White Paper

Advanced Management of Radio Access Networks using AI

Table of Contents

Introduction

Networks are evolving every day and becoming more intertwined with society. Social media with video sharing has become popular as a means of communication, with online games and avatar experiences playing over networks and various viewing channels. As lifestyles change, remote work and online meetings at home have become commonplace. In the industrial field, networks are used in sensing and remote control in multiple workplaces, including factories, agriculture, and transportation.

5G features high capacity (10 G), low latency (1 ms), and massive terminals (1 million units/km^2), with a variety of applications. To create a digital society that continues to evolve, including holograms and augmented reality, conversations around 6G are emerging. 6G expands 5G functions, with environmental considerations that seek to reduce power consumption.

Base stations and other network equipment directly provide radio access network services. These network devices will evolve, such as millimeter-wave support providing broadband and higher-performance hardware platforms. However, as network requirements diversify and usage changes significantly, it is necessary for the entire network ecosystem to respond flexibly to these requirements while considering the environment. The network may be suddenly and locally overwhelmed in a disaster or emergency. We believe that the role of artificial intelligence (AI), which can make appropriate decisions on events that are difficult to handle manually, will be necessary to effectively respond to diversifying applications and unexpected events.

The expansion of AI technologies outside of the communication networking world is remarkable. AI is advancing various fields by centralizing and using accumulated big data. In addition to improving the efficiency of human interactions in areas such as translation, call centers, as well as diagnostic support at hospitals, AI can also enrich our lives and industries by suggesting events and relationships that people have not noticed, and by introducing automated text generation services that use large language models with nearly the same fluency and logic as human writing has enabled us to support multiple languages and improve the efficiency of many operations.

As networks become more open, virtualized and small-cell, resources are more flexible just like in the cloud. In addition, a network architecture that classifies data in “units," called slices, grows in importance. It enables optimal resource allocation for each application. In Radio Access Networks (RAN), AI-powered controllers called a RAN Intelligent Controller (RIC) is defined architecturally.

This white paper discusses the evolution of RAN, which are starting to be ready to utilize AI effectively. It introduces advanced use cases and technologies that combine RAN with AI. AI, which has become a major force in society, will bring significant innovation to networks in the future.

Figure 1 shows the scope of this white paper.

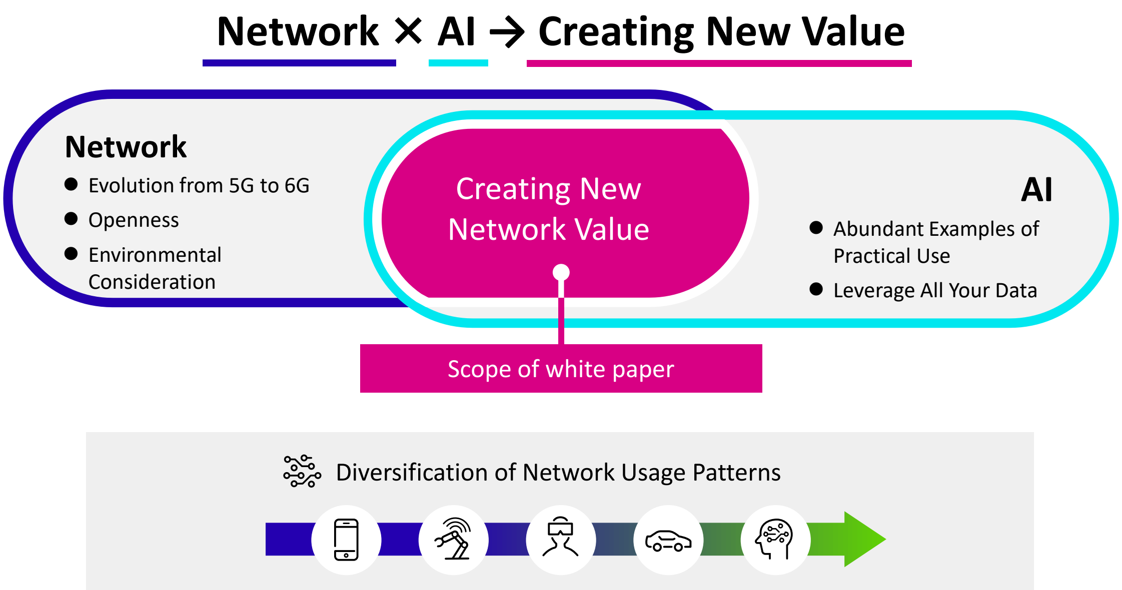

Figure 1 White Paper Scope

Direction of Network Technology

Network Technology Trends

In the past, network products like base stations, switches, and routers were hardware products. Now, virtualization makes it possible to decompose the various elements that make up the network, enabling flexible network setups, such as changing on a per-element basis or combining elements from multiple vendors. Intelligent orchestration that properly combines the disassembled components is vital to realize a network that can operate safely with low power consumption.

RAN that connect smartphones, cars, industrial machinery, VR devices, and other objects is critical. Their orchestration and operational sophistication will be significant points of network control.

Figure 2 shows current network technology trends.

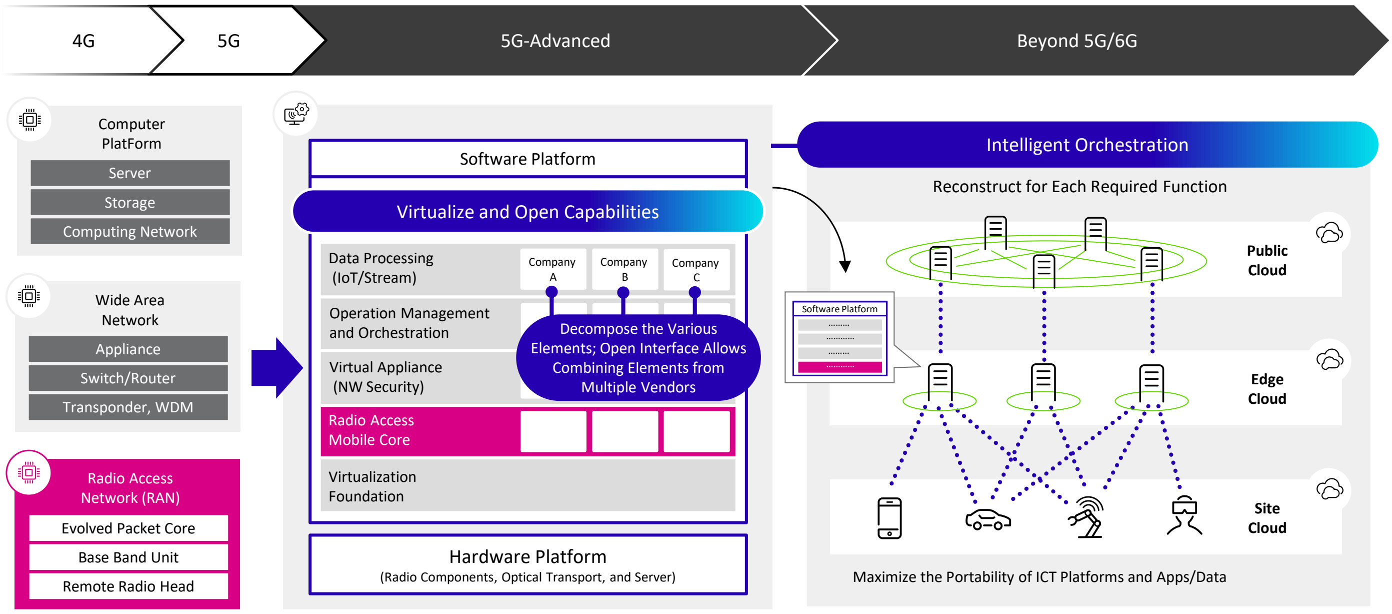

Figure 2 Current Network Technology Trends

Standardization

This section describes the 3rd Generation Partnership Project (3GPP), an international organization for the standardization of mobile communication systems, and the O-RAN Alliance, one of the business alliances that are promoting the opening and mutual verification of the 3GPP. We will discuss trends in RAN standardization activities at the 3GPP and the O-RAN Alliance which Fujitsu is actively contributing to.

Figure 3 shows RAN standardization.

The 3GPP plans to develop a standard specification for 5G-Advanced, which is an evolution of 5G. With the continuous improvement of 5G, new considerations related to intelligent orchestration, such as the introduction of AI and Network Data Analytics Function (NWDAF), as well as the energy efficiency of networks, are underway.

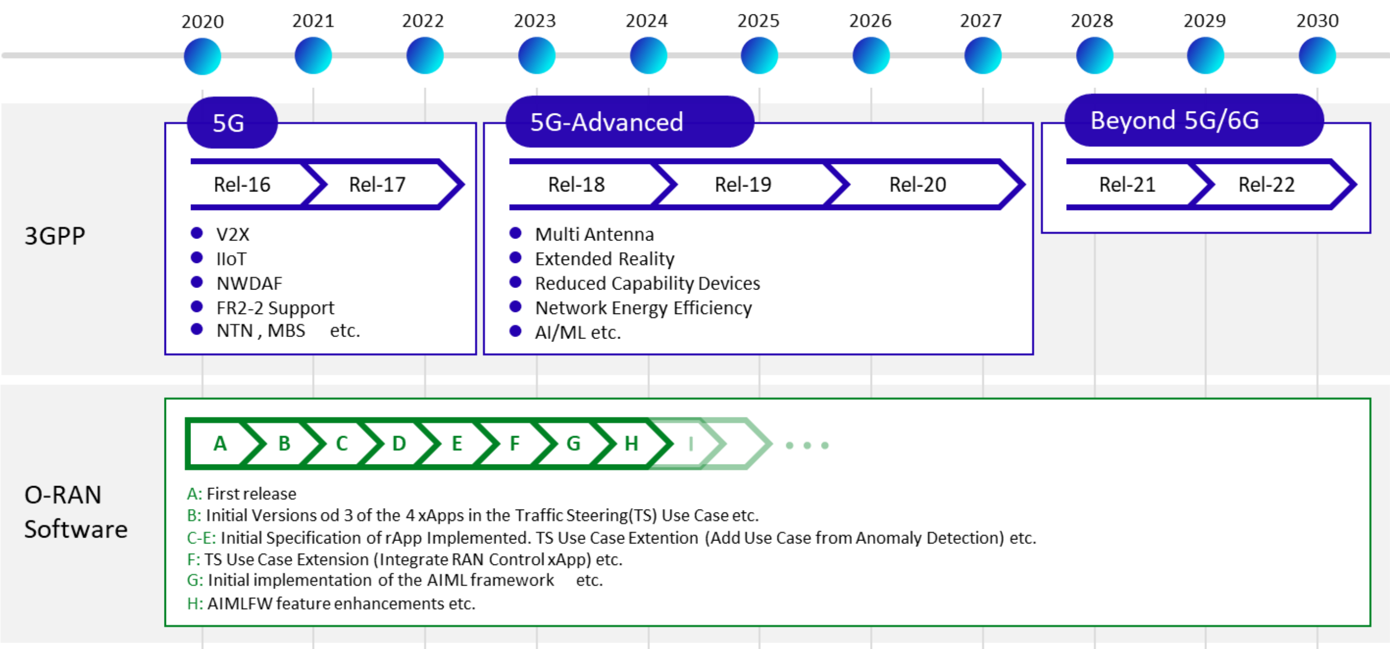

Figure 3 RAN Standardization

The O-RAN Alliance has two visions:"open" and "intelligent." The architecture that defines these visions appears in Figure 4.

RIC is a platform that optimizes RAN resource management and automates operations. RIC are divided into the Non-Real Time RIC (Non-RT RIC), which performs non-real-time processing, and the Near-Real Time RIC (Near-RT RIC), which performs quasi-real-time processing, depending on the control cycle.

The Non-RT RIC are deployed inside the "Service Management and Orchestration (SMO)" which performs maintenance and orchestration of the RAN, and configuration parameters optimized by AI-driven analysis can be set to the O-RAN Centralized Unit (O-CU) and O-RAN Distributed Unit (O-DU) via the O1 interface. It generates policies related to RAN control and report them to the Near-RT RIC via the A1 interface.

The Near-RT RIC collects O-CU and O-DU information via the E2 interface and controls the O-CU and O-DU according to the control policy notified by the Non-RT RIC.

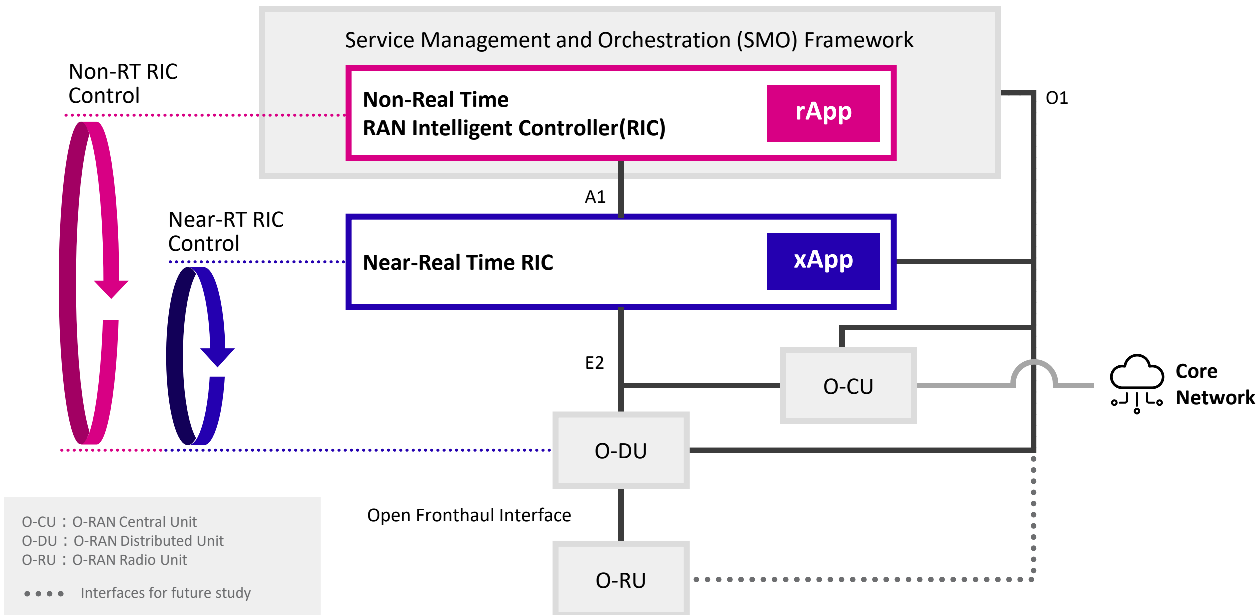

Figure 4 O-RAN Architecture

The Non-RT RIC uses an application called rApp, and the Near-RT RIC uses an application called xApp to analyze information and create and execute control policies. rApp and xApp are architected independently of the RIC framework.

The A1, the E2, and the O1 are open interfaces that allow for flexible component-by-component changes and interconnection between components, making it easy to configure multi-vendor systems that combine elements from different vendors.

O-RAN compliant software, which implements the above architecture and specifications defined by the O-RAN Alliance was first released in November 2019 and has continued to expand its functionality since then. In December 2022, G Release, which implements the AIML framework, was released.

Network Technology Outlook

Wireless access technology, including base station equipment, will continue performance improvements and multi-vendor integration. Performance improvements include communication speed and delay for 5G and beyond using high-frequency communication technology and edge compute. Integrations include virtualized network functions in software base stations and support for open interfaces standardized by the O-RAN Alliance.

In addition, new network operation technologies will monitor and control the RAN, providing network slicing, optimal resource management, and energy efficiency. Intelligent orchestration will provide flexible control to the entire RAN.

Figure 5 shows the future direction of technologies related to the RAN domain.

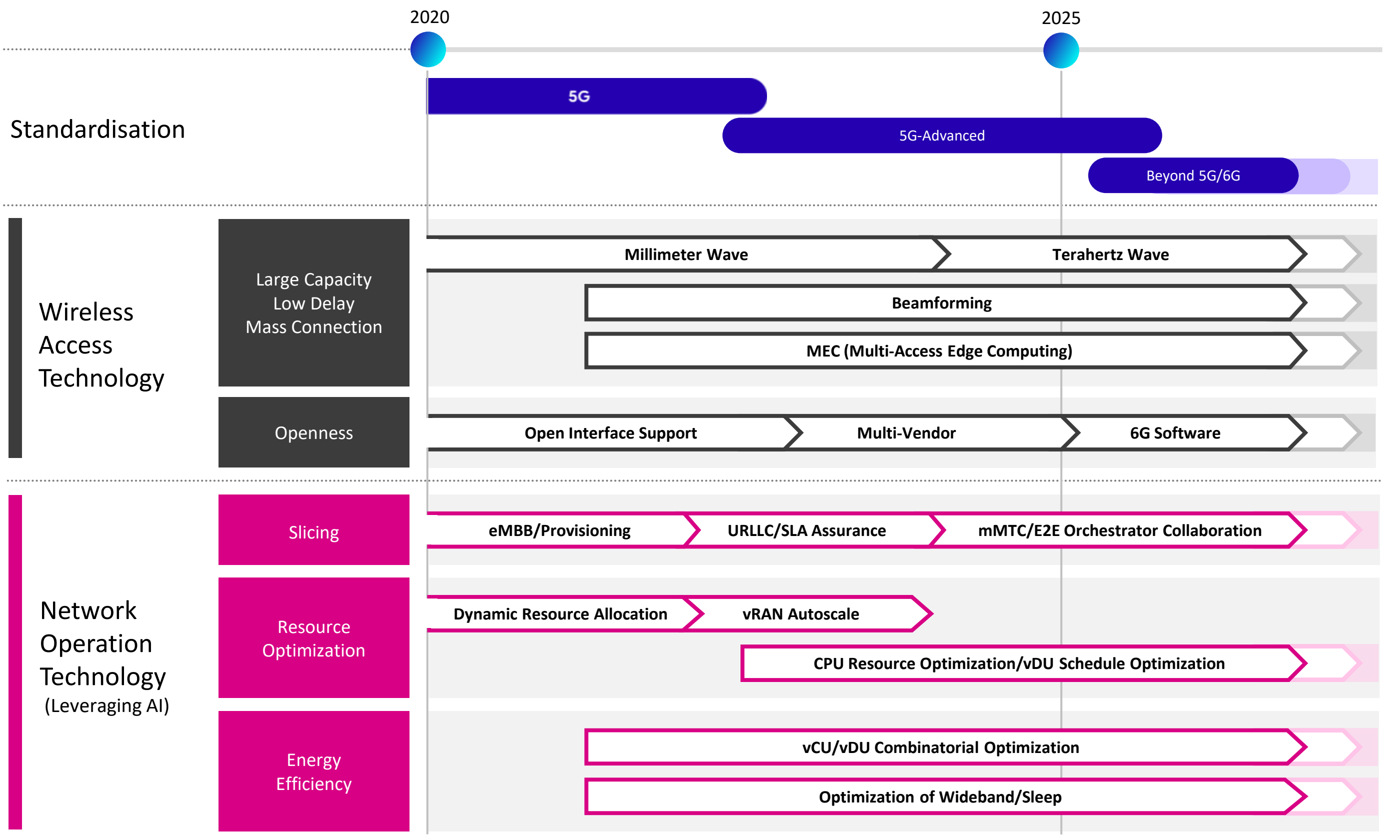

Figure 5 Network Technology Outlook

High-Performance RAN Utilization

RAN Operational Challenges

Network complexity due to service diversification and increased power consumption are significant challenges.

Network Complexity due to Service Diversification

Network connections and quality fluctuates from moment to moment due to short-term changes in the flow of people and traffic. These changes can be due to discrete events or new building construction in the communication environment. There is a strong demand for prompt restoration in a sudden disaster, breakdown, or failure. Thus, immediate reconstruction of networks in response to environmental changes is required.

A significant challenge is how to quickly combine elements with complex relationships that support diversified service delivery. Optimal combinations of various components, service types, devices, and traffic volume are required to meet user expectations and partner Service Level Agreement (SLA).

Increased Network Power Consumption

Expectations for companies to achieve global targets in the Paris Agreement and the Sustainable Development Goals (SDGs) are growing. Various industries are stepping up efforts to reduce greenhouse gas emissions and promote renewable energy, and that include mobile network operators.

If we look at the global network power consumption forecast[1], we can observe increases to 395 TWh in 2018 and 2,400 TWh in 2030. The breakdown shows that RAN power consumption is projected to increase exponentially (RAN power consumption: 93% in 2018, 88% in 2030).

An enormous number of base stations and RAN equipment are needed to support projected increases in traffic volume, along with more sophisticated services. To holistically reduce the power consumption of the RAN, on top of the lowing power consumption of the base station equipment itself, upgrading the RAN operation that manages and operates the base stations is a significant challenge.

Fujitsu's RAN Operational Management

Fujitsu will solve the abovementioned challenges with "proactive automatic RAN optimization," which controls network equipment functions in real-time based on current and predicted network quality. Proactive automatic RAN optimization enables timely responses to network quality degradation. Proactive responses to service-affecting quality degradation will allow users to comfortably use various advanced services that leverage high-quality 5G networks.

The Fujitsu Approach

Fujitsu will achieve proactive automatic RAN optimization in the two steps shown in Figure 6.

We will deliver predictive and automatic operational management with advanced AI technologies in the first step. Specifically, it automatically predicts degradation of network quality of service (QoS), such as throughput and delay, which is difficult for humans to detect. Proactive automatic RAN optimization will also perform root cause analysis and take actions to recover the degradation.

We will introduce the quality of experience (QoE) in the second step, which means actual user experience. Conventional QoS based operational management systems cannot detect QoE degradation. By responding to QoE degradation with resource allocation from idle network functions, Fujitsu RAN operational management system can help maintain the QoE to deliver services that meet user expectations.

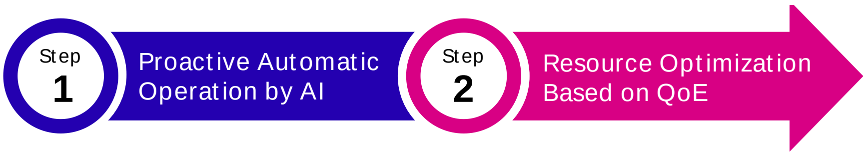

Figure 6 The Fujitsu Approach

[1] Japan Science and Technology Agency, Center for Low Carbon Society Strategy "The impact of the progress of the information society on energy consumption (Vol. 5)" (February 2022) https://www.jst.go.jp/lcs/en/proposals/fy2022-pp-05.html

Value Provided

With conventional RAN control, operators measure network quality, adjust parameters, and respond to failures based on traffic volume and packet loss statistics at the time of periodic inspections or after a failure occurs. As a result, QoE is degraded and recovery from failures becomes slow.

In contrast, proactive automatic operation by AI (Step 1) automatically detects QoS degradation by forecasting the QoS score in real-time and adjusting network resources accordingly (1-a). AI releases over-used network resources compared to the required QoS (1-b). This approach lowers power consumption by reducing excess resources while preventing QoS degradation.

In Step 2, AI resource optimization tools apply an evaluation index to QoE. To understand actual resource requirements for maintaining QoE, AI predicts resource fluctuations and QoE scores. If the network has more resources than is required to maintain QoE, AI can reduce excess resource allocations. This reduces power consumption while preventing QoE degradation.

Figure 7 shows balancing low power consumption with network quality and QoE.

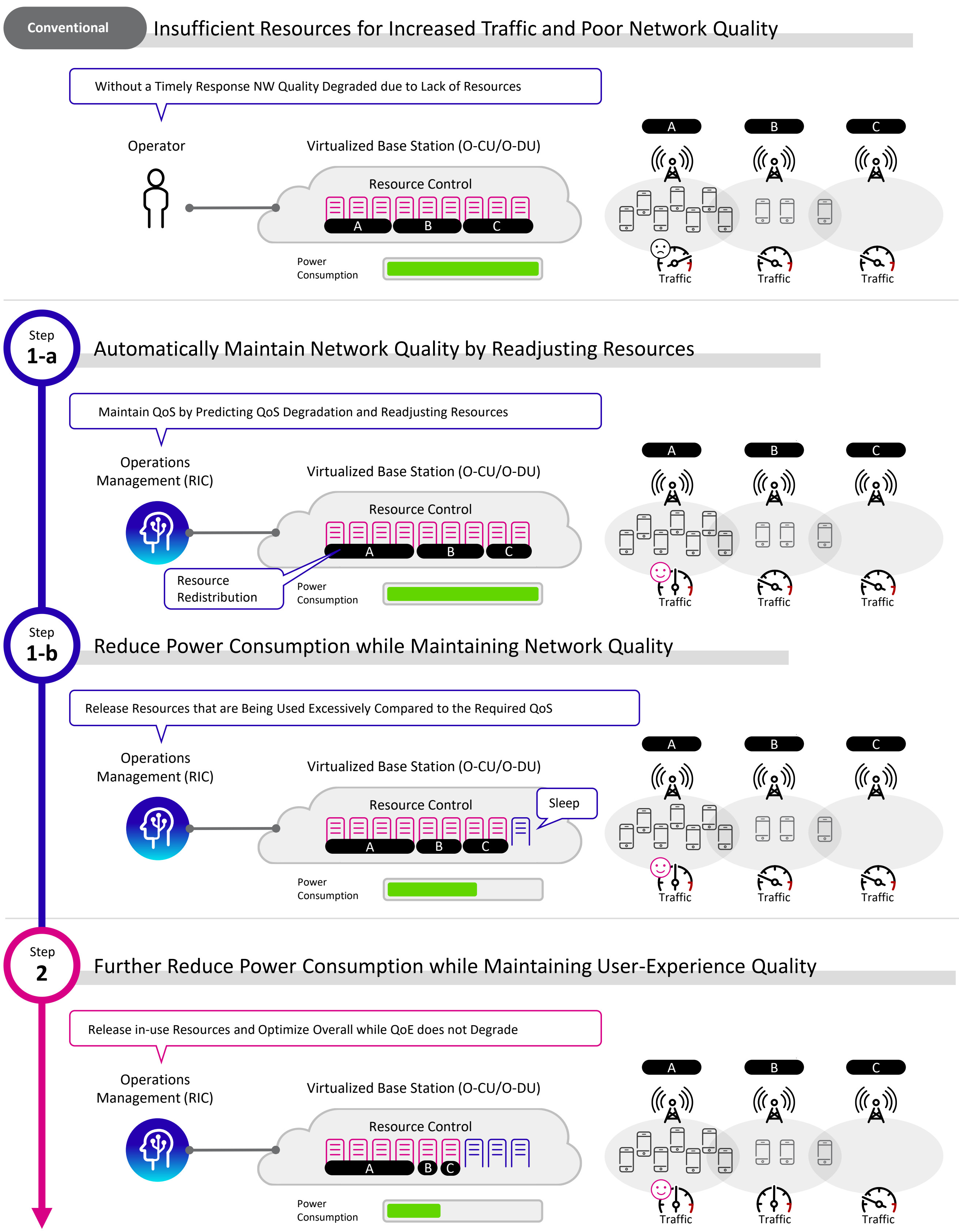

Figure 7 Balancing Low Power Consumption with Network Quality and QoE

RAN Operational Management Architecture

The architecture to achieve proactive automatic RAN optimization is shown in Figure 8. It has four components as follows:

- QoS Monitoring and Prediction
- Real-Time QoE Monitoring
- Dynamic RAN Optimization
- Packet Analysis for QoE Monitoring

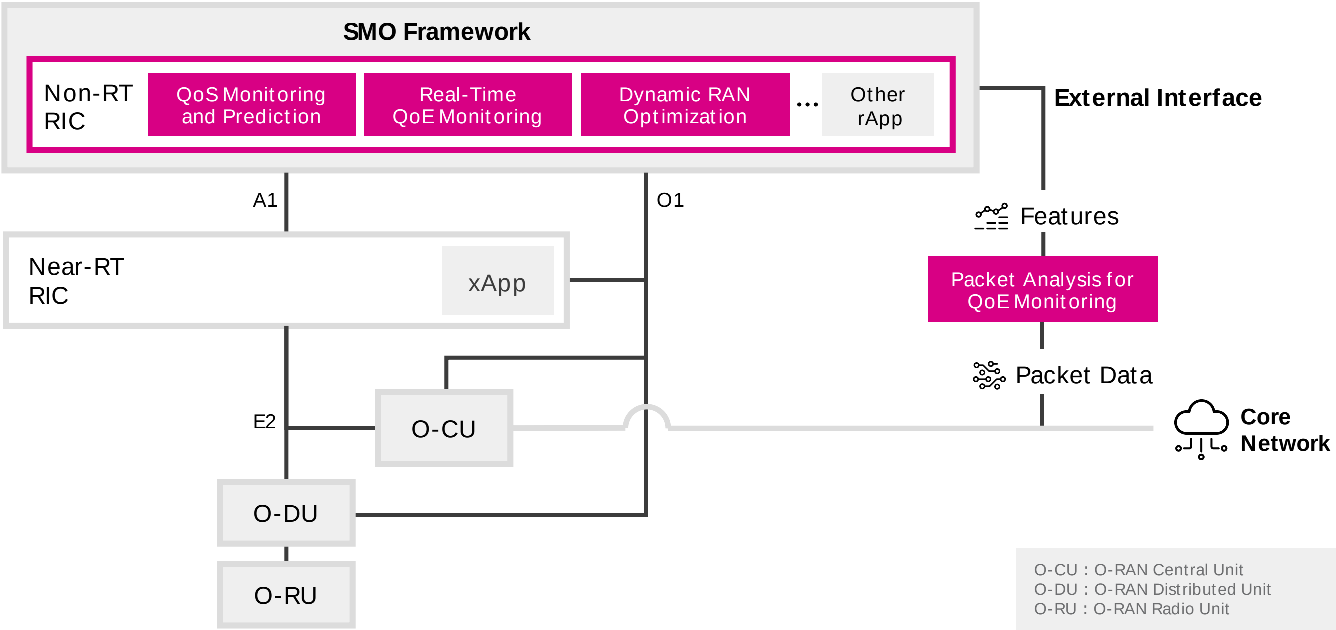

Figure 8 RAN Operational Management Architecture

QoS Monitoring and Prediction

This rApp calculates the current QoS score and predicts future scores of network quality. It does this by calculating the current QoS scores using statistical performance data collected from the O-DUs and O-CUs via the O1 interfaces. The SMO stores those scores and predicts future scores using time series data analysis.

Real-Time QoE Monitoring

This rApp estimates the current QoE score, which indicates the quality of user experience. The current QoE score is estimated based on features from the "Packet Analysis for QoE Monitoring" component. By using the analysis results of packet data acquired in real-time, it is possible to detect degradation of QoE that occurred in a short period, which cannot be seen by current QoS scores calculated from the statistical performance data of the O-DUs and O-CUs.

Dynamic RAN Optimization

This rApp controls the operating status and parameters of the O-DUs and O-CUs via the O1 and A1 interfaces. The rApp meets various performance requirements and constraints for the RAN, such as current or predicted QoS scores, estimated QoE scores, the delay time of wireless communication processing, and base station power consumption. Proactive responses that recover quality degradation can be achieved by actively using predicted QoS scores.

Packet Analysis for QoE Monitoring

This external component collects enormous amounts of real-time packet data from data traffic without any leakage. The component extracts features that are used for estimation of the current QoE score and exposes the features via an external interface.

Fujitsu's Advanced AI Technologies for RAN Operational Management

Proactive automatic RAN optimization requires accurate quality predictions and appropriate operating control of the O-DU and O-CU parameters to meet quality, performance requirements and constraints. Various AI-driven prediction and control technologies exist, but they cannot answer important questions for mission-critical systems, such as,

- "How reliable are the predictions?"
- "Why did the AI make such predictions?"
- "Is it OK to control them?"

Fujitsu is developing advanced AI technologies, including "reliable AI" and "explainable AI," so that persons can confidently use those AI technologies in various situations. In the following, we describe Fujitsu's advanced AI technologies under research that enable proactive automatic RAN optimization.

Time Series Prediction Technology that Considers Crucial Periods of Time and Prediction Uncertainty

Communication traffic provides the basis for resource allocation in the RAN. Predicting communication traffic requires that predicted values are as close as possible to actual demand without falling below, while predicting reliable values at crucial times, such as sudden changes or peaks.

This technology automatically determines crucial periods of time for improving performance of a target system by analyzing a function which mathematically defines required performance that optimization or control should achieve. Then it constructs a prediction model focusing on the accuracy during the periods. In addition, the uncertainty (variation) of the predicted values based on the predetermined reliability is calculated, and a time series prediction model is constructed by setting an appropriate margin based on the variation of the individual predicted values for the predicted values at each time (see Figure 9).

This calculation makes it possible to predict communications traffic that fluctuates over time with reliability and safety. Applying this technology to the "QoS Monitor and Prediction" component enables to predict QoS variations accurately and proactively allocate resources to network systems.

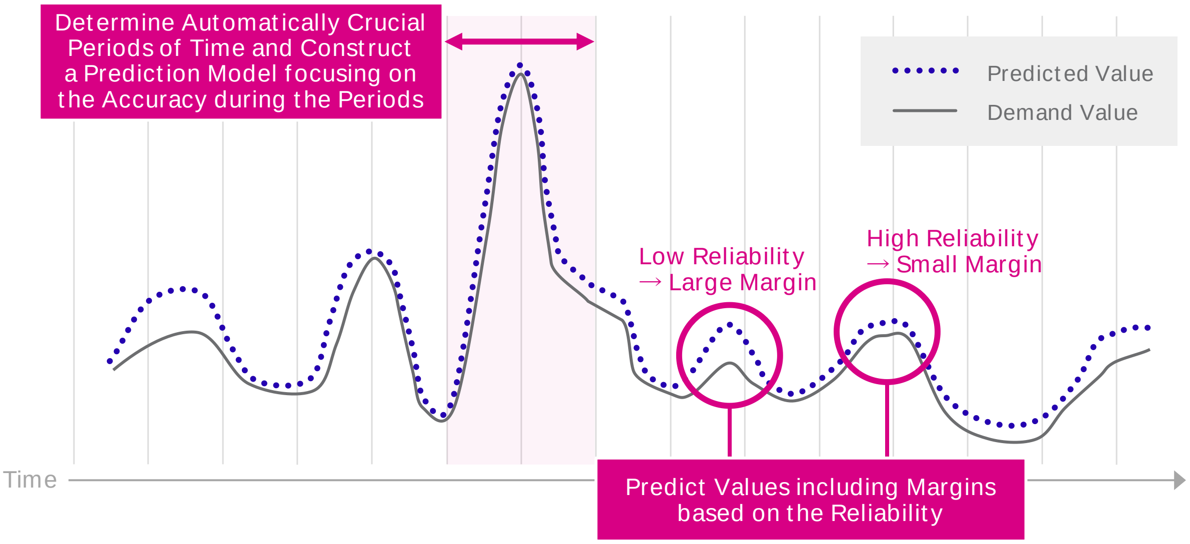

Figure 9 Time Series Prediction that Considers Crucial Periods of Time and Prediction Uncertainty

Wide Learning™

When mission-critical operations, such as mobile network operations, apply AI technologies, it is essential to ensure the reliability and safety of the predicted results. It is also important to explain the reasoning behind decisions. However, in today's general AI technologies, the decision basis is a black box, and people cannot deconstruct the decision basis of AI.

Wide Learning™ quickly and comprehensively enumerates many "hypotheses" described by all combinations of input data items. It statistically verifies the hypotheses and discovers critical ones. Then it automatically makes intelligent decisions such as prediction and classification, and shows the premises used for the decision (see Figure 10).

This approach enables operators to derive important hypotheses in estimating QoE affected by various network metrics and build a highly explainable inference model. In addition, if different combinations of input data items change the estimation of QoE, the model would recommend actions to address the differences in input data that make up the hypotheses. Therefore, applying this technology to the "Realtime QoE Monitor" rApp and "Packet Analysis for QoE Monitor" component makes it possible to achieve highly explainable QoE estimation from the packet data and identify necessary actions in the event of a change in QoE.

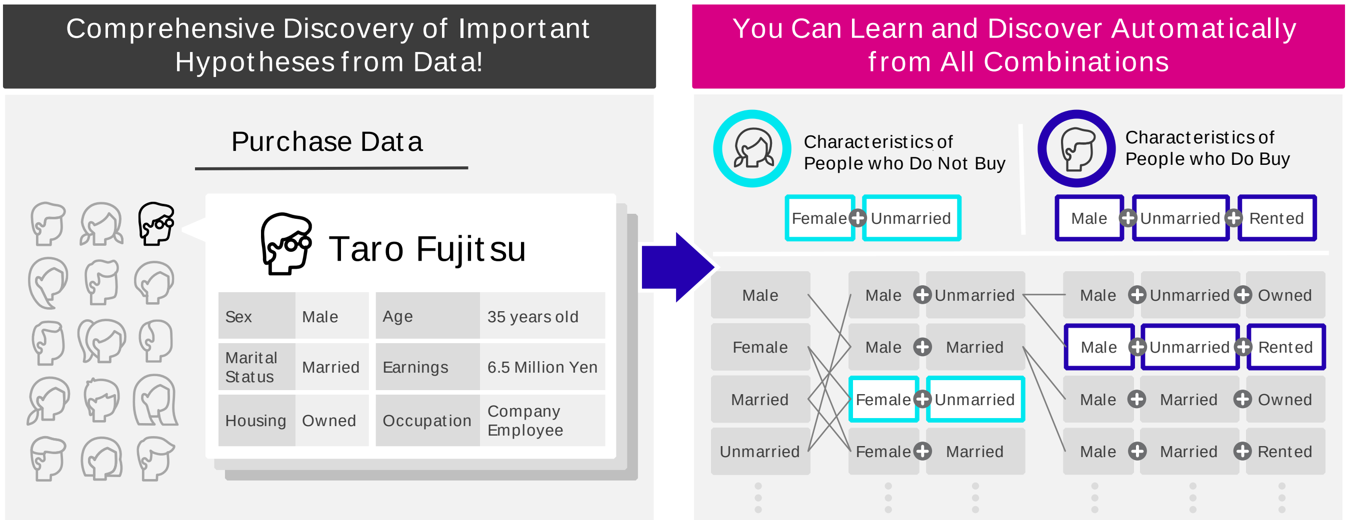

Figure 10 Wide Learning™

Constrained KPI-managing Multi-Agent Reinforcement Learning (CK-MARL)

An AI technology called "reinforcement learning" realizes optimal control by allowing an AI agent to learn a control policy through experiences that result from actions in its surrounding environment. However, in centralized single-agent reinforcement learning, where a single AI agent manages lots of objects (see Figure 11 left), it isn't easy to process a large amount of data generated from the entire target area in real-time. Therefore, single-agent reinforcement learning cannot apply to mobile networks where data is collected and processed in real-time from an enormous number of the O-DUs and O-CUs, which are deployed over a wide area and should be meticulously controlled.

This technology is a distributed multi-agent reinforcement learning that divides a target area to be managed into multiple small areas and assigns an AI agent for each area . In CK-MARL, each agent operates the objects in the area to meet the constraints of the corresponding area. In addition, each agent interacts with other agents to exchange information and optimize the entire area (see Figure 11 right). In this way, each AI agent only needs to process the data in the divided area and the data exchanged with other agents, so even if the area to be optimized is expanded and the amount of data is increased, the process would be scalable by dividing the area appropriately.

By applying this technology to the "Dynamic RAN Optimize" component, even in large-scale mobile networks, it is possible to achieve complex real-time optimization. That can include suppressing the total power consumption of the entire area below a specified value while controlling QoS parameters like throughput and communication delay in each divided area.

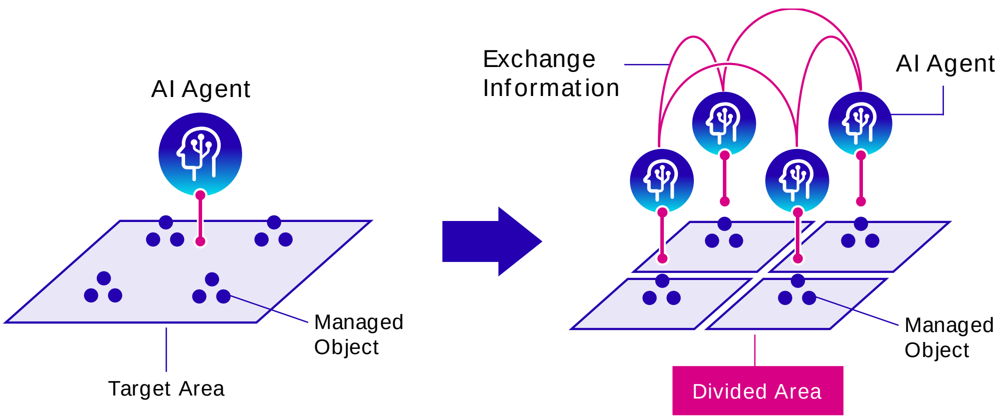

Figure 11 CK-MARL

In addition to the advanced AI technologies discussed in this section, Fujitsu is conducting development on technologies that enhance RAN operational management by utilizing various AI technologies. The following section introduces solutions that we are currently developing.

Fujitsu's Advanced RAN Operational Management Solutions

This section presents the solutions that Fujitsu is currently developing.

First, we will explore the solutions in the Step 1 that enable proactive automated operational management with AI, including an energy-efficient operation of base stations by RU sleep control and repair for out-of-service areas.

Next, we will discuss a QoE monitoring for video streaming services and a QoE analysis for various services as early-stage solutions in the Step 2 to achieve resource optimization based on QoE.

Energy-efficient Operation of Base Stations by O-RU Sleep Control

Fujitsu has developed a solution for energy-efficient operation of base stations that achieves both quality and power saving using the advanced AI technology CK-MARL described in the previous section. This solution aims to achieve power saving while maintaining high QoS, such as high throughput and low latency as a feature of 5G networks. The solution sets the active or a sleep state for each O-RU depending on varying communication traffic. Upon transitioning an active O-RU to a sleep state, power consumption decreases. Concurrently, user terminals connected to the initial O-RU are required to reconnect to alternative neighbor O-RUs, resulting in an increased load on the newly connected O-RU. Therefore, the solution sets the state of each O-RU so that the load of all O-RUs does not exceed a certain threshold. This approach reduces gross power consumption while meeting all O-RU load constraints. Such control policies can be acquired automatically by CK-MARL using traffic data with a wide range of regional characteristics and time variations, eliminating the need for manual design work.

Figure 12 shows an example of applying this solution to actual traffic data in Milan, Italy. In this solution, the city of Milan is divided into areas of approximately 250 meters square, and each area is further divided into four areas that display light red for low traffic, dark red for high traffic, green for active O-RUs, and blue for sleeping O-RUs. In Figure 12 left, when traffic is low, more than half of the O-RUs are in a sleep state (blue). However, when traffic increases, as shown in Figure 12 right, the O-RUs that were in a sleep state are switched to an active state (green). We confirmed that CK-MARL is capable of controlling approximately 1000 O-RUs every 30 minutes.

Figure 12 Example of Dashboard for the Solusion

Figure 13 shows the effect of applying conventional reinforcement learning with the sole purpose of reducing power consumption and CK-MARL, compared to the case when all O-RUs are active, using traffic data for some areas in the city of Milan. In terms of power consumption, the results show that conventional reinforcement learning can reduce power consumption by 25.3% and CK-MARL can reduce it by 23.5%.

However, since conventional reinforcement learning does not satisfy the constraint on the maximum load of O-RUs, communication quality problems such as delays in communication may occur. On the other hand, CK-MARL was able to reduce gross power consumption by more than 20% while ensuring that the constraints were met.

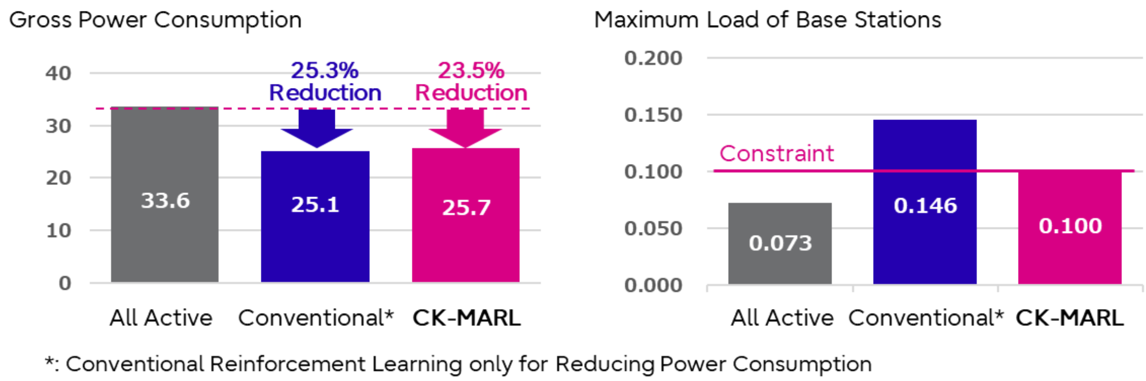

Figure 13 Example of Effect by the Solution

The CK-MARL solution is applied through the rApp on the SMO Non-RT RIC platform. The CK-MARL uses traffic data acquired from each node of the RAN and the operation status of the O-RU to determine control policy for each O-RU. It is also known that up to 50% of power consumption can be reduced by combining this solution with a next-generation O-RU that has fine-grained sleep modes. Through this solution, we will contribute to realize a safe, secure, and sustainable society.

Repair solutions for out-of-service areas [2]

Beyond the 5G RAN, all people and things will be connected, creating critical social infrastructure, and ensuring service continuity. During emergencies such as disasters, it is vital to quickly detect and repair service outages. However, all too often, it takes several days from identifying service outage areas to restoring service, posing a significant challenge to consumers.

To address this issue, Fujitsu has developed a solution that rapidly restores service outages by using the AI technique. AI identifies service outages and determines tilt angle settings of neighboring base stations that are still in service, to cover the service outage area from neighboring base stations.

As shown in Figure 14, the area where service outage occurred due to a disaster is detected by using AI Anomaly Detector from performance data collected at the base station.

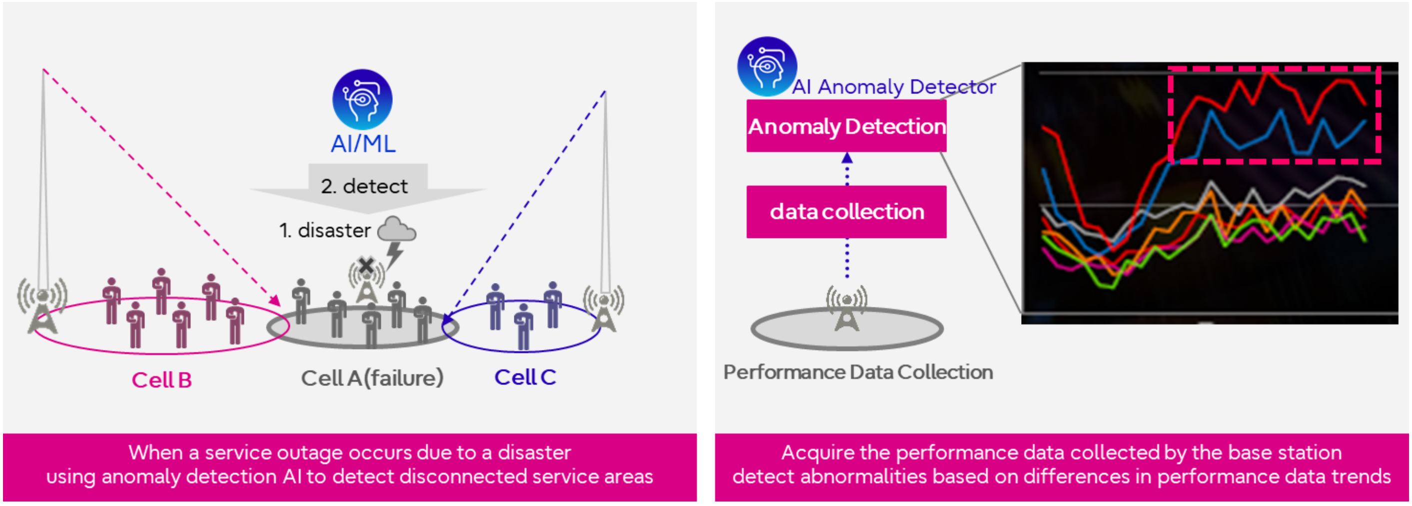

Figure 14 Detecting Disconnected Areas

As shown in Figure 15, based on the results of the AI Tilt Angle Calculator, we adjust the tilt angle of the neighboring base stations that are still providing service, and expand the coverage area to restore service outages. This enables service recovery in less than one hour, compared to days required by field engineers.

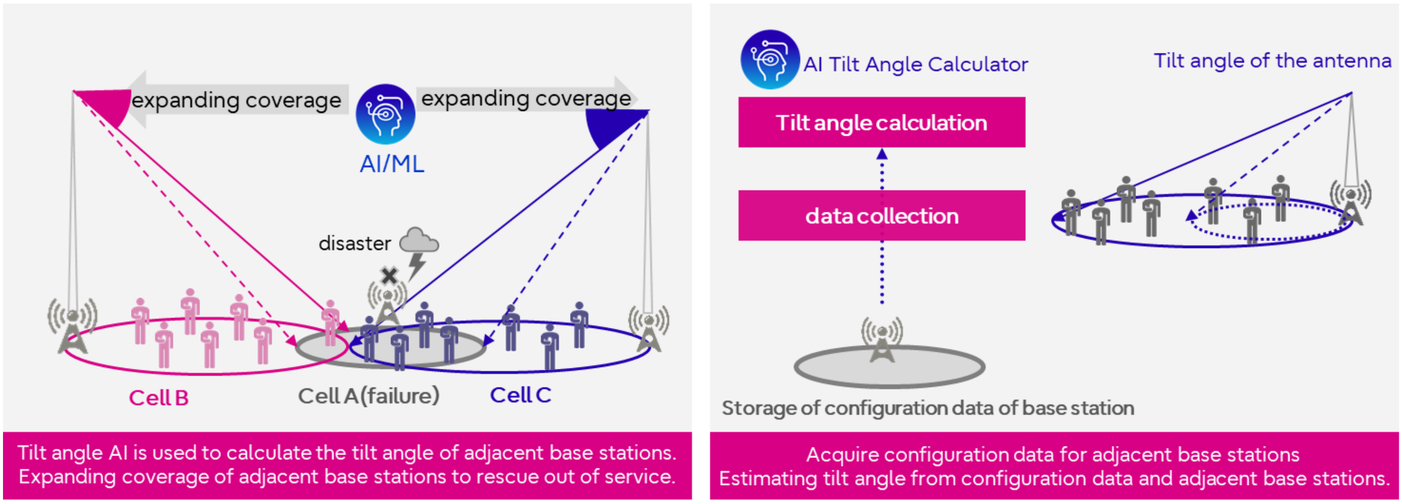

Figure 15 Rescuing Service Loss Area by Calculating Tilt Angle of Adjacent Base Station

[2] This article is based on results obtained from "Research and Development Project of the Enhanced Infrastructures for Post 5G Information and Communication Systems" (JPNP20017), commissioned by the New Energy and Industrial Technology Development Organization (NEDO)..

QoE Monitoring for Video Streaming Services

To establish a network that balances quality and efficient resource usage, employing QoE as a metric is advantageous. Specifically, Fujitsu has focused on the Mean Opinion Score (MOS), a subjective measure of media quality that encompasses human perceptual characteristics among QoE. Fujitsu developed Real-time Quality of Experience Sensing™ (RQS), an AI technology for video streaming services, which constitute over 70% of mobile network traffic, to estimate MOS in real-time with high precision utilizing solely encrypted packets.

As shown in Figure 16, RQS consists of two components as follows:

- A video feature estimation model that outputs video features such as video encoding bitrate using packet features calculated from packets flowing through the network as input
- A QoE estimation model that outputs MOS using the video features as input

To reduce computational resources required to obtain the packet features, we calculated them from uplink packets, which are communications from the device to the video streaming server.

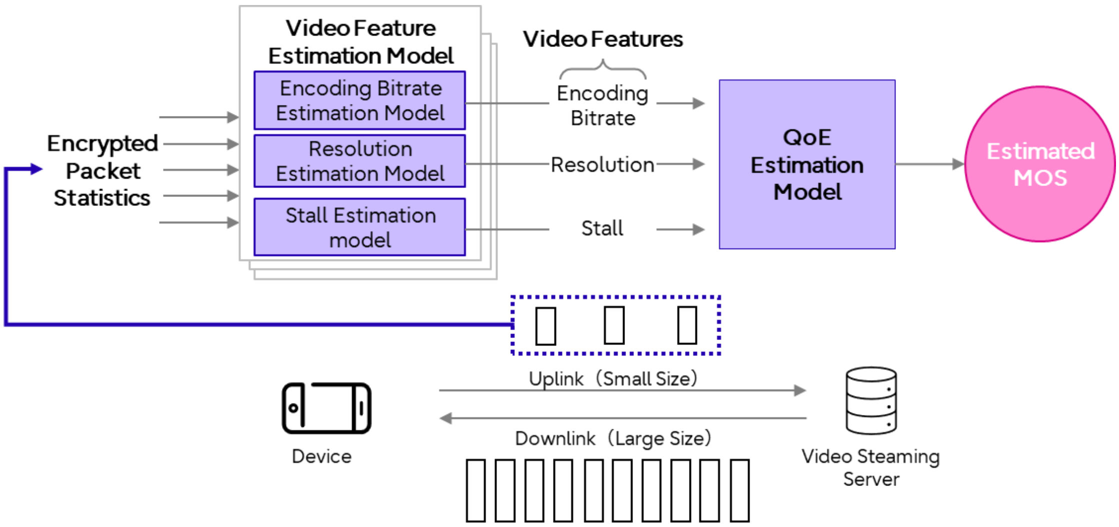

Figure 16 Overview of RQS

This approach allows us to adjust to custom-tailored video streaming services and new communication protocols by only retraining or altering the initial video feature estimation model. In experiments using popular communication protocols for video streaming services, such as HTTP Live Streaming (HLS) and MPEG-DASH, we managed to estimate video features with nearly the same accuracy while cutting down the processing data volume by 98% compared to using all packets. Additionally, we estimated MOS with over 85% accuracy to the value estimated by international standard ITU-T P.1203, which calculates MOS based on video quality information from video playback applications.

Figure 17 shows a QoE monitoring solution for video streaming services using RQS. RQS obtains uplink encrypted packets for each video stream between the RAN and the core network. Furthermore, the video features are estimated from the obtained packet statistics and sent to the MOS Estimation rApp implemented in SMO. The MOS Estimation rApp estimates MOS from received video features and displays the scores in real-time on the QoE monitoring dashboard for network administrators.

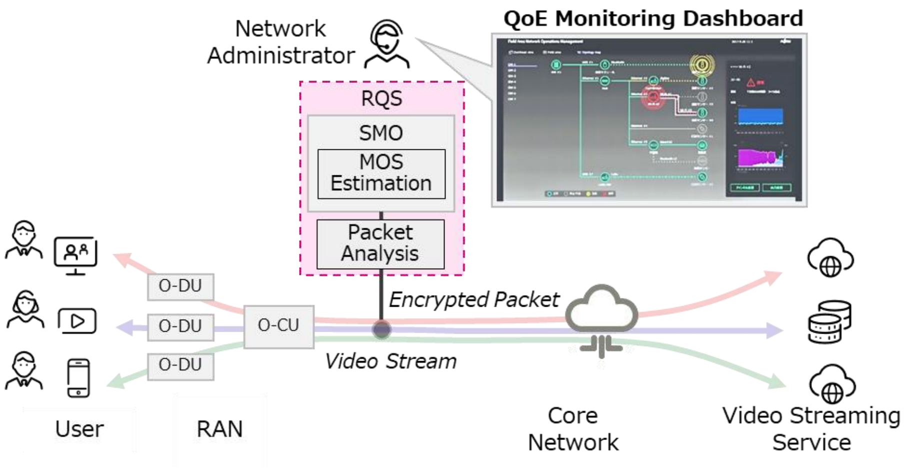

Figure 17 Overview of the QoE Monitoring Solution for Video Streaming Service

At present, our solution provides real-time visualization of MOS for video streaming services. In the future, we plan to expand its features, such as applying to next-generation services using Extended Reality (XR) to merge real and virtual worlds, and offering solutions to tackle QoE (including MOS) decline with Wide Learning™, as mentioned earlier. Additionally, we strive to deliver efficient, high-quality networks by implementing network operational management based on QoE and incorporating cutting-edge network resource control technologies under development.

QoE Monitoring for Various Services [3]

In the era of 5G and beyond, all services for individuals, businesses, and the public will be based on network connectivity. This requires the provision of networks that meet the requirements and characteristics of a wide variety of services (low latency, very large capacity, very large number of connections). To achieve this, it is necessary to understand the user's QoE of each service.

Fujitsu has developed a framework that enables rapid implementation of service monitoring based on QoE estimation to accomodate wide variety of services. In the framework, shown in Figure 18, a QoE estimation model is generated following a specific process when a new service is introduced. By using the QoE estimation model to analyze packets in real-time, we can monitor the quality of each services.

First, we extract and analyze packets corresponding to the target service from the captured packets. The quality KPIs output from the analysis consist of two types, which are common regardless of the service. The first type is the network quality KPI (loss, delay, throughput, etc.) that indicates the network behavior at the TCP/IP level. The second type is the application quality KPI, which quantifies the groups of packets received by the application to estimate the service behavior (number of packet groups, intervals between packet groups, etc.).

Next, we select the quality KPIs that strongly correlate with the QoE of the target service based on multiple quality KPIs and MOS values (QoE) evaluated by people or applications. Finally, we select the AI algorithm with the highest prediction accuracy from multiple AI algorithms and generate a QoE estimation model tailored to the service. By separating and combining service-independent and service-specific parts, we can accommodate various services. By continuously registering the generated QoE estimation model in the QoE estimation model library, the range of services that can be supported will be expanded.

By applying this framework and performing real-time service monitoring, QoE degradation can be detected at an early stage, and based on this, countermeasures such as network resource optimization and expansion can be taken to maintain service quality. In addition, the QoE estimation model can be easily applied to a growing number of new services in a short period of time.

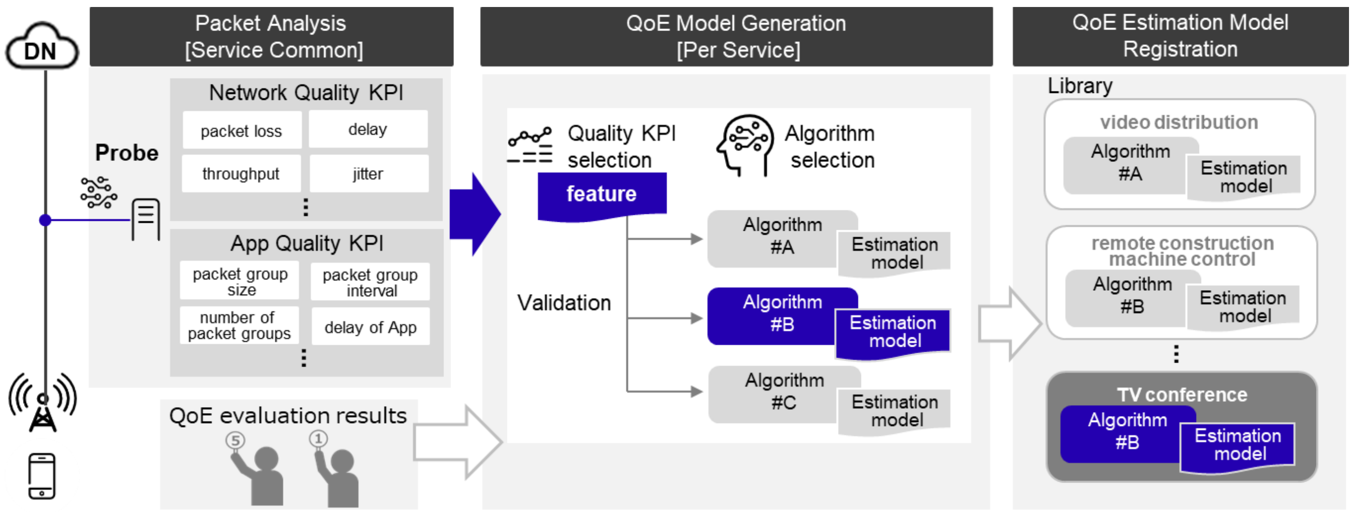

Figure 18 Overview of the QoE Estimation Framework for Various Services

[3] This article is based on results obtained from "Research and Development Project of the Enhanced Infrastructures for Post 5G Information and Communication Systems" (JPNP20017), commissioned by the New Energy and Industrial Technology Development Organization (NEDO)..

Conclusion

This white paper introduced the approaches and key technologies for using AI in RAN, and solutions to the challenges of increasing network complexity and power consumption.

Looking ahead to 2030, networks will cover a variety of functions and services while also considering the environment. AI is an essential technology to dynamically control networks being increasingly sophisticated. Going forward, Fujitsu will expand the scope of AI from RAN to the entire end-to-end network and will work to develop advanced network and AI technologies while also considering overall network operation.

Acronyms

3GPP	3rd Generation Partnership Project
5G	5th Generation
6G	6th Generation
AI	Artificial Intelligence
CPU	Central Processing Unit
E2E	End-to-End
eMBB	enhanced Mobile Broadband
FR2-2	Frequency Range 2-2
HLS	HTTP Live Streaming
ICT	Information and Communication Technology
IIoT	Industrial Internet of Things
IoT	Internet of Things
KPI	Key Performance Indicator
MBS	Multicast and Broadcast Services
MEC	Multi-access Edge Computing
ML	Machine Learning
mMTC	massive Machine Type Communications
MOS	Mean Opinion Score
Near-RT RIC	Near-Real Time RIC
Non-RT RIC	Non-Real Time RIC
NTN	Non-Terrestrial Network
NW	Network
NWDAF	Network Data Analytics Function
O-CU	O-RAN Central Unit
O-DU	O-RAN Distributed Unit
O-RAN	Open Radio Access Network
O-RU	O-RAN Radio Unit
QoE	Quality of Experience
QoS	Quality of Service
RAN	Radio Access Network
rAPP	Non-Real Time RIC Application
RIC	RAN Intelligent Controller
SDGs	Sustainable Development Goals
SLA	Service Level Agreement
SMO	Service Management and Orchestration
TCP/IP	Transmission Control Protocol/Internet Protocol
TS	Traffic Steering
URLLC	Ultra-Reliable and Low Latency Communication
V2X	Vehicle to X (Vehicle-to-everything)
vCU	virtual Central Unit

vDU	virtual Distributed Unit
VR	Virtual Reality
WDM	Wavelength Division Multiplexing
xAPP	Near-Real Time RIC Application
XR	Extended Reality

For more information ...

https://www.fujitsu.com/global/products/network/

Fujitsu Limited

Shiodome City Center
1-5-2, Higashi Shimbashi
Minato-ku, Tokyo 105 -7123, JAPAN

https://www.fujitsu.com/global/