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Special Articles on Smart OPS for Further Efficiency and Advancement of Network Operations

Achieving Advanced Maintenance Works with AI

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Mobile networks are becoming increasingly sophisticated with the implementation of new technologies such as network virtualization and 5G. The accompanying amount of mobile network maintenance work has burgeoned dramatically, leading to demands to reform conventional reactive maintenance (follow-up measures). Thus, as Phase 3 of the Smart OPS concept, we have taken initiatives to develop systems with AI technology that will enable advanced analysis to achieve proactive maintenance (advance preventive measures) based on predictions that would be difficult for humans to make.

1. Introduction

With the implementation of network virtualization*1 and 5G, mobile networks are expected to become more complicated and mobile services more diverse in future. Hence, maintenance operations (hereinafter referred to as "operations") to identify and rectify network failures would clearly entail increased amounts of work and time taken for work since rapid and accurate analysis using only conventional human-centered methods to identify and analyze impacts on user services would be problematic.

Thus, to shift away from conventional follow-up

*1 Network virtualization: A method of implementing network control functions as software running on virtualized operating systems on servers.

maintenance measures enacted after an alarm is detected (hereinafter referred to as "reactive"), NTT DOCOMO is implementing Artificial Intelligence (AI) in operations which is anticipated to bring efficiency to a range of fields.

This article describes usage of AI in operations, and initiatives to shift from reactive maintenance to advance preventive maintenance (hereinafter referred to as "proactive").

2. Circumstances Surrounding Mobile Networks and Work Issues

2.1 Mobile Network Circumstances

Going forward, accompanying network virtualization, 5G implementation and the rapid spread of devices on the Internet of Things (IoT), mobile networks will require update to accommodate communications for various services with different traffic characteristics and network specifications than conventional communications, such as the low latency and multiple simultaneous connections. Thus, new technologies such as virtualization and network slicing*2 have been introduced into the systems providing these services. The logical network structures that provide these services are complex structures with multiple virtualized logical resources that require an enormous workload in their operation compared to the conventional maintenance work done by humans.

2.2 The Current State of Operations

To provide a comfortable and easy to use network to users 24 hours a day, 365 days a year, network operations must maintain high network communications quality and are thus predicted to become even more complicated as services diversify into the future. In addition, so that network quality is maintained, and users are able to enjoy comfort and cutting-edge innovations, operations need to be reformed for proactive maintenance based on predictions and warning signs in place of reactive maintenance only enacted as recovery measures after a problem has occurred.

Achieving such proactive maintenance requires advanced operations such as detecting "silent failures*3" in which alarms are not received from Network Elements (NE)*4 despite affecting users, visualizing network quality based on user Quality of Experience (QoE), detecting signs of failure, swift identification of locations of failures when they occur, and fast service recovery methods [2].

Operations are generally classified as work for monitoring, analysis, and countermeasures. These works are described in general as follows.

1) Monitoring Work

This entails monitoring services and network operating conditions to detect anomalies. Mainly, monitoring is based on warning information, equipment status and traffic information, etc. collected and notified from NE.

2) Analysis Work

This entails determining causes and locations of malfunctioning NEs or sections when errors are detected with a service or on the network.

3) Countermeasures Work

This entails enacting countermeasures in response to the determined cause of the failure to recover normal status. This work can include remote control or on-site replacement work, etc. according to NE recovery procedures.

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*2 Network slicing: Technology for providing services according to their application by virtualizing the network and splitting network resources.

*3 Silent failure: Failures caused by breakdowns of the fault detection package or main processor, etc. that the equipment itself cannot recognize and hence maintenance personnel cannot detect.

*4 NE: A generic term for a base station, switching station, or relay device that makes up the system.

2.3 Work Efficiency with AI Usage

AI technologies are currently experiencing their "third boom." AI with "machine learning" to automatically learn from patterns and rules based on certain standards from a large amount of data called "big data" has been commercialized, and "deep learning" to accumulate knowledge data so that the AI can learn patterns and rules itself without any particular standards has appeared.

According to the "Information and Communications in Japan" White Paper of 2016, functions that AI actually brings to services are generally classified as "identification," "prediction" and "execution" [1]. NTT DOCOMO has applied AI's identification and prediction functions to the monitoring and analysis work involved in its operations, and has applied execution functions to countermeasures work. There are hence also great expectations on AI to bring efficiency to operations.

3. Study on Sophistication of Operations with AI

We also studied the general areas of the respective monitoring, analysis and countermeasure work to advance these enormous operations through the use of AI. **Figure 1** shows an image of these advances.

1) Monitoring Work

Through the use of AI technologies such as machine and deep learning with vast amounts of data collectible from the network such as warning information, equipment status and traffic, operation systems can detect signs of equipment failures and predict impacts on services that would be impossible for a human to accomplish. When events are detected, any resulting service quality*5 deteriorations are displayed on a map screen for each area and service alerts are displayed as a

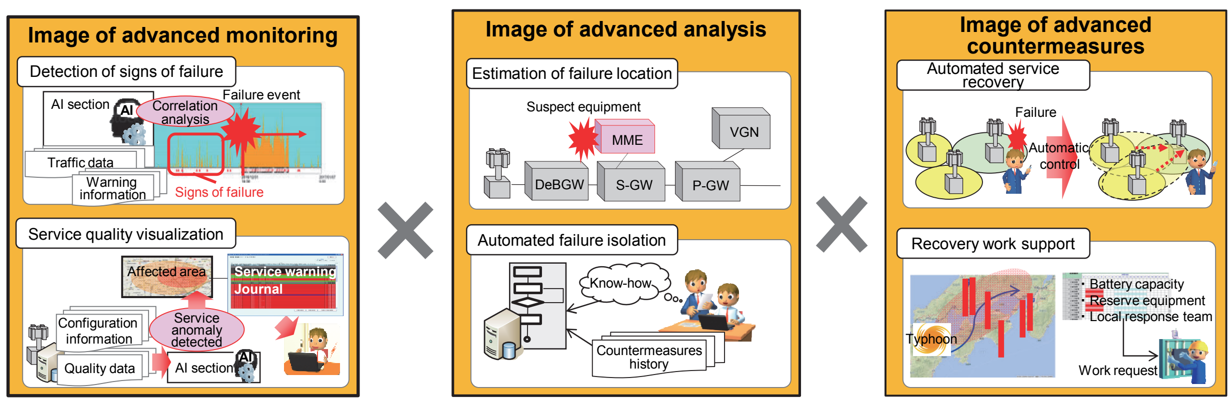

Figure 1 Image of advanced operations with AI

*5 Service quality: A level of quality on the network that can be set for each service. The amount of delay or packet loss is controlled by controlling the bandwidth that the service can use.

journal.

The following describes cases of these advanced measures.

(1) Connection quality anomaly detection in radio base stations

In this case, AI enables detection of signs of events impacting user services by learning trends in normal data in radio base stations and detecting data that is different from usual.

(2) Detection of user quality of experience deterioration

AI enables detection of deteriorated QoE by numeric quantification of user QoE from the time required to display a webpage.

2) Analysis Work

When service quality deterioration is predicted with monitoring work, the operations system estimates the cause of the failure or its suspect locations based on data analyzed from the complex logical network structure. Also, using past human know-how to isolate failures, the operations system supports work by recommending optimized analysis procedures triggered by equipment alarms.

3) Countermeasures Work

The operations system automatically enacts recovery countermeasures for failure causes identified with analysis work. For example, at a location and time where many people gather such as an event venue, adjustments to base station tilt[*6] can be made to optimize for coverage of the area to prevent impacts on services before they occur. Not only with remote maintenance, for on-site maintenance works, the operations system also provides workers with support through guidance by suggesting parts that may be required for a project or optimized response procedures in cases where work is required on multiple base stations, etc.

4. The System Structure and Example Application of AI Technology

This section describes the system structure using AI technology to achieve advanced operations, using cases of connection quality anomaly detection in a radio base station and user QoE deterioration detection as examples.

4.1 A System Structure Enabling Multiple Simultaneous AI Usage

Essentially, operations consist of analysis of text data such as system log and numeric data such as traffic. This may include multiple data patterns depending on the work. There are also algorithms and products available with AI technologies that excel at analysis of text and numeric data, and hence there are demands for this kind of analysis depending on the work.

For this reason, a diverse range of AI technologies must be executed simultaneously in operations, and NTT DOCOMO has developed a system to enable this. **Figure 2** shows a schematic of system we developed.

In this system, the "data management platform section" that manages big data, the "AI engine function section" that analyzes big data and the "screen display section" that displays the results of AI analysis exist independently. Thus, as well as adopting multiple AI engines, future implementation of new AI products or replacement of existing AI products can be done easily.

*6 Tilt: The inclination of an antenna's main beam direction in the vertical plane.

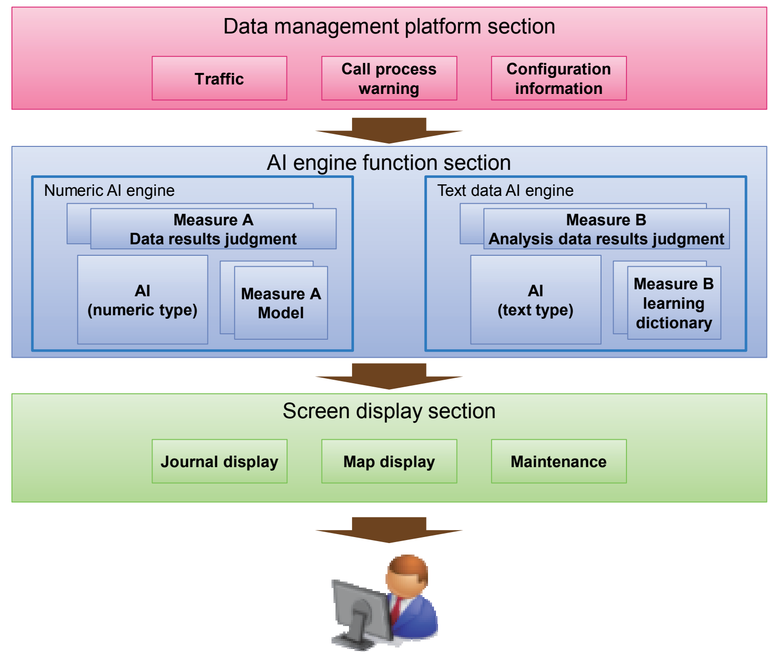

Figure 2　System structure

4.2 Connection Quality Anomaly Detection in Radio Base Stations

1) Detecting Connection Quality Anomalies through Equipment Alarm Monitoring

Conventional maintenance of radio base stations makes it possible to respond to equipment anomaly events through analysis and countermeasures work triggered by equipment alarms, without the need for detailed knowledge of the radio base station. However, by the time of the alarm event, equipment anomalies may have already significantly impacted users. Thus, to address this issue, anomalies must be detected before equipment alarm events occur and the necessary countermeasures taken.

2) Connection Quality Anomaly Detection with AI

We have developed technology (hereinafter referred to as "connection quality anomaly detection") that detects signs of anomaly events in radio base stations by looking for anomalous trends in the network data such as traffic, warnings and logs, etc. that NTT DOCOMO regularly accumulates (**Figure 3**).

This technology is divided into a learning phase in which normal statuses are learned from network data (**Figure 4** STEP (0)), and an analysis phase in which anomalies are detected based on the learning model (Fig. 4 STEP (1) to (3)). In network data

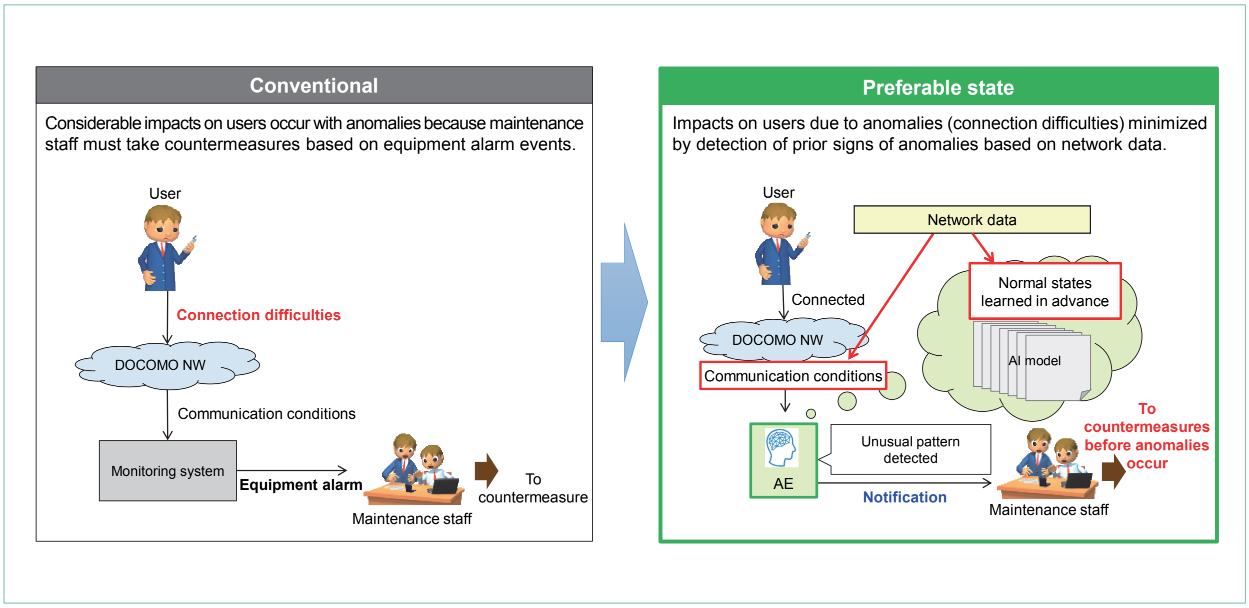

Figure 3 Connection quality anomaly detection with AI technologies

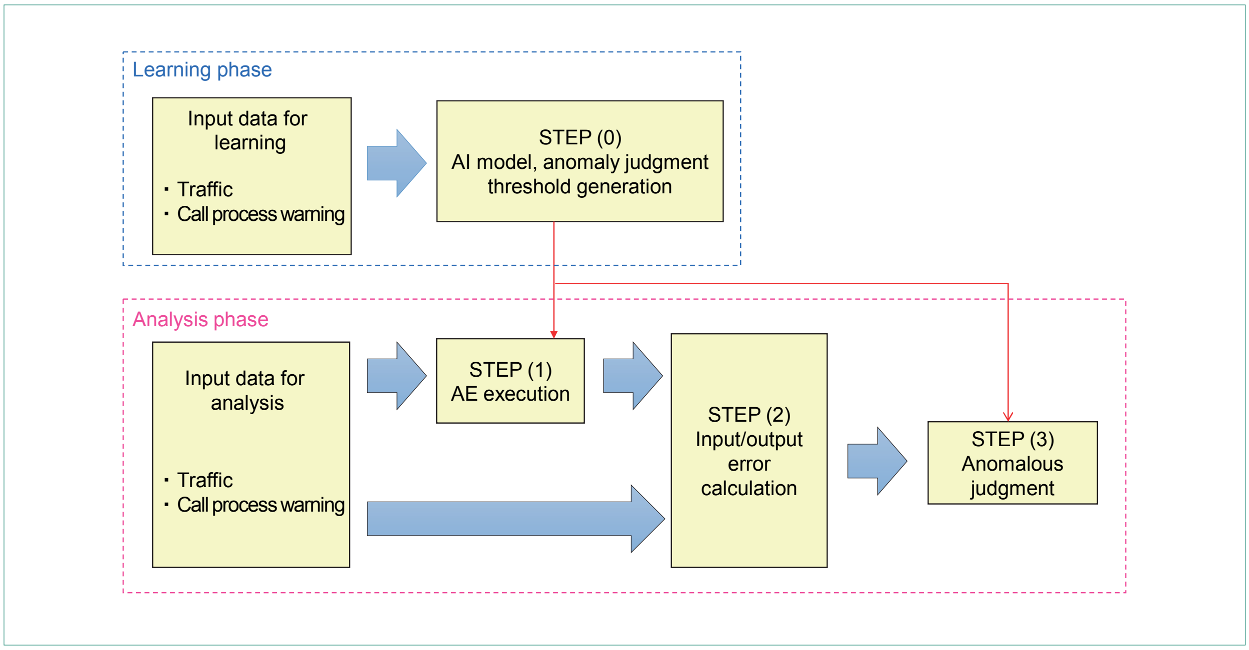

Figure 4 Process overview of connection quality anomaly detection with AI technology

used for model learning and analysis, the amount of time for anomalous events is only a small amount of the overall working time of the radio base station, and data for anomalous events is tiny compared to normal times. Thus, we adopted Auto Encoders (AE)*7 often used for anomaly detection in recent

*7 AE: A type of algorithm designed for dimensional compression using neural networks in machine learning. Conventionally used for prior learning with deep learning.

years, because they can learn from data from normal times. Learning is done by reproducing normal time input data with the AE. Then, when input data appears that cannot be reproduced with the learning model, it is judged as anomalous to enable detection.

(a) Learning phase

In the learning phase, normal time network data is input to generate the AE model. This technology makes use of call processing alarm data, a type of warning information in mobile communications connection processing, and traffic data collected from mobile base stations. We used the call processing alarm data and traffic data excluding data for equipment failures, etc. judged beforehand as periods of anomaly as normal learning data, so that learning data can be faithfully reproduced when learning the model.

(b) Analysis phase

Newly acquired network data is given as input data to the model generated in the learning phase, and the model output result and input data are compared. If the input data is acquired during normal times, the input and output will not be that different. However, if data that does not appear normal is input, there will be a significant difference between the input and output. Then, the Residual Sum of Squares (RSS)*8 is calculated for the input and output, and an anomaly is judged if the RSS exceeds the threshold calculated in the learning phase.

Figure 5 shows an example of application of this technology to a radio base station in which an equipment alarm event has occurred.

The plotted red points in Fig. 5 represent degrees

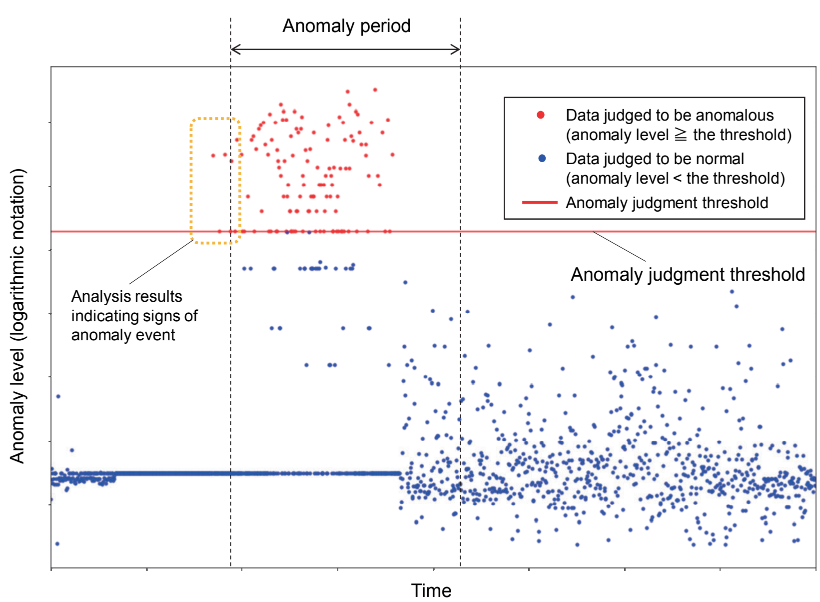

Figure 5 Connection quality anomaly detection application example

*8 RSS: The squared and summed value of the residual error (the difference between the input value and our value in this case). A scale for evaluating mismatches between input values and model output values.

of anomaly that are RSS calculated in a single analysis phase. If the level of anomaly exceeds the threshold, an anomaly is judged (the red points in Fig. 5). In Fig. 5, signs of anomalous events were detected with this technology because a number of analysis results judged as anomaly were detected in the stage prior to the anomalous period the equipment alarm events occurred.

We also confirmed consistent results of anomaly detection because anomalies were judged by the system in the stages prior to 60% of equipment alarms events in the results of similar testing done on randomly selected base stations.

4.3 Detection of User QoE Deterioration

1) Current Issues with Network Monitoring

Current network monitoring entails analysis and countermeasures triggered by equipment alarms to prevent large-scale impacts on networks. However, it is not possible to detect situations in which users cannot comfortably enjoy Web browsing or video streaming services at locations that become crowded such as events where large numbers of people gather or major terminal stations.

2) Approaches to Solving These Issues

A solution to the aforementioned issue of not being able to detect situations in which users cannot comfortably use network services, can be achieved by quantification of QoE and visualization of quality conditions to quickly detect and rectify QoE deterioration.

3) QoE Visualization Method

DOCOMO has developed a visualization method that entails estimation of the Mean Opinion Score (MOS)*9 of QoE on a scale of 1 to 5 of feature values*10 for traffic data collected from NE, as shown below (**Figure 6**).

(1) The traffic data collected by NE for each area is input into a preestablished QoE estimation model to estimate the average QoE for the area.

(2) The predicted QoE is quantified for each time and area so that the operator can confirm conditions of deteriorated QoE.

4) QoE Estimation Model

To build a QoE estimation model to reproduce

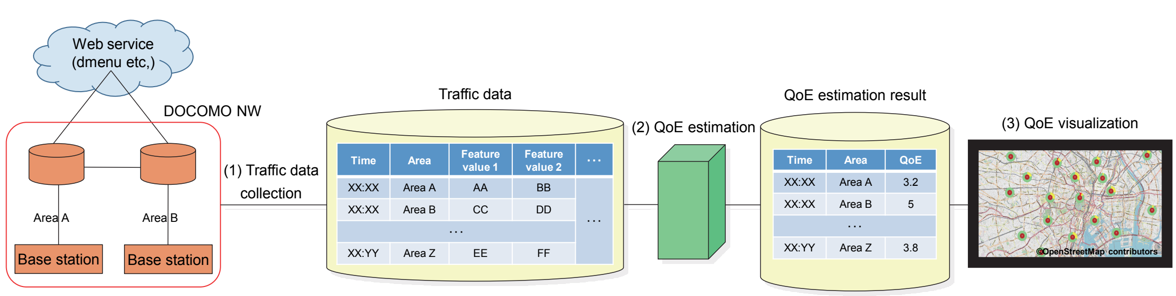

Figure 6 QoE visualization method overview

*9 **MOS**: A widely used measure of subjective quality representing the average value of subjective evaluations given by multiple subjects.

*10 **Feature value**: An amount (a numeric value) extracted from data to characterize the data. In this article, feature values represent the average throughput acquired from nodes, etc.

actual usage conditions, we took field measurements in a wide range of areas and analyzed the relationship between the QoE measured with mobile devices and the traffic data in the areas. As a result of analyzing the correlation*11 between the feature values of various traffic data collected by NE and QoE, we found the two feature values of average throughput*12 and number of users have particularly large impacts on QoE. Therefore, we built our QoE estimation model based on these two parameters.

Next, to confirm the effectiveness of the estimation model, we tested its accuracy using the data measured in the field. We defined deteriorated QoE as lower than 2.5 for the average value of QoE measured with a number of test mobile devices, and then assessed the percentage of actually estimated QoE deterioration with this technology. We found it to be 82.5% accurate in detecting deteriorated conditions, which we confirmed to be sufficient to enable QoE deterioration detection.

5. Conclusion

NTT DOCOMO implemented systems that use AI technologies in its operations at the end of March 2019. Going forward, we will continue to increase monitoring targets and advance operations in stages for analysis and countermeasures to achieve proactive maintenance work.

REFERENCES

[1] Ministry of Internal Affairs and Communications: "Present and Future of Artificial Intelligence (AI)," Information and Communications in Japan 2016, White Paper, Part 1, Chapter 4, Section 2.

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*11 Correlation: An indication of the relationship between two feature values. If one feature value increases, and another feature value increases or decreases with a similar trend, they are said to be in a correlative relationship. If the trends of increase and decrease are dissimilar, there is no correlation.

*12 Throughput: The amount of data transmitted without error per unit time.