network Optimization Will Be the Leading AI Application in the Telecom Market

According to the report from Tractica/Ovum, the leading AI application in the telecom industry will be network or IT operations monitoring and management, accounting for nearly 61% of total telecom AI expenditure between 2016 and 2025. Other key AI applications will include virtual digital assistants (VDAs) for customer service and marketing, intelligent customer relationship management (CRM) systems, customer experience management, and cyber security.

To put it simply, network or IT operations monitoring and management refer to network optimization. Operators use AI technologies to understand network events in real time and dynamically adjust their networks for service delivery. AI-driven network management solutions involve the following: network design, network load balancing, and network coverage and capacity optimization.

Telecom AI Software Revenue by Use Case, World Markets: 2016-2025



(Source:Tractica)

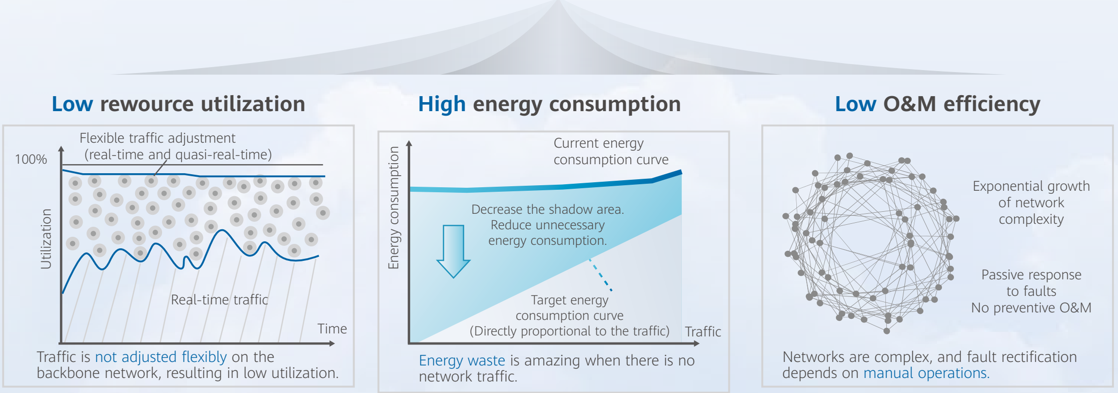
2）Opportunities and Challenges Facing Operators

An era of cross-industry competition is approaching. Each industry is facing structural challenges, especially the telecom industry.

First, from the perspective of revenue structure, operators' services are facing challenges from the IT industry. In the past, telecom services were divided into three layers: user devices, networks and IT infrastructure, and upper-layer applications. Network access rates have increased greatly and continue to increase, and the IT industry is shifting its focus from selling products to selling services. Backbone networks and IT infrastructure are now provided as cloud services. If operators can do well in cloud services, they can compete with cloud service giants, such as AWS, to seize trillion-dollar market shares. Otherwise, operators may also lose many traditional telecom services, such as the voice service, SMS, and private line services between data centers (DCs).

Second, operators' efficiency and costs are also facing structural challenges. Nowadays, the structure of telecom networks is complex. As a result, the operating expenditure (OPEX) due to device maintenance is about three times the capital expenditure (CAPEX). Operators are facing the following problems.

OPEX
≈3 times of CAPEX



Low rewource utilization
Flexible traffic adjustment (real-time and quasi-real-time)
100%
Utilization
Real-time traffic
Time
High energy consumption
Energy consumption
Current energy consumption curve
Decrease the shadow area. Reduce unnecessary energy consumption.
Target energy consumption curve (Directly proportional to the traffic)
Traffic
Low O&M efficiency
Exponential growth of network complexity
Passive response to faults No preventive O&M

Traffic is not adjusted flexibly on the backbone network, resulting in low utilization.

Energy waste is amazing when there is no network traffic.

Networks are complex, and fault rectification depends on manual operations.

Low resource utilization: Wireless resources, IP addresses, and optical transmission resources are not fully utilized. For example, the utilization of IP backbone networks between hotspot DCs is close to 70%, but the network utilization between non-hotspot DCs is only 30%. Supply and demand are not balanced, and elastic traffic adjustment is not provided. As a result, network utilization is low. The traditional Massive MIMO beam and tilt parameters of wireless base stations are roughly estimated based on user distribution and cannot be accurately adjusted based on traffic distribution, interference, or cell load. The air interface resource utilization is low.

High energy consumption: The energy consumption of base stations does not decrease with the decrease of network traffic. Energy waste is severe. The data center power usage effectiveness (PUE) remains high, and the ratio of cooling energy consumption to non-IT system power consumption is high.

Low O&M efficiency: According to Gartner's report, 37% of network faults are caused by network changes. Network structures are becoming increasingly complicated, creating network operations and maintenance (O&M) challenges that too complex to address manually. 75% of network problems are found only when customers submit complaints to operators. Customer experience and satisfaction are difficult to guarantee. O&M personnel spend 90% of their time on fault location.

75% of network problems are reported by end users.

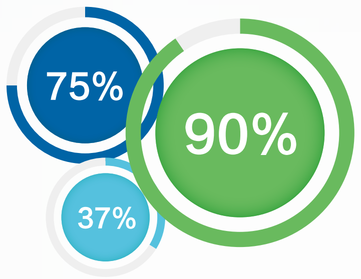
・ It is difficult to pre-emptively address potential network faults.

・ Customer experience and satisfaction are difficult to ensure.

37% of network faults are caused by network changes.

・ Network complexity increases exponentially with time. The four generations of basic networks are symbiotic (2G, 3G, 4G, and 5G), and the ten domains of the core network coexist (such as CS, PS, IMS, and IoT).

・ Network management has become too complex for human minds to cope with. People can understand only 3 to 4 dimensions (X, Y, Z, plus a limited grasp of time). Network management involves N dimensions.



O&M personnel spend 90% of their time locating problems.

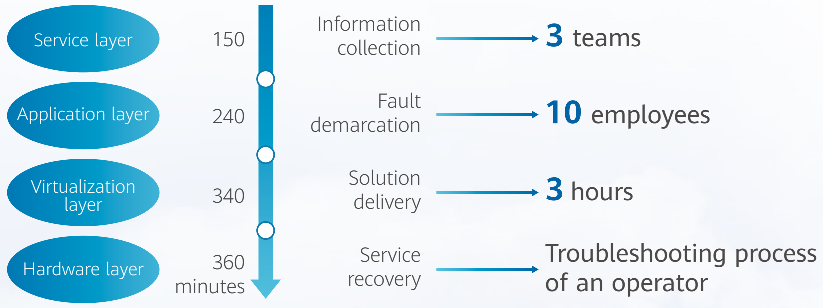
・ Network problem sources are difficult to trace and cross-domain problems are difficult to demarcate.

・ The demarcation of a problem's root cause is difficult and relies heavily on experts' experience.

Source: Gartner

With the introduction of the network functions virtualization (NFV) and software-defined networking (SDN) technologies to telecom networks, network cloudification and layered decoupling greatly improve operations efficiency. However, cross-layer fault demarcation and analysis require the participation of multiple teams. The analysis efficiency is low and the maintenance and emergency recovery requirements of a large number of sites cannot be met.

Layered Network Decoupling Is Supported, but Manual Troubleshooting Is Time-consuming and Labor-intensive



Mere product innovation is insufficient to address the challenges faced by the telecom industry. Innovation at the level of the system architecture and business model is needed, to improve operator competitiveness and resolve structural problems. To give a clearer idea of what this means, we can take cloud computing as an example. System architecture innovation is not innovation at the level of a server or storage product. Instead, it uses a new distributed system to improve resource utilization efficiency and is a system-level innovation. Product innovation, system architecture innovation, and business model innovation mutually support each other. The innovation system of the telecom network AI must be designed based on the three dimensions. At the product level, the idea of designing network devices is "Olympic spirit", that is, large capacity and low latency. The goal of system architecture innovation is to build agile and intelligent networks. In the business model innovation, the online intelligent service mode will be constructed.

3）Operators Are Taking Action

Top Three Operators in China

The top three operators in China have been actively engaged in AI technologies. China Mobile has released an AI platform — Jiutian, which is mainly used in areas such as intelligent customer service, deep learning platforms, intelligent marketing bots, and network intelligence. Jiutian dives deep into the telecom industry and focuses on operators' market operations, networks, and services. Furthermore, driven by application scenarios, it provides end-to-end (E2E) AI application solutions and implementation for vertical industries.

China Telecom and its partners have jointly built an AI open platform — Dengta, which focuses on enablement and is mainly used in areas such as the smart home, intelligent customer service, and user identification.

Since its partial privatization in 2017, China Unicom has cooperated with Baidu and other partners to engage in AI technologies. It is reported that China Unicom is currently cooperating with Baidu, iFLYTEK, FiberHome and other companies on AI projects. China Unicom is working with iFLYTEK on smart devices and with FiberHome on smart cities. The cooperation between China Unicom and FiberHome promotes the development of standards in the smart city sphere.

Operators Outside China

Telefonica has launched a new AI project and enabled AI analysis technologies in three service operations centers (in Argentina, Chile, and Germany) for mobile network usage analysis and problematic region prediction. In addition, Telefonica use AI technologies to obtain user experience data in real time, helping discover new methods for improving user experience.

SoftBank has acquired a number of AI companies and collaborated with IBM to introduce the Watson AI system into its own network. NTT has also launched an AI platform, focusing on four AI technologies: Agent-AI, Heart-Touching-AI, Ambient-AI, and Network-AI.

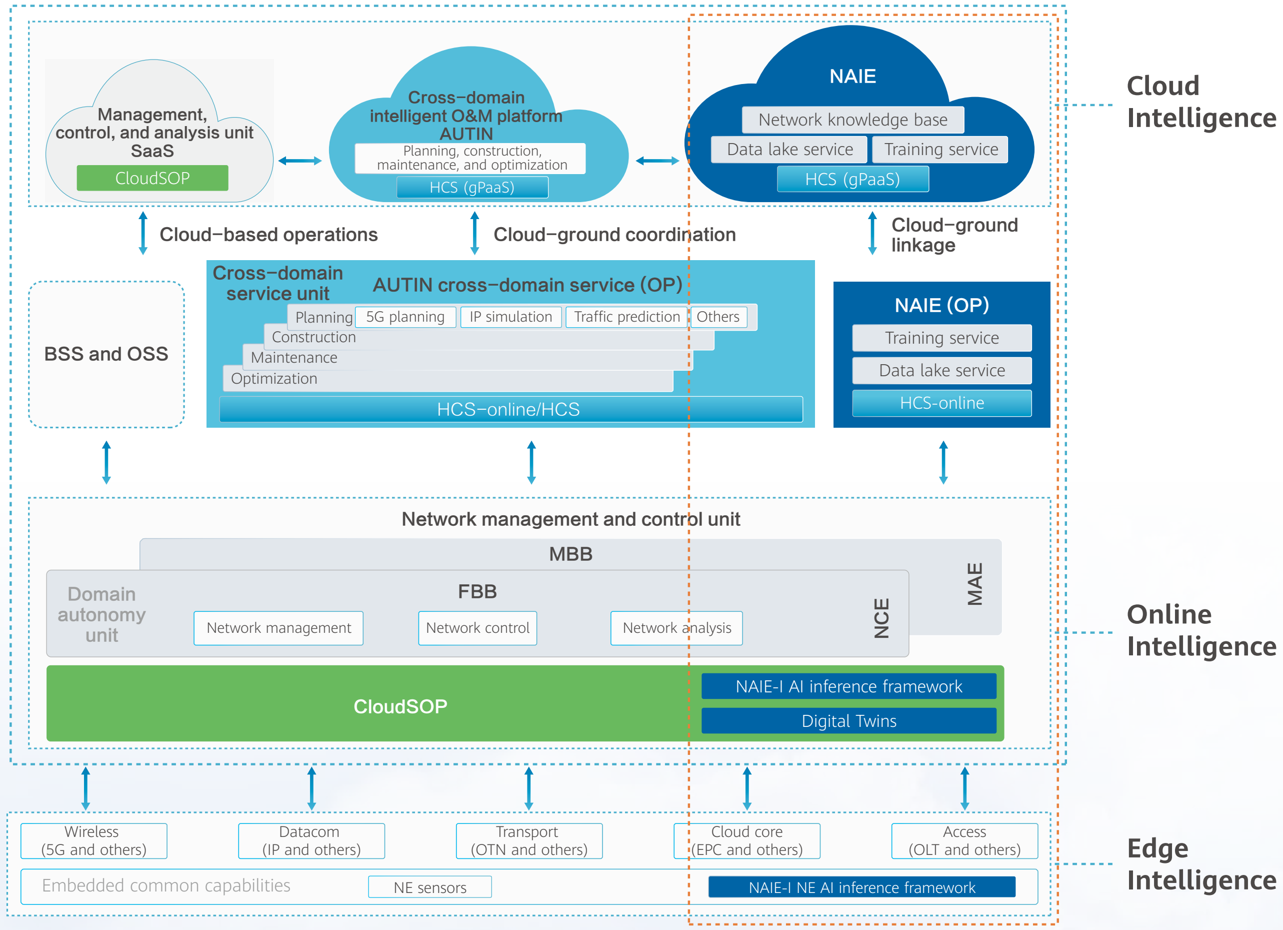
In recent years, the use of AI technologies to explore new business opportunities and improve network performance and customer experience has become the top concern of operators. Although they face many challenges, not least because they are entering the AI market later than incumbent Internet giants, telecom operators cannot afford to neglect the AI domain.

Huawei's Autonomous Driving Network Strategies Explained

1) Huawei Autonomous Driving Network Brief

The autonomous driving network is a telecom network automation and intelligent solution. It atomizes network capabilities and forms network resources. The centralized network control unit schedules network resources in a unified manner to support global orchestration of upper-layer service orchestrator. The autonomous driving network can improve carriers' operation efficiency and is a key part of carriers' digital transformation.

The autonomous driving network is divided into three layers: The physical network is digitalized gradually to generate and collect more network data and implement edge intelligence. The AI inference framework is added. Network management and control systems and cross-domain network management and control systems in each domain are gradually automated to implement online intelligence. In the cloud. an AI platform is added to implement data management and model training to implement cloud intelligence.



iMaster NAIE Enables ADN

Autonomous driving network, the iMaster NAIE builds data lake and AI training platform in the cloud, an AI inference framework in the control unit and each NE device. As a solution of Huawei's service domain, the AUTIN solution provides network planning, construction, maintenance, and optimization of automatic and intelligent services throughout the entire process. MAE is the (MBB) automation and intelligent solution in the mobile broadband domain. NCE is the (FBB) automation and intelligent solution in the fixed broadband domain. NAIE is an intelligent automatic driving network enabler that provides basic AI data management and model training services for service, wireless, fixed network, core network, and data center domains. The trained model can be used for inference analysis in various fields, helping each domain effectively realize automation and intelligence.

This white paper focuses on the NAIE (Network AI Engine) solution and its practice which is the intelligent engine of autonomous driving network.

2) Five Development Phases of Autonomous Networks

The development of autonomous networks is a long-term process and cannot be accomplished at one stroke. Self-driving cars are rated according to five levels. Using a similar scheme, Huawei proposes five levels for autonomous networks, taking into account aspects of customer experience, network environment complexity, and automation.

Level Definition	L0: Manual Operation & Maintenance	L1: Assisted Operation & Maintenance	L2: Partial Autonomous Network	L3: Conditional Autonomous Network	L4: Highly Autonomous Network	L5:Full Autonomous Network
Execution (Hands)	👤	👤 🤖	🤖	🤖	🤖	🤖
Awareness (Eyes)	👤	👤	👤 🤖	🤖	🤖	🤖
Decision (Minds)	👤	👤	👤	👤 🤖	👤 🤖	🤖
Service Expenrience	👤	👤	👤	👤	👤 🤖	🤖
System Complexity	Not appliable	Sub-task Mode-specific	Unit-level Mode-specific	Domain level Mode-specific	Service level Mode-specific	All modes

L0: manual O&M with auxiliary monitoring capabilities. All dynamic O&M tasks are performed manually.

L1: assisted O&M. The system repeatedly executes a subtask based on known rules (for example, GUI-based configuration wizard or script-based batch configuration tools). This simplifies operations, lowers skill requirements, and improves efficiency of recurring tasks.

L2: partial autonomous network. The system continuously executes a specific control task in a unit based on a certain model. For example, in the cloud computing scenario, the data center network (DCN) provides APIs for the system, so that the system can perform automatic network configuration operations according to the scheduling requirements of cloud platforms such as the OpenStack. The entire process requires no manual operations.

L3: conditional autonomous network. L3 differs from L2 in that the system can observe and analyze a specific environment that changes dynamically and perform automatic control operations to maintain a desired state. L3 indicates that the system can continuously execute a control task for a given objective within a single domain. For example, within a single domain, the system can use AI technologies to complete the operations of alarm aggregation and fault scenario identification. Fault location modules are triggered to quickly find troubleshooting measures and automatically dispatch trouble tickets.

L4: highly autonomous network. Compared with L3, the major change of L4 is that the system can implement autonomous networks based on customer experience in more complicated cross-domain service scenarios. For example, for the home broadband service, the system perceives and analyzes customer experience in real time, continuously identifies network anomalies that change dynamically, and proactively optimizes customer experience, rectifies faults, or automatically dispatches trouble tickets based on customer experience-related and network anomalies. In this way, the system can implement predictive O&M and resolve problems before customer complaints are lodged, minimizing service interruption and significantly improving customer satisfaction.

L5: fully autonomous network. A fully autonomous network that works under all network conditions and across all service domains is almost impossible to construct. However, it is worth exploring and innovating in cloud DCs or on fully virtualized networks with simple services and high network standardization.

3）Introduction of Unique AI Features

The new value of introducing AI into telecom networks is predictability. The management and control center of a telecom network uses certain policies and rules to manage and schedule the entire network based on the southbound interface and data collection of equipment. These rules and policies are based on three factors: network reachability, service level agreement (SLA), and resource utilization efficiency. These three factors are the basis of network automation. However, as networks become increasingly complex, other factors must also be taken into account. Algorithm-based network management and online AI inference and data analysis need to be introduced to provide traffic prediction, quality prediction, and fault prediction. Prediction is the core value of AI. Network resources can be scheduled based on unknown conditions to locate faults before faults occurs, optimize quality before quality is deteriorated, and adjust traffic before networks are congested. This helps provide steadfast autonomous networks that have features of automation, self-optimization, self-healing, and autonomy, structurally improving the O&M efficiency.

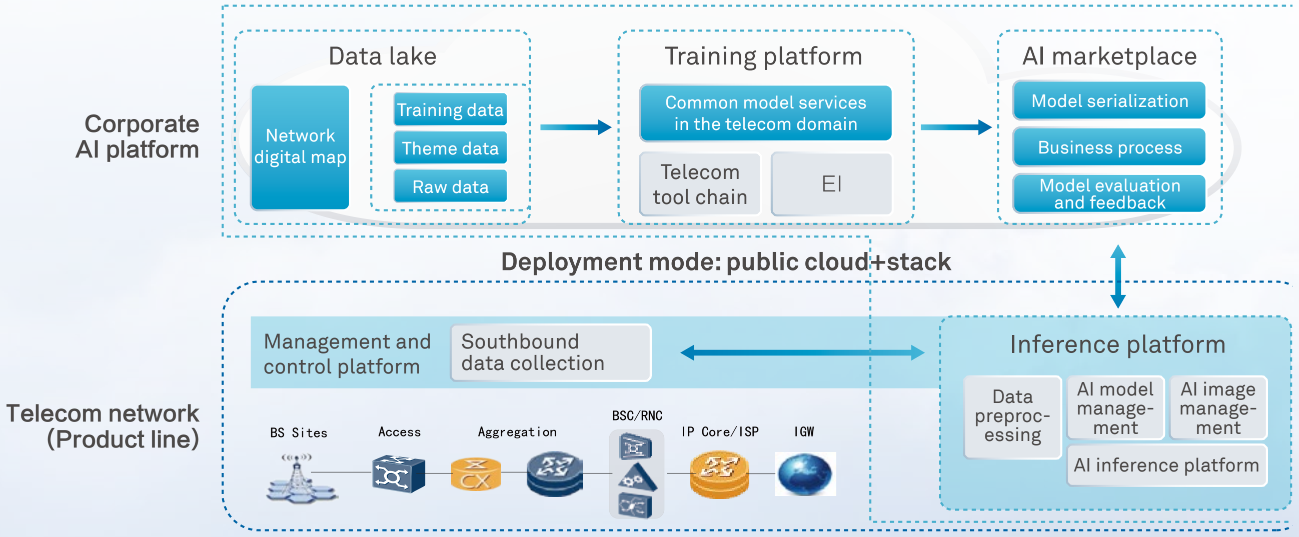
Huawei iMaster NAIE Solution

1）Solution Overview

The iMaster NAIE(Network AI Engine) solution consists of four parts: data lake, training platform, AI Marketplace, and inference framework. The inference module in the inference framework collects training data from the device control platform, and sends the data to the data lake for data preprocessing, or directly sends the data to the training platform for data training (raw data can be used on the training platform without being preprocessed in the data lake). After the training platform completes the training, the trained model is released to the AI Marketplace. Then the AI Marketplace pushes the model to the inference module.

The inference platform invokes a service model to perform inference and analysis based on real-time network data, and delivers the inference result to the control platform or NEs, on which the inference result is executed to control network behavior. The analysis result of network behavior is collected for further model training and optimization. In this way, the closed-loop control is implemented.

The following sections describe the data lake, training platform, and inference framework in detail.



2）Data Lake

Pain Points: Data acquisition is difficult and data quality is poor in the telecom industry.

Difficulty of data acquisition

Although telecom networks have a large amount of data, very little of it can be effectively used. This is due to the fact that data semantics, data formats, and data storage, management, and application mechanisms of different organization levels and departments are inconsistent, and data usage is strictly supervised and restricted. For example, for abnormal KPI detection, the number of abnormal samples on the network is small and the samples are difficult to obtain.

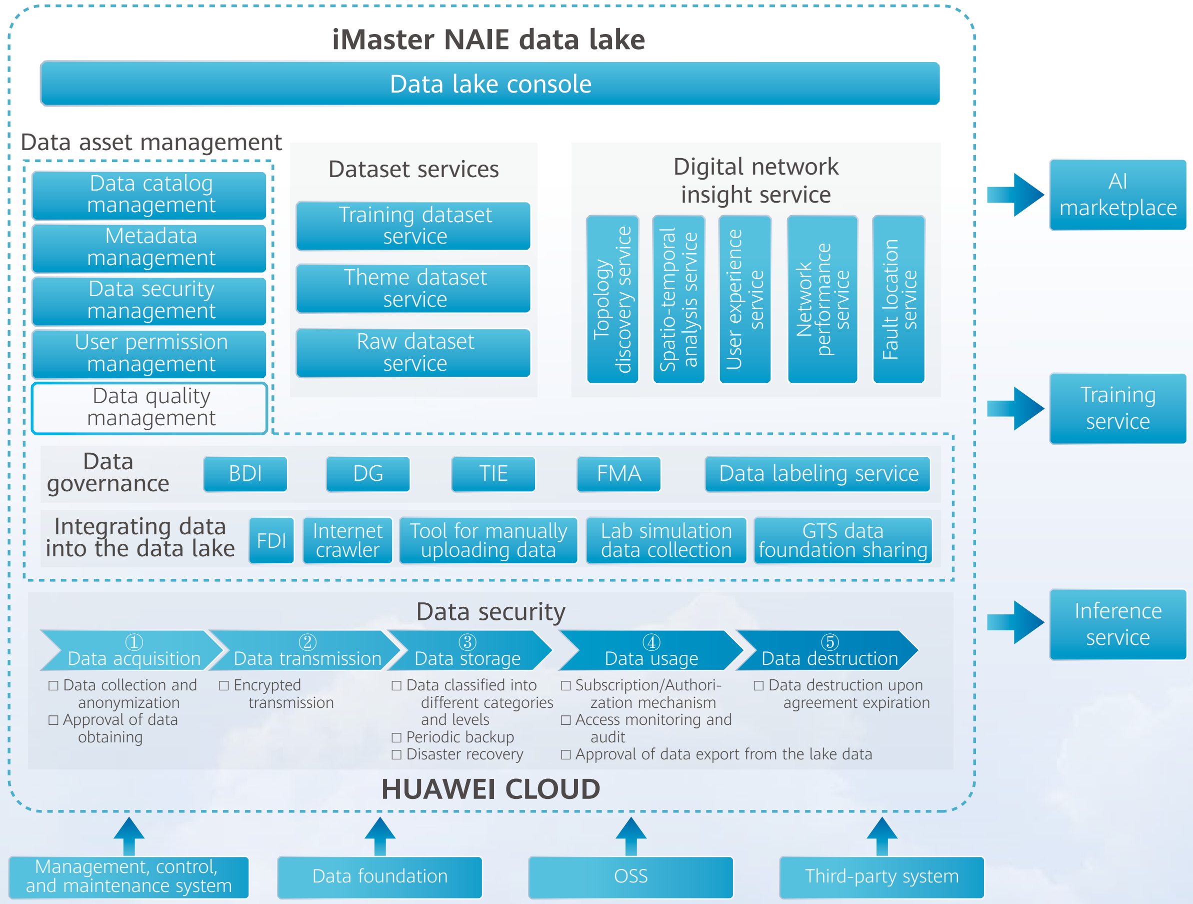
Difficulty of data governance
Because the telecom domain is highly specialized, it is difficult to understand data and create models.

Poor data quality
Data may be missing, abnormal, or repeated. Poor-quality data cannot be used.

High data security risks
Data platforms and data itself have security vulnerabilities. If a security event occurs, its impact is great.

Main Functions and Highlights

The data lake of the iMaster NAIE solution provides subject and training dataset services. The data lake can precisely meet various model training requirements and provide data governance services based on experts' experience and live network feedback. Data asset management is supported, such as data catalog, metadata, data security, and user permission management.



- An abundance of data and 90% decrease in training set acquisition time: The data lake focuses on the 4 major AI trends that operators pay attention to, and accumulates tens of millions of labeled sample data points gleaned from telecom networks.

Comprehensive network data
More than 1,000 AI training sets and more than 30,000 network feature attributes are included. Anonymized data of major NEs in all domains is obtained, including data on the access network, bearer network, and core network, and in DCs. Data is obtained through formal channels, for example, data on operators' networks (authorization is obtained) and in Huawei's historical fault library, and data generated in labs.

Abundant labeled sample data
A professional team labels data based on time, fault root causes, and network status to form high-value sample sets. Currently, there are about 100 million labeled samples.

- Efficient telecom data governance and over 5-fold data processing efficiency improvement: Efficient data governance and application development are implemented based on the one-stop extract, transform, and load (ETL) platform and visualization of data and networks.

Easy-to-understand data attributes
The data lake integrates Huawei data dictionaries in all service domains, lowering the knowledge threshold for users to process Huawei telecom equipment data.

Easy-to-understand data relationships
Data (such as user experience, network, status, and topology data) is associated to establish a data relationship map based on the mapping between the data and telecom networks (subject domain and digital network map). In this way, data and data relationship are visualized, so that users can easily understand and use the data relationship and network services.

High efficiency of data governance tools
The data lake supports the import of a number of common file formats (including .txt, .csv, .xml, .gzip, and .json files) and automatic ELT processing capability. The data lake constitutes a single hub where data cleansing, conversion, and governance can all be implemented.

- Good telecom data quality: The layer- and domain-based telecom data quality management capability is built, providing data assets with unified quality standards.

Systematic data quality standards
Data quality metrics, governance rules, and audit rules, and data model quality constraints are defined for different data sources and subject domains based on experts' experience and industry standards.

Telecom data quality monitoring and evaluation tools
The tool-based data quality management capability is provided to ensure high data quality.

Specialized data governance team
The team is responsible for standardized operations such as data cleansing, conversion, denoising to ensure high data quality. Users only need to focus on application development.

- Multi-tenancy isolation, implementing E2E user data security: Data can be managed, audited, and traced throughout the data lifecycle, and fine-grained permission control is implemented. In this way, data security governance and compliance with data use regulations can be guaranteed.

Full-lifecycle monitoring of data
Systematic security logs are provided throughout the data lifecycle, so that data can be managed, audited, and traced.

Secure data storage
Data is stored based on categories and levels. Measures such as data encryption and bucket isolation are used to prevent data from being used by unauthorized users.

Secure data usage
Fine-grained permission control of data and table-level permission control of databases are supported. A certain resource or user is visualized, and can be searched for and assigned permissions.

3）Training Platform

Pain Points: Technical requirements are high, efficiency is low, and effects are uncontrollable in terms of AI application development in the telecom industry.

Insufficient service knowledge：Algorithm scientists need to spend a lot of time understanding service scenarios. In the telecom domain, AI technology accumulation is insufficient and operators have little relevant experience to draw on.

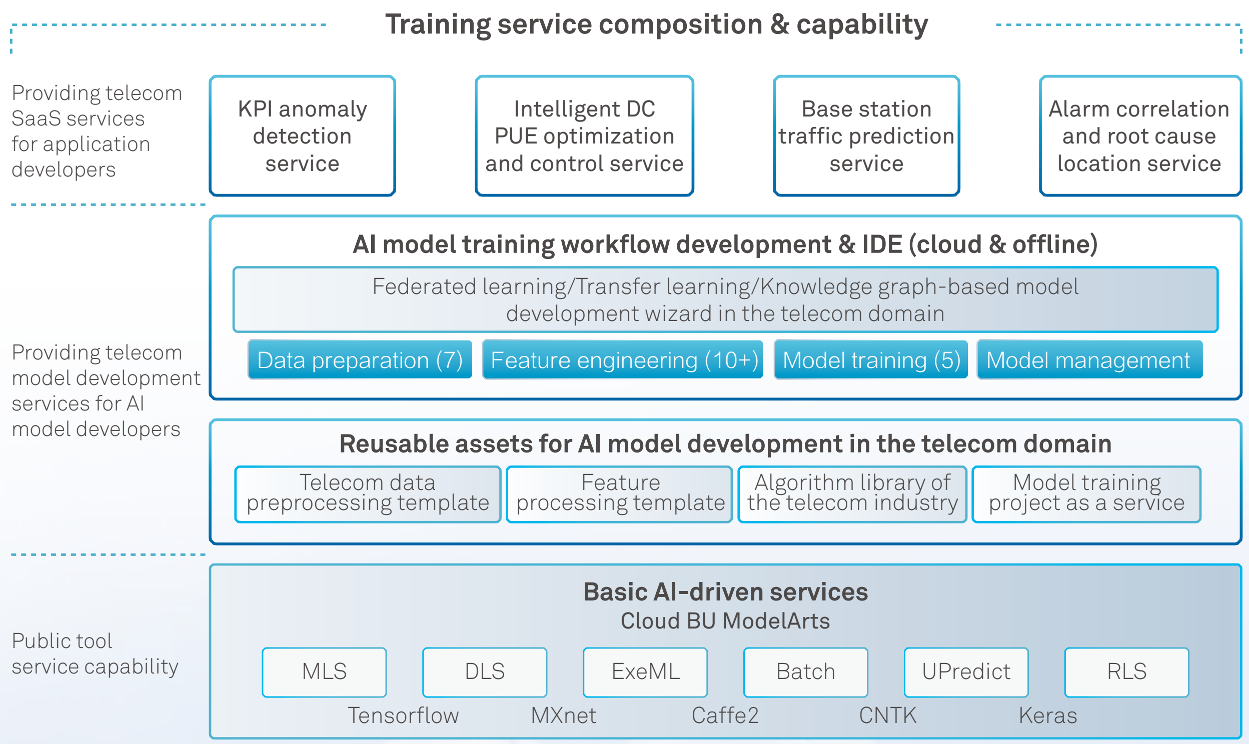
Low algorithm development efficiency: There is a wide range of AI algorithms to choose from and the trial-and-error costs are high. Online development tools have no intelligent prompt and breakpoint debugging capabilities. The code development efficiency is low.

Long model training period: Model training depends on a large number of expensive computing resources. The optimization period of hyperparameters is long, and the time required for a single training is long.

Poor model replicability: Models heavily rely on data. Therefore, it is difficult to replicate the delivery mode among different sites. The actual application effect is uncontrollable.

Main Functions and Highlights

The training platform of the iMaster NAIE solution supports efficient one-stop model training and quick model verification. It integrates processing capability for telecom domain features (meaning that key features can be quickly identified), and has built-in AI algorithms for exception detection, root cause analysis, optimization control, and service prediction.


Training service composition & capability
Providing telecom SaaS services for application developers
KPI anomaly detection service
Intelligent DC PUE optimization and control service
Base station traffic prediction service
Alarm correlation and root cause location service
Providing telecom model development services for AI model developers
AI model training workflow development & IDE (cloud & offline)
Federated learning/Transfer learning/Knowledge graph-based model development wizard in the telecom domain
Data preparation (7)
Feature engineering (10+)
Model training (5)
Model management
Reusable assets for AI model development in the telecom domain
Telecom data preprocessing template
Feature processing template
Algorithm library of the telecom industry
Model training project as a service
Public tool service capability
Basic AI-driven services
Cloud BU ModelArts
MLS
DLS
ExeML
Batch
UPredict
RLS
Tensorflow
MXnet
Caffe2
CNTK
Keras

Embedded telecom experience: The training platform is preconfigured with four classes of more than 30 pre-integrated telecom model services. No coding is required. Model services are provided, including traffic prediction, KPI anomaly detection, intelligent control, and alarm correlation. Experience in the telecom domain is standardized as services, and users can obtain models by simply entering data. The wizard-based model development process provides telecom templates for data preparation, feature extraction, and model training, improving training efficiency. The platform integrates the telecom knowledge graph, with more than 50 built-in data analysis tools. Telecom experience is converted into tools to facilitate decision making by experts.

Efficient tools: Federated learning, distributed model training, and joint training are supported, to facilitate the creation of models that can cope with the small data volume and data loss scenarios that occur in the telecom domain, and to meet the data security requirements of the industry. Transfer learning is supported for quick model adaptation, that is, model training on a non-first site can be implemented with a small amount of data. Enhanced data processing capabilities such as parameter editing, sample evaluation, intelligent repair, and script repair are provided, and data distribution is visualized. An E2E development and deployment environment is provided, so that data preparation, feature extraction, model training, model rollout, model sale, and model deployment can all be performed on one platform.

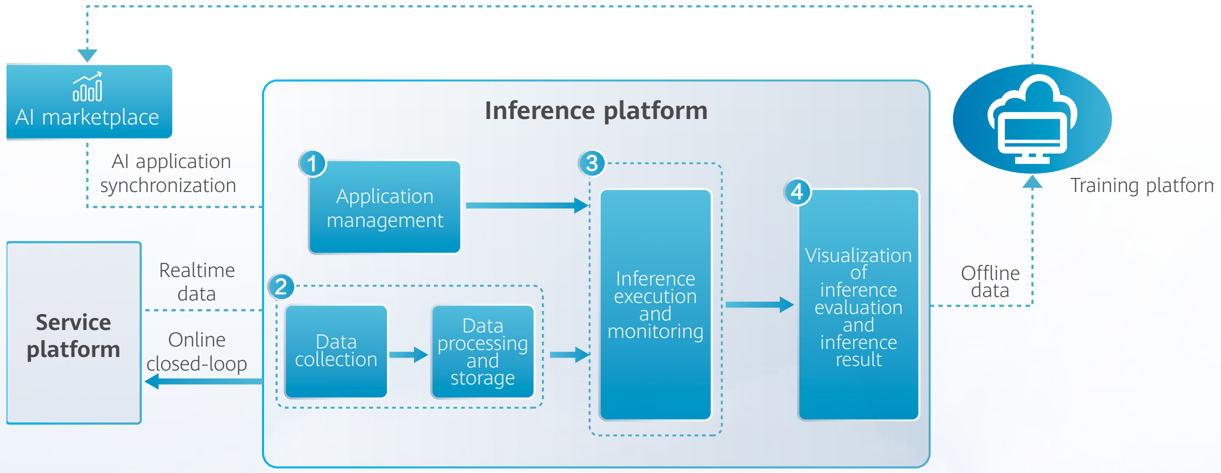
Openness and collaboration: An offline integrated development environment (IDE) is provided for collaborative development with the cloud platform. Members of the same development team can collaborate. The platform supports multiple machine algorithm frameworks and algorithm transplantation. All mainstream algorithm frameworks are supported, such as TensorFlow, MXNet, Caffe2, and Spark ML. Tools are provided to quickly transplant algorithms developed on other platforms to Huawei's platform.

4）Inference Framework

Pain Points: The development period of inference applications is long and model effects are difficult to evaluate.

Typical AI inference applications include data collection, data preprocessing, model execution, inference result delivery, and inference result evaluation. Development personnel need to develop each component or service. Development is time consuming and component interconnection is complex. After the application is brought online, the service O&M pressure is high, the actual running effect of the model is difficult to predict, and application value cannot be manifested.

Main Functions and Highlights:


AI marketplace
AI application synchronization
Service platform
Realtime data
Online closed-loop
Inference platform
1
Application management
2
Data collection
Data processing and storage
3
Inference execution and monitoring
4
Visualization of inference evaluation and inference result
Training platform
Offline data

Main Functions

The inference framework supports the following functions:

Application management：The browsing, subscription, automatic update, installation, deployment, and gray release of application models are supported. (Gray release refers to a launch mode that allows for smooth transition from a gray version to an official version.) A/B testing is a type of gray release. Some users continue to use the original version (A), while some other users start to use the new version (B). If users of version B approve of this new version, all users will be gradually migrated to version B. Gray release enables fault discovery and rectification in the early stage, minimizing the negative impact of upgrade on the system and ensuring the system stability.) Convergent orchestration and scheduling of multiple models are supported.

Data collection and processing: Cross-network data transmission is supported. Raw data such as NE topologies, alarms, and KPIs can be collected from various network management systems and service systems. The inference framework imports raw data through a real-time flow or in batches, and then cleans and converts the raw data.

Inference execution and monitoring: The TensorFlow library for deep learning, MLlib library for machine learning, and Python/Java AI model running framework are supported. The inference framework supports the inference execution, scheduling, and monitoring of multiple models, and provides APIs for external systems.

Inference evaluation: Inference results can be automatically evaluated or manually evaluated by users. The inference framework supports inference visualization, historical inference result query, and statistics report generation.

Highlights

The inference framework has the following key highlights:

Agile rollout of application models: The inference framework supports one-click subscription, automatic deployment, real-time monitoring, automatic scaling, flow control, fault self-healing, and simplified O&M management of AI cases. The inference framework is easy to upgrade and is decoupled from service systems. Independent upgrade and gray release of applications and models are supported. Various inference modes are supported, including one-off, batch, real-time, asynchronous, streaming, and scheduled inference.

Online model optimization: Online incremental learning and self-optimization capabilities are provided. Online data can be used for incremental learning to obtain optimal values of measurement indicators such as model precision. The inference framework is integrated with the best practices and professional knowledge in the telecom domain and is combined with AI reinforcement learning to provide O&M support and experience in the telecom domain.

Intelligent feedback evaluation: Model inference results are displayed in real time, so that users can quickly complete inference result feedback and high-value data can be generated for users. Based on the inference feedback, the inference framework periodically and automatically collects statistics on model performance and generates an inference evaluation dataset for further model optimization.

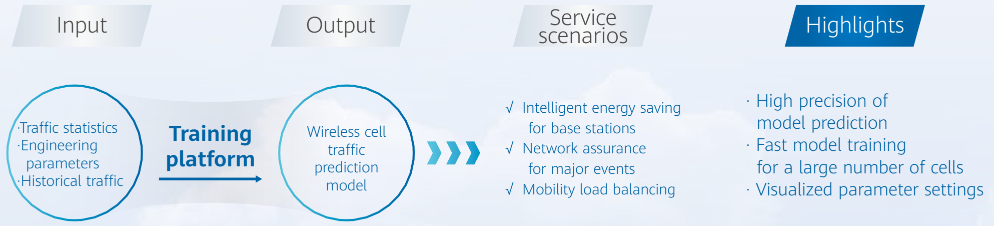
5）Telecom AI Model Services

Model Generation Services:

The following professional and efficient AI model generation services with applications in the telecom domain are provided based on the Huawei iMaster NAIE training platform:

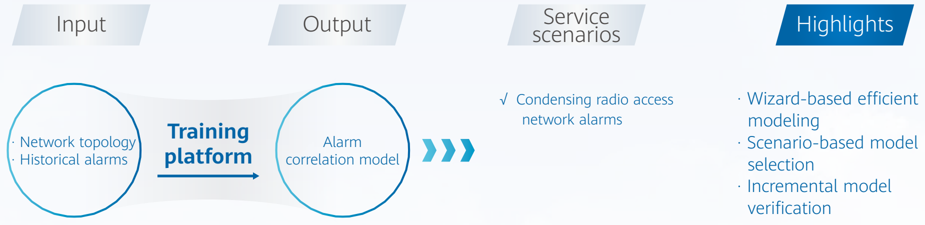
Traffic prediction model generation service for wireless cells

The iMaster NAIE platform integrates feature extraction, data modeling, and data algorithms of the wireless cell prediction model, allowing developers to quickly generate a prediction model by entering cell traffic statistics and engineering parameters. This model can predict the traffic, load, and number of users in a wireless cell and is used in intelligent base station control.


Input
Output
Service scenarios
Highlights
·Traffic statistics
·Engineering parameters
·Historical traffic
Training platform
Wireless cell traffic prediction model
√ Intelligent energy saving for base stations
√ Network assurance for major events
√ Mobility load balancing
· High precision of model prediction
· Fast model training for a large number of cells
· Visualized parameter settings

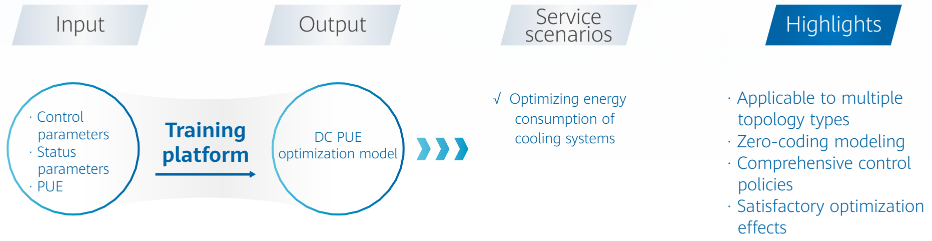
Alarm correlation model generation service

AI algorithms analyze a large number of network alarms, topologies, and work orders, extract alarm correlation rules, and generate an alarm correlation model. This model applies to scenarios where duplicate work orders are generated after a network fault occurs. The model allows work orders to be condensed, reducing repeated work orders and O&M costs.


Input
Output
Service scenarios
Highlights
· Network topology
· Historical alarms
Training platform
Alarm correlation model
√ Condensing radio access network alarms
· Wizard-based efficient modeling
· Scenario-based model selection
· Incremental model verification

DC PUE optimization model generation service

This service provides a set of automatic modeling tools (such as the DC topology template, PUE feature/algorithm library, and model training platform) that combine the AI technologies and DC engineering experience. With these tools, energy engineers without AI and coding knowledge only need to enter data.

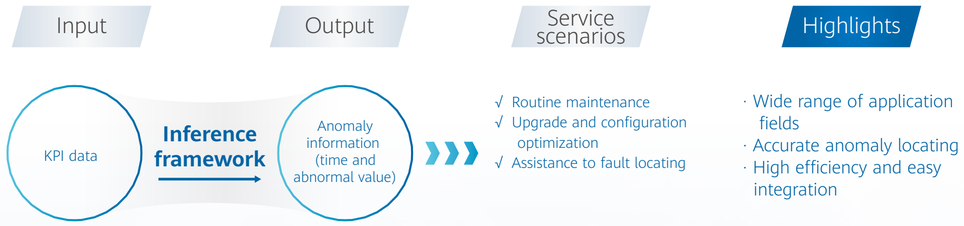

Input
Output
Service scenarios
Highlights
· Control parameters
· Status parameters
· PUE
Training platform
DC PUE optimization model
√ Optimizing energy consumption of cooling systems
· Applicable to multiple topology types
· Zero-coding modeling
· Comprehensive control policies
· Satisfactory optimization effects

Communication Model Services:

Professional and efficient communication model services are provided based on the Huawei iMaster NAIE inference platform.

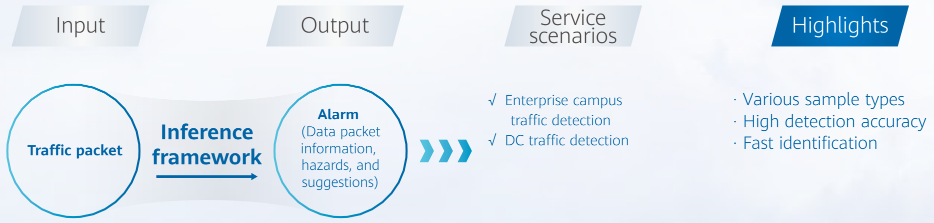
KPI anomaly detection model service

This service identifies KPI anomalies from a large amount of KPI input data, identifies the KPI input mode based on the service configuration and data type, automatically optimizes algorithms, and helps to predict system faults or quickly locate faults.


Input
Output
Service scenarios
Highlights
KPI data
Inference framework
Anomaly information (time and abnormal value)
√ Routine maintenance
√ Upgrade and configuration optimization
√ Assistance to fault locating
· Wide range of application fields
· Accurate anomaly locating
· High efficiency and easy integration

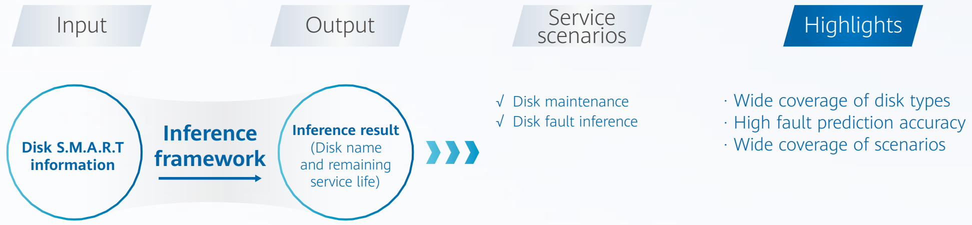
ECA anomaly detection model service

Based on AI algorithms, this service extracts malicious traffic characteristics from large amounts of sample data, and delivers detection results through anomaly detection model training. It can quickly check network traffic security and identify malicious encrypted traffic without decrypting the traffic or destroying data privacy, helping customers improve network defense capabilities and reduce system risks.



Disk anomaly detection model service

Based on the industry's standard Self-Monitoring, Analysis and Reporting Technology (S.M.A.R.T) indicator set for hard disks, this service extracts over 30 key features to build an AI model, delivers the health status detection result of hard disks, and predicts hard disk faults. It helps customers build a proactive fault handling mechanism for hard disks to ensure the reliable operation of systems and services.

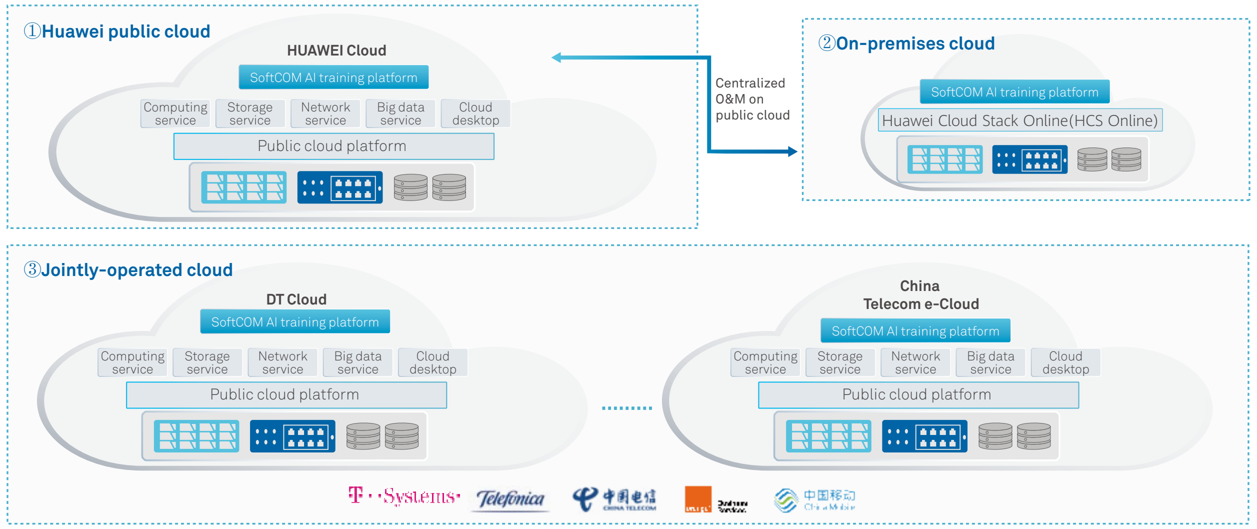

Input
Output
Service scenarios
Highlights
Disk S.M.A.R.T information
Inference framework
Inference result
(Disk name and remaining service life)
√ Disk maintenance
√ Disk fault inference
· Wide coverage of disk types
· High fault prediction accuracy
· Wide coverage of scenarios

6）Deployment Scheme

The iMaster NAIE solution supports flexible deployment based on different scenario requirements (for example, delay sensitivity and data sensitivity of application cases, and whether cloud services need to be deployed). The training platform or data lake implements offline model training and development, focusing on deployment convenience and data sensitivity. The inference framework mainly serves to implement real-time inference and it also focuses on delay sensitivity of application scenarios.

Training Platform/Data Lake

The training service platform is deployed mainly in three modes: HUAWEI CLOUD deployment, jointly-operated cloud deployment, and FusionCloud Stack (FCS) on-premises cloud deployment.



HUAWEI CLOUD deployment

The training platform is deployed on HUAWEI CLOUD. This deployment mode is not used in scenarios in which data privacy is an important concern.

Jointly-operated cloud deployment

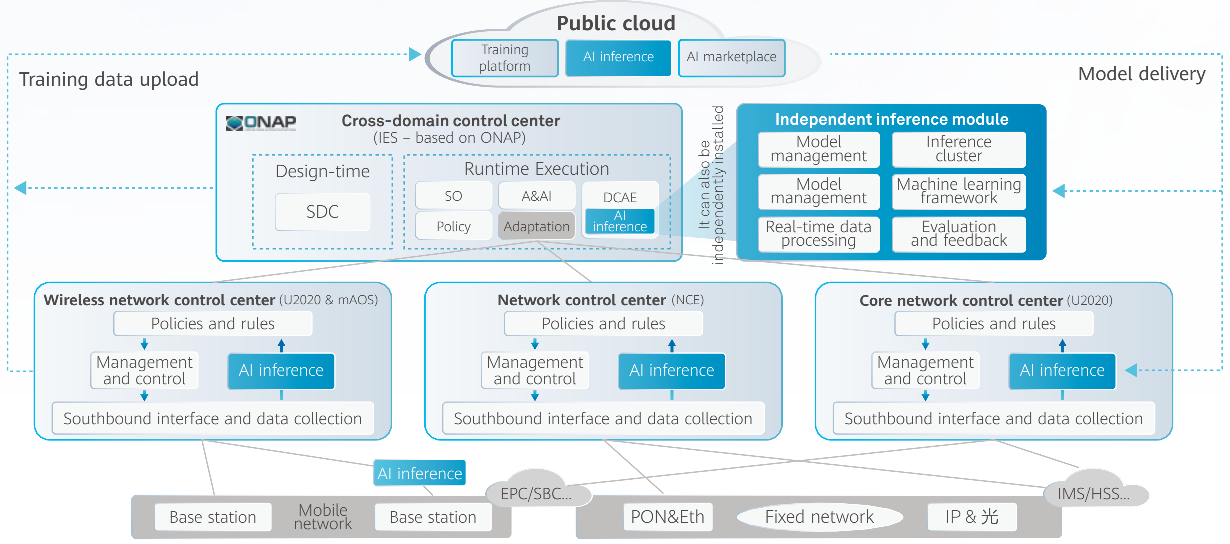
For operators who have their own cloud platforms, the training platform is deployed on their private clouds in jointly-operated cloud mode. The operators are responsible for O&M of the training platform and preventing data from being disclosed.

HCS on-premises cloud deployment

For operators who do not have their own private clouds and are sensitive to data privacy concerns, the training platform is deployed in HCS on-premises cloud mode. The HCS solution is an extension of HUAWEI CLOUD, which delivers a complete cloud service platform in full-stack mode and shares unified architecture, services, and APIs with HUAWEI CLOUD. HCS can be deployed in equipment rooms of jointly-operated clouds or satellite sites to meet customer requirements for dedicated cloud resources and data compliance. HCS can also be deployed in the nearest equipment rooms of users to reduce service delay and protect against data leakage. The O&M of the HCS training platform is in centralized mode. Maintenance information (such as alarms, logs, and traffic statistics) of the HCS training platform is sent to and managed by the training platform of HUAWEI CLOUD (such as the management of data lifecycle, version upgrade, and model upgrade). Huawei is responsible for unified O&M.

Inference Framework

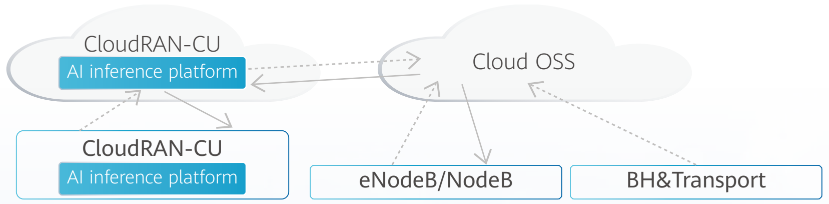
Based on the delay requirements and inference function scope of application cases, the inference platform supports various deployment modes, including device embedding deployment, single-domain network management system (NMS) integration deployment, cross-domain private cloud deployment, and HUAWEI CLOUD deployment.



Device embedding deployment

AI inference functions are embedded into devices and are executed in real time on the devices.

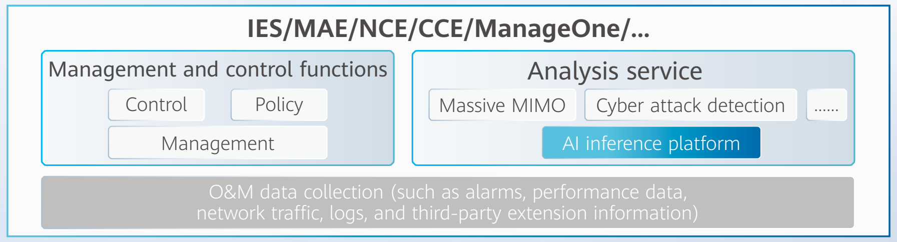
This deployment mode is featherweight. The memory space allocated to an application can be less than 50 MB. The deployment mode supports only the execution of AI algorithm models, but does not support functions such as data batch processing, stream processing, and PaaS functions such as software lifecycle management. The deployment mode is applied to scenarios with high timeliness requirements. A typical use case is multi-carrier optimization by intelligent grid.



NMS integration deployment

The inference platform is embedded into each single-domain control system or edge device.

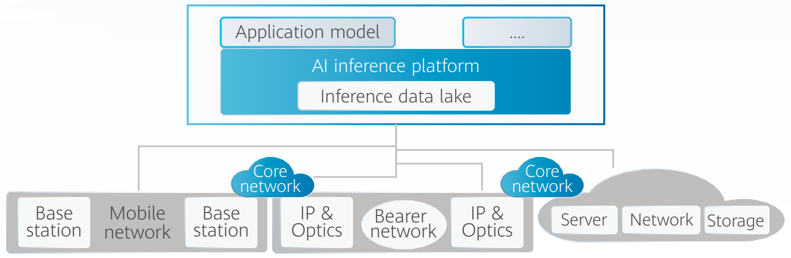
AI inference functions are integrated into multiple single-domain or cross-domain NMS products. This deployment mode is lightweight. The inference platform is deployed on one to three VMs and self-managed through the lightweight gPaaS. Applications share the online computing platform. This deployment mode applies to the real-time stream data processing scenario, in which data is not stored locally, the existing NMS is used, and the requirements on real-time performance are not high. Typical use cases include Massive MIMO, cyber attack detection, intelligent shutdown of base stations, passive optical network (PON) fault prediction and location, optical-layer commissioning, core network anomaly detection, and DC power usage effectiveness (PUE) optimization.


IES/MAE/NCE/CCE/ManageOne/...
Management and control functions
Control
Policy
Management
Analysis service
Massive MIMO
Cyber attack detection
......
AI inference platform
O&M data collection (such as alarms, performance data, network traffic, logs, and third-party extension information)

Private cloud deployment

The inference platform is deployed in the form of a data lake and in centralized mode on an operator's entire network.

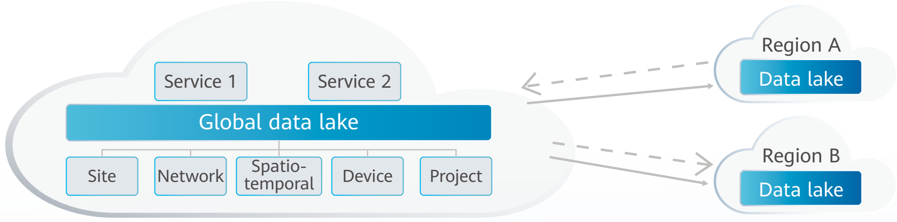
The inference platform is provided as a private cloud service. Multi-tenant management and isolation capabilities are supported. With the built-in data lake, the platform provides stream data processing and batch data processing capabilities. Long-term and cross-domain data can be imported to the data lake for comprehensive analysis. It is a medium-level deployment mode. The inference platform is deployed on more than three VMs on cloud networks. This deployment mode applies to scenarios in which the inference is implemented across multiple applications and domains, and cyber security requirements are high. Typical use cases include DCI resource utilization improvement and video service experience optimization.



HUAWEI CLOUD deployment

The inference platform is deployed in distributed data federation form.

This deployment mode provides inference services for global customers, and supports service subscription and operations management. Platforms are physically scattered, logically centralized, and managed in a unified manner. This deployment mode applies to scenarios in which inference tests are provided to developers and inference services are provided to users or trial users. This deployment mode is not used in scenarios in which data privacy is an important concern. Typical use cases include assigning one work order for one fault and DC disk fault prediction.



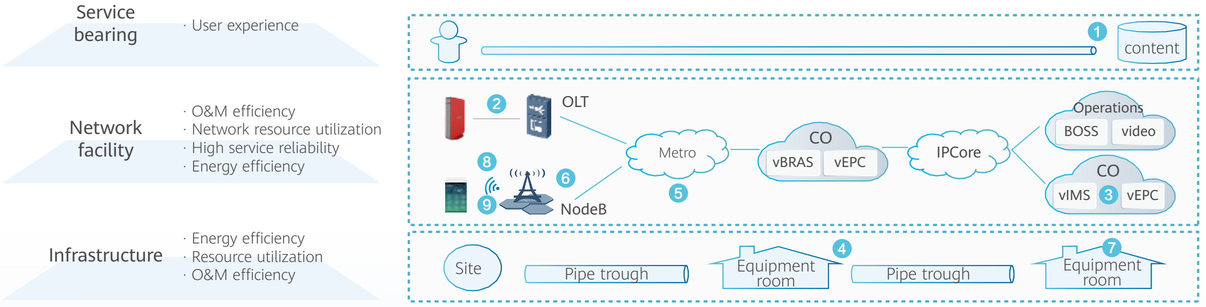
Typical Application Scenarios of the Huawei iMaster NAIE Solution

AI is well suited to solving network problems. Complicated multi-dimensional software-based problems can be solved using AI technologies. AI confers significant advantages when dealing with complicated network and service problems involving multiple layers, domains, protocols, interfaces, parameters, and vendors. The functions and introduction paths of AI vary depending on the layer and domain.

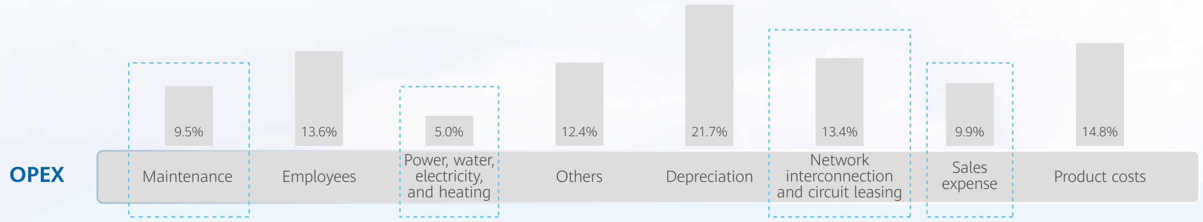
AI is applied to the infrastructure layer to provide AI accelerators for active hardware facilities, implementing training and inference capabilities at different levels. For example, AI accelerators can be preferentially introduced to infrastructure of core DCs to meet the centralized training and inference requirements of global policies or algorithm models. AI accelerators can be gradually introduced to access sites as required. For example, AI accelerators embedded in base stations support device-level AI policies and applications.

AI is applied to the network infrastructure layer to implement intelligent network optimization, O&M, and control for networks and services. Specifically, AI is used to optimize network KPIs, routing, and network policies, such as coverage optimization, capacity optimization, and load optimization in the wireless domain. AI is also used to perform preventive and proactive network maintenance, such as KPI anomaly detection and trouble ticket condensing.

AI is applied at the service bearer layer. With the deployment of virtualized networks, AI capabilities can be added to the orchestration layer to improve the automation and intelligence of service orchestration and E2E resource orchestration, optimizing the service quality. AI can also be used to identify service features, identify malicious traffic attacks in the early stages, and generate warnings against viruses, protecting privacy.



Typical iMaster NAIE applications can deliver severalfold increases in O&M efficiency, energy consumption efficiency, and resource utilization efficiency. User experience is significantly improved.



leap in O&M efficiency

Active devices managing passive devices

Access network: PON network and wireless network fault location and prediction
Optical network: WDM optical route commissioning
Core network: VoLTE fault location
Data center: hard disk fault prediction

leap in energy efficiency

Bits determining watts

Communication: site, equipment, and network
IT: DC, server storage, and application

leap in resource utilization

Time-space multiplexing

Air interface: Massive MIMO and virtual grid
Backbone network: WAN usage improvement
Infrastructure: pipeline and equipment room

Service experience improvement

Application-driven experience

Individual: application-driven experience
Family: video experience
Enterprise: cyber security

Enhancing operators' network intelligence is a long-term project and cannot be accomplished all at once. Huawei will start with cases with significant improvement in operators' efficiency, increase cases, collect data, improve algorithms, accumulate experience, explore deployment modes, and gradually use AI on operators' networks.

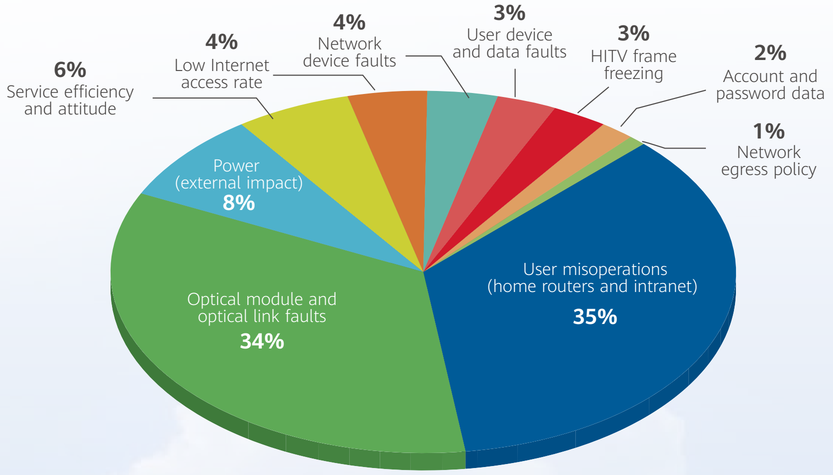
1）Leap in O&M Efficiency

In the O&M domain, O&M practices can be divided into three categories, based on how proactive or passive they are. The first category is called Run-to-Failure (R2F). If there is a fault on a network, the O&M personnel immediately go to the site and rectify the fault. This is the lowest level. The second category is called Preventive Maintenance (PvM). With PvM, each device is checked to prevent faults, but the efficiency is low. The third category is called Predictable Maintenance (PdM). With PdM, we can calculate the probability that a device will become faulty in the future and then perform targeted maintenance. With PdM, we hope to reduce the workload required for alarm handling and fault locating on telecom networks by 90%, predict the failures and deterioration of 90% of key components, and further achieve network self-healing. In addition, more than 70% of the problems in network faults lie in passive equipment, such as aging or bent optical fibers, and ports that have become loose. In all of these situations, signals change. AI is introduced to learn the characteristics of these changes, and enables operators to predict the changes in advance and use solutions to solve passive faults. Fault location and prediction for PON optical modules and optical links provides an instructive example of the effect AI can have on O&M practices.

Fault Location and Prediction for PON Optical Modules and Optical Links

As a broadband solution used to solve the "last mile" problem, the PON technology has been widely deployed around the world due to the proliferation of the "fiber-in and copper-out" strategy. However, although new technologies bring benefits, faults of passive PON components are difficult to locate and there is no efficient remote locating methods. As a result, the O&M cost is high.

According to the statistics of one operator, 25,000 complaints were received from July to December in 2016, and the ratio of faults regarding optical links and OLT/ONT optical modules (optical-to-electrical conversion modules) was 34%. In addition, due to urban reconstruction, rain, snow, and damage caused by rodents gnawing on cables, the fault ratio of devices covered by leather materials exceeded 20%, and the ratio of faults regarding various outdoor connectors (such as mechanical splicers and RJ45 connectors) exceeded 6%. Passive components cannot send any information. If a fault occurs on a device, it is difficult to locate the fault.



Optical fibers are buried in pipes and cannot be detected. According to the current process, once a home broadband user complains about a fault, O&M personnel must go to the site for fault location by checking the entire link on the optical network terminal (ONT) using the optical time domain reflectometer (OTDR). However, the cost of dispatching onsite O&M operators is high. The average cost is EUR175 in Europe and CNY50 in China. In 2017, the total onsite O&M cost of an operator was more than CNY100 million.

The iMaster NAIE solution uses NMSs (such as U2000 and uTraffic) to obtain historical data from ONT/OLT optical modules (such as module types, module voltages, module currents, module temperature, optical-layer alarms, optical-layer statistics, transmit power, receive power, and luminosity distance), extract features from the data, and label the features for AI training. The models obtained after the AI training can be used for inference based on real-time data to obtain the fault type and fault demarcation information, thereby implementing accurate fault location and prediction. The iMaster NAIE solution provides remote locating methods, improving remote fault location accuracy from 30% to 80%.

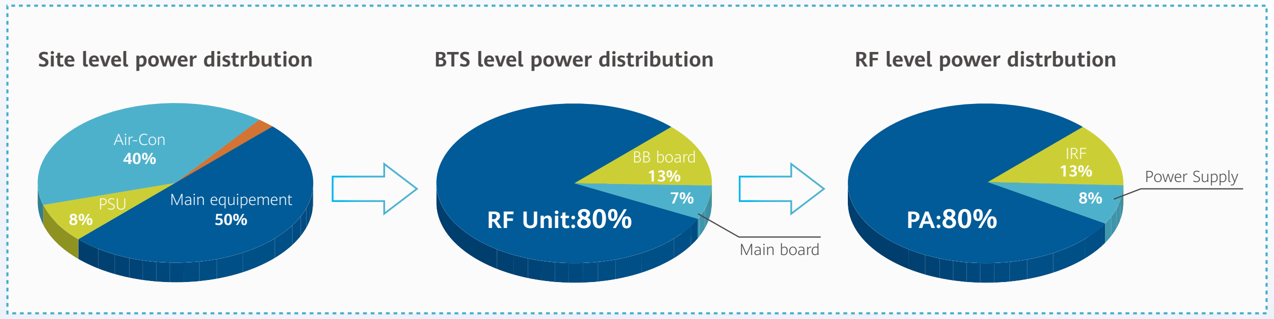
2）Leap in Energy Efficiency

When it comes to energy efficiency, the number of bits should determine the number of watts. That is, lower traffic volume should result in lower power consumption. In an equipment room or at a site, each system is configured with dozens of parameters. The heat dissipation, environment, and service load models are generated through AI training to maximize the energy consumption efficiency for sunlight, temperature, and auxiliary facilities, such as diesel generators, solar energy devices, and batteries. At the equipment layer, dynamic energy distribution is performed based on service loads. If there is no traffic, power consumption is reduced by using timeslot shutdown, RF deep sleep, and carrier shutdown. In addition, energy consumption of data center hardware, such as server components, can be dynamically reduced. The power consumption of the network system must also be taken into account. The accurate service load prediction model is constructed to balance the traffic on the entire network and achieve the optimal energy consumption efficiency.

Intelligent Energy Saving for Base Stations

Statistics show that the base station power consumption cost (electricity fee) accounts for more than 16% of network operations costs. Optimizing the cost structure and promoting social development, energy saving and emission reduction of base stations have become main goals of operators.

In the case of a conventional macro base station, the power consumption of the main equipment accounts for 50% of total power consumption, and the power consumption of RF units accounts for 80% of the main equipment power consumption. The power consumption of power amplifiers (PAs) accounts for 79% of the power consumption of RF units. Distributed base stations are becoming the industry standard, and this trend results in the main equipment taking an increased share of the total power consumption. Meanwhile, the traffic volume on the network is subject to regular ebb and flow. Peak traffic volume can reach four times off-peak traffic volume. However, a majority of base stations keep running 24 hours a day (with all resources occupied). The power consumption does not dynamically change with traffic volume, which results in resource waste. Therefore, in terms of main equipment, reducing energy consumption by shutting down base station carriers is key to energy saving for base stations.



Generally speaking, the intelligent energy saving strategy of base stations is to reduce or shut down power amplification modules that carry carriers. Power amplification modules are hardware entities, which are used to amplify the power of modulated carrier signals and transmit those signals. Carrier shutdown is applicable to scenarios where a sector is covered by two or more carriers. Amplification modules of capacity cells are shut down, and only coverage cells are reserved for basic coverage requirements. Base station carrier shutdown is not a new feature, but the usage of this feature is low. This is due to the fact that traditional shutdown modes (such as scheduled shutdown) rely heavily on a unified default value, which occasionally affects users' call and Internet access experience.

How to make full use of this feature? If radio resource usage of base station cells can be predicted, a customized sleeping time can be set for each cell, meaning that operators no longer have to worry about the unintended consequences of using the base station carrier shutdown feature. However, prediction is not easy. First, it is necessary to obtain the historical data of tens of thousands of cells, such as the time, neighboring cell relationship, event, and radio resource usage features. In addition, we need to monitor the changes of KPIs or KQIs and dynamically adjust the shutdown parameters based on the KPI or KQI changes after the solution is deployed based on adjustment policies. Associating uncertain factors that affect the prediction result with radio resource usage is difficult and cannot be implemented in practice.

Using the neural network algorithm of the spatio-temporal computing module on the AI training platform, we can find the mapping relationship between the historical data of features that affect the prediction result and radio resource usage, and determine the weight matrix and bias matrix. In this way, we can generate a radio resource usage prediction model. After the prediction model is generated, it can be deployed in the system. We can set the sleeping threshold based on the prediction result of radio resource usage, and calculate the time segment that meets the cell sleeping threshold requirements.

Take the result at a first office application (FOA) site as an example. The AI-based intelligent shutdown of base stations can help operators reduce base station power consumption by 10% to 15% while the coverage area remains unchanged and KPIs and KQIs are not affected.

3）Leap in Resource Efficiency

Regarding network resources, on most present-day networks, the flow of traffic simply follows the physical topology of the network, and resource usage may be unreasonable. If network scheduling took into account the direction of traffic flow, the resource usage efficiency could be greatly improved. At present, however, networks do not have this capability. To address this issue, AI must be introduced, and a traffic prediction model must be created. In this way, precise traffic prediction and the optimal network topology can be provided, and the network paths can be determined by traffic instead of just by physical connections.

Massive MIMO Intelligent Optimization

5G is the next major opportunity for the telecom industry. Progress has been driven by all parties in the value chain, 5G is no longer far away from us. In the network domain, preparations for the 5G era must be made today.

In urban areas, wireless spectrum resources are gradually becoming saturated. To meet the rapid growth of service requirements, it is essential to increase the number of 4G and 5G antennas. Massive MIMO is one of the core technologies of 5G. To make full use of its advantages, it is necessary to flexibly adjust the parameters of Massive MIMO base stations to cope with service changes.

However, antenna parameter combinations vary with location, scenario, and user distribution. In the 3G era, there were only 13 parameter combinations (horizontal beamwidth and vertical beamwidth) and it is easy to make a selection based on the judgment of experienced experts. In the 4G era, there are hundreds of antenna parameter combinations (horizontal beamwidth, vertical beamwidth, and downtilt angle), making it difficult to determine which should be selected, even for experienced experts. In the 5G era, thousands of parameter combinations (horizontal beamwidth, vertical beamwidth, downtilt, and horizontal angle) are available, and as 5G is a brand new technology, experience cannot be relied upon. Since there are a large number of parameter combinations, services are rapidly changing, and manual operations are inefficient, risky, and difficult to implement, Massive MIMO base stations urgently need a mechanism that is optimized and more intelligent.

AI is introduced to analyze and process the relationships between various complex scenario features and beam parameter combinations. In this way, the debugging becomes less time-consuming and optimal configuration parameters of beams in a certain scenario and at a certain location can be quickly obtained.

One operator who adopted this AI-based approach, found that the optimal initial value at a site could be obtained in just a few days. Compared with the traditional method, efficiency was greatly improved.

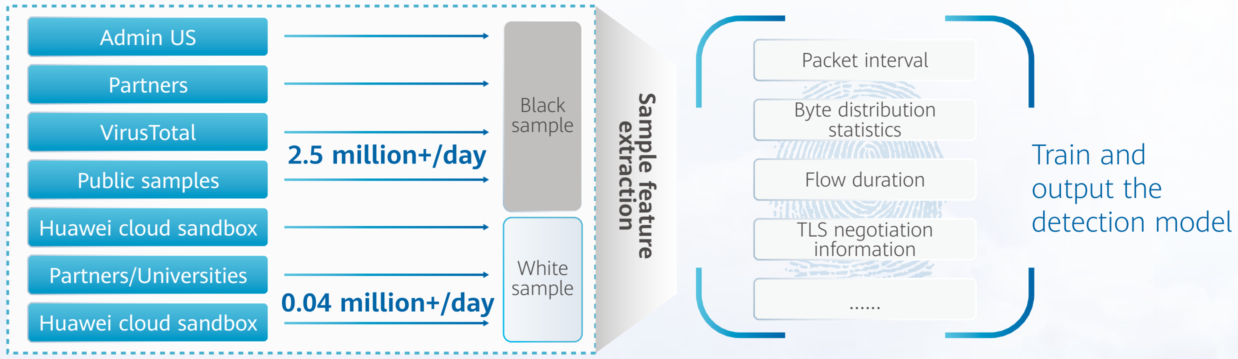
4）User Experience Improvement

Network design, planning, and configuration are automatically performed and the service rollout time can be shortened to one tenth of the original time. For individual users, device and application data is used to achieve optimal user experience based on the automatic closed-loop mechanism. For enterprise users, multi-domain global networks can be deployed in minutes with cloud-network synergy enabled, and network-wide routes are automatically advertised and learned, implementing scheduling and routing in ways that are invisible to users. For home users, device-cloud synergy improves home broadband quality and extends experience improvement and problem handling to home networks.

Intelligent Detection of Malicious Encrypted Traffic Through ECA

Cyber security threats are evolving with new features in recent years, and advanced persistent threats (APTs) are developing rapidly. Gartner predicts that by 2020, 70% of malicious attacks will utilize encryption techniques. At that point, traditional feature detection methods based on plain text will no longer be effective. For example, hackers may use encrypted links to establish control channels and covertly implement remote control over "zombies". How to identify malicious encrypted traffic without decryption is the key to defense against APT attacks.

Encrypted Communication Analytics (ECA) is an AI-based threat detection solution in which decryption is not required and is used to extract a large number of black and white sample features, train the features, and generate a detection model.



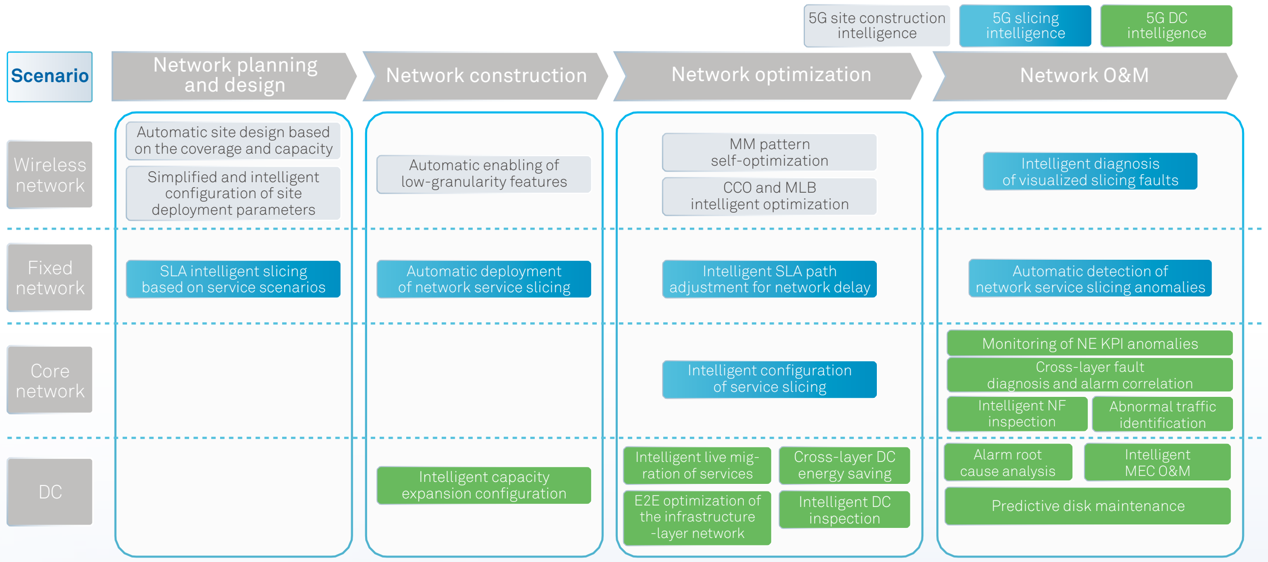
When a hacker establishes an encrypted control channel to control "zombies", the next-generation firewall (NGFW) extracts encrypted traffic packets and reports them to the cybersecurity intelligence system (CIS) for feature detection. The CIS uses an AI model to detect traffic features and interworks with the NGFW to intercept north-south traffic and corporates with switches to perform east-west isolation of infected hosts. The CIS delivers the detected traffic features to tools, so that the tools can locate, analyze, and clear malicious files.

The ECA solution implements encrypted traffic detection without decryption based on AI technologies, with which user privacy can be protected. The detection accuracy is high, reaching 99.9%, while the false positive rate is lower than 0.001%. Intelligent detection of five categories covering 30 families of malicious files is supported.

5）5G Intelligent Networks

AI will become a native capability of 5G, enabling scalable, flexible, and intelligent 5G networks. Huawei will integrate AI into E2E networks (wireless network, fixed network, core network, and DCs) based on network planning, deployment, optimization, and O&M, to achieve intelligent 5G networks.

In the near future, we will implement 5G base station deployment intelligence, 5G slicing intelligence, and 5G DC intelligence. During the deployment of a 5G site, the site location and deployment parameters will be automatically recommended based on multi-attribute site planning. Low-granularity features are automatically enabled and parameters are automatically optimized. Intelligent 5G slicing is the process of continuously enhancing network slicing based on the automation capability built up by the central cloud and edge cloud. The system predicts resource consumption based on service scenarios to recommend the optimal slicing model and orchestration policy, implementing real-time resource awareness, on-demand adjustment, and simplified configuration. In this way, service rollout time is shortened. 5G DC intelligence involves intelligent scale-out configuration, L1 to L4 cross-level energy saving, intelligent inspection, hard disk fault prediction and maintenance, and intelligent O&M through mobile edge computing (MEC). In addition, the KPI anomaly monitoring, alarm correlation and diagnosis, and abnormal traffic identification for the core network that is cloudified through NFV and is running on DCs are also involved.


5G site construction intelligence | 5G slicing intelligence | 5G DC intelligence

Scenario	Network planning and design	Network construction	Network optimization	Network O&M
Wireless network	Automatic site design based on the coverage and capacity Simplified and intelligent configuration of site deployment parameters	Automatic enabling of low-granularity features	MM pattern self-optimization CCO and MLB intelligent optimization	Intelligent diagnosis of visualized slicing faults
Fixed network	SLA intelligent slicing based on service scenarios	Automatic deployment of network service slicing	Intelligent SLA path adjustment for network delay	Automatic detection of network service slicing anomalies
Core network			Intelligent configuration of service slicing	Monitoring of NE KPI anomalies Cross-layer fault diagnosis and alarm correlation Intelligent NF inspection Abnormal traffic identification
DC		Intelligent capacity expansion configuration	Intelligent live mig-ration of services Cross-layer DC energy saving E2E optimization of the infrastructure -layer network Intelligent DC inspection	Alarm root cause analysis Intelligent MEC O&M Predictive disk maintenance

AI-driven E2E Simplification of 5G Network Deployment

AI is applied to the planning, deployment, optimization, and maintenance of 5G networks, greatly simplifying network deployment. During site planning, base station coverage status and the distribution of sites across the entire network are visualized and measurable. During site deployment, hardware is automatically discovered and configured, cells are automatically bound, and radio parameters are automatically configured (Scenario-based policy parameters are intelligently defined: transmission or radio parameters are greatly simplified, base stations with low-granularity features enabled are automatically configured, and no O&M engineers are required for intelligent commissioning), implementing automatic 5G site deployment. During network optimization, networks accurately identify various network coverage scenarios and automatically adjust network parameters to achieve optimal network performance based on the optimization objective, 3D map, online map, and 5G traffic map. During network maintenance, the system automatically analyzes network logs and alarms and automatically identifies and predicts network fault.

Visualized planning

Automatic site construction and deployment

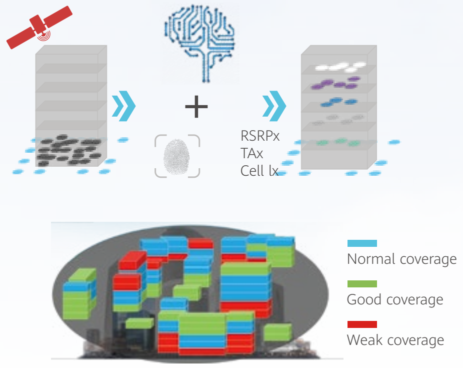
Automatic hardware discovery

Automatic hardware configuration

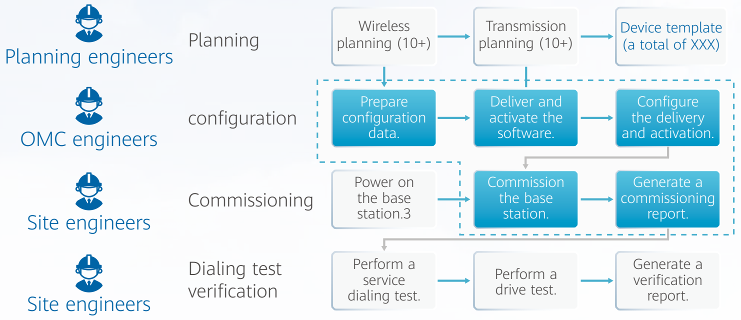
Automatic cell binding

Automatic wireless configuration

3D visualization



Automatic site deployment enabling PnP



Planning engineers — Planning: Wireless planning (10+) → Transmission planning (10+) → Device template (a total of XXX)

OMC engineers — configuration: Prepare configuration data. → Deliver and activate the software. → Configure the delivery and activation.

Site engineers — Commissioning: Power on the base station.3 → Commission the base station. → Generate a commissioning report.

Site engineers — Dialing test verification: Perform a service dialing test. → Perform a drive test. → Generate a verification report.

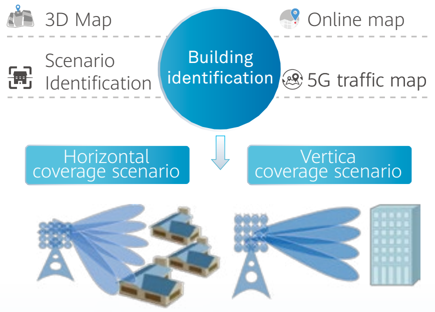
①Intelligent definition of scenario-based policy parameters: The number of transmission/wireless parameters is reduced (from 200+ to 20+) and hardware templates are no longer needed.

②Base stations are automatically configured and intelligently commissioned, and OMC engineers are no longer required to be on site.

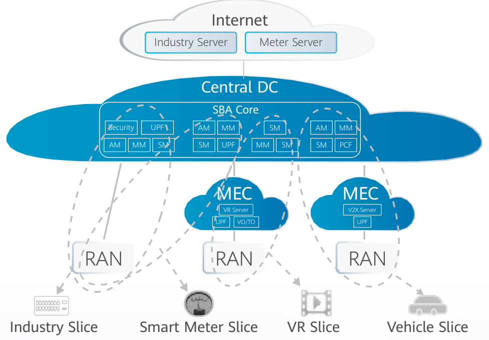
Precise optimization

Simplified O&M

Automatic adjustment based on optimization targets



Intelligent analysis of logs, alarms, and call chains



Abbreviation

Abbreviation	Description
AI	Artificial Intelligent
SDN	Software Defined Network
NFV	Network Function Virtualization
NAIE	Network AI Engine
CRM	Customer Relationship Management
IT	Information Technology
AWS	Amazon Web Services
OPEX	Operating Expense
CAPEX	Capital Expenditure
IP	Internet Procotol
DC	Data Center
PUE	Power Usage Efficiency
Massive MIMO	Massive Multiple Input Multiple Output
GUI	Graphical User Interface
DCN	Data Center Network
API	Application Programming Interface
SLA	Service Level Agreement
KPI	Key Performance Indicator
ETL	Data Extraction Transformation Loading
BDI	Big Data Integration
DG	Data Governance

Abbreviation	Description
FMA	Fault Management Analysis
OSS	Operations Support System
FCS	Fusion Cloud Stack
IES	Infrastructure Enabling System
MAE	MBB Automation Engine
NCE	Network Cloud Engine
CCE	Cloud Container Engine
OLT	Optical Line Terminal
PON	Passive Optical Network
ONT	Optical Network Terminal
RF	Radio Frequency
PA	Power Amplifier
ECA	Encrypted Communication Analytics
APT	Advance Persistent Threat
NGFW	Next-Generation Firewall
CIS	Customer Information System
MEC	Mobile Edge Computing
CCO	Coverage and Capacity Optimization
MLB	Mobility Load Balancing
PnP	Plug and Play
OMC	Operation and Maintenance Center

Conclusion

The future will be shaped by intelligence. Enhancing operators' network intelligence is a long-term project and cannot be accomplished overnight. iMaster NAIE is the implementation of Huawei's All Intelligence strategy in the telecom domain. The key AI capability of iMaster NAIE is developed based on both Huawei's long-term strategic investment and growth in All Intelligence and telecom scenarios. iMaster NAIE helps operators build "never faulty" autonomous networks and achieve digital and intelligent transformation.

Currently, the iMaster NAIE solution is open to industry insiders for trial use. We welcome you to go to our cloud service website and experience our telecom AI development platform and intelligent communication model services.

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