A Study of Communication Quality Estimation Methods for LTE Using Communication Indexces Considering Time Variability

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***Abstract*—In recent years, the network traffic load using mobile communication networks has been increasing. In addition to the impact of the increase in the number of users, the rise of high-capacity data communication services such as video streaming and online games is a major factor. Traffic load is expected to become even tighter in the future. There is concern that the increased traffic load may cause communication quality degradation, and it is important to understand communication quality in order to determine whether reliable services can be used. It is known that the throughput is an important indicator for evaluating communication quality, but it is not realistic to evaluate quality by constantly measuring the throughput value, because it is a factor of traffic load. With this background, estimation using LTE communication indexes has been considered as an existing method, but no study has taken into account the time variability of communication logs. Therefore, this paper proposes a communication quality estimation method that takes time variation into account by treating LTE communication indexes by linking them to day-of-week and time-of-day data.In the proposed method, throughput values are predicted by machine learning using Random Forest and classified by communication quality. LTE communication indexes are input as explanatory variables and throughput as the objective variable, and communication quality is output by learning with Random Forest. We confirmed that the estimated correct response rate for communication quality improved by approximately 5-6% compared to the case where the day-of-week and time-of-day data were not associated with the data.**

***Index Terms*—LTE, machine learning, RSRP, throughput.**

I. Introduction

In recent years, mobile devices such as smartphones have been utilizing Long Term Evolution (LTE) for wireless communication. The usage of LTE for various communication purposes, including high-capacity data services like online gaming and video streaming, has been increasing. Consequently, there has been a significant rise in the network traffic load. This trend is expected to continue, making it imperative for communication service providers to maximize the efficiency of frequency band usage and provide the best user experience [1]. In addition, the application of LTE communications to services such as autonomous driving and connected cars is being considered, and assurance of communication quality that meets requirements for high speed, reliability, and low latency is essential for providing such services.

To address these challenges, resource allocation, load balancing, and prediction of the variability in communication quality experienced by users are being studied. Predicting future throughput values for users allows proactive actions such as allocating additional resources or switching channels to buffer certain content. Continuous throughput measurement, while providing an accurate picture of communication quality, is not ideal because it increases extra traffic load. Therefore, research is currently underway to use LTE communication logs to estimate communication quality. Prior studies have emphasized the usefulness of throughput values in estimating wireless communication quality. They proposed a statistical method to predict throughput using LTE communication logs. They also focused on temporal variation and showed that the trend differs between weekdays and holidays [2].

Various approaches using machine learning have been explored. For example, a system called PROTEUS was developed using regression trees to predict network quality based on network performance observed over the past 20 seconds [3]. It has also been suggested that Random Forest (RF) is the most accurate estimation method for predicting Reference Signal Received Power (RSRP) from LTE communication logs, considering the computation time and other factors [4].However, machine learning has not been used to estimate communication quality from LTE communication logs, taking into account time variability at a certain point.

Therefore, this paper proposes an estimation method of communication quality that takes into account time variability at a certain point in time by linking LTE communication logs to day-of-week and time-of-day data. First, LTE communication logs and throughput values are measured at a fixed point using a measurement device. The collected data is used as input for Random Forest (RF), a supervised machine learning method, to estimate an originally defined communication quality level. In this paper, we compare the accuracy of communication quality estimation with and without linking LTE communication logs to day-of-week and time-of-day data, and show that linking LTE communication logs to day-of-week and time-of-day data improves the accuracy of communication quality estimation.

The structure of this paper is as follows. In Chapter 2, the system model is presented. Chapter 3 provides an overview of

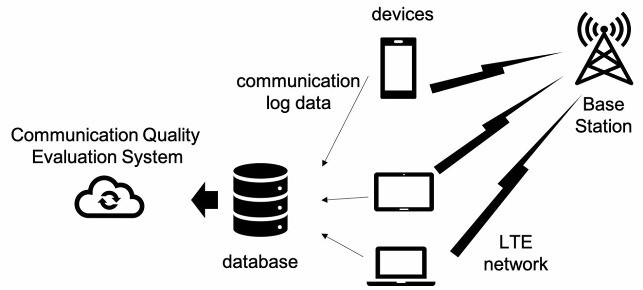

Fig. 1. System Model.

the LTE communication logs collected in this study. Chapter 4 explains the proposed method, while Chapter 5 describes the measurement experiments. In Chapter 6, the results of the proposed method are evaluated, and finally, Chapter 7 concludes this paper.

II. System Model

The system model diagram is shown in Fig 1. In this paper, we assume a device that is conducting LTE communication at a fixed point in a real environment. We obtained the LTE communication logs and the UDP throughput values of the downlink from the communication with the base station at mobile device. We create a learned model at that point in the communication quality estimation system using the collected data stored in a database. This makes it possible to estimate real-time wireless communication quality using LTE communication logs. Service providers will be able to easily monitor the state of wireless communication quality at a particular location and determine whether they can provide reliable communication services.

III. LTE Communication Logs

Physical layer evaluation is very important in assessing LTE communication quality. Commonly used evaluation metrics at the physical layer include received signal strength indicator (RSSI), reference signal received power (RSRP), reference signal received quality (RSRQ), and signal-to-interference/noise power ratio (SINR). RSSI indicates received signal strength including interference power; RSRP indicates received signal strength excluding interference power; SINR indicates received signal quality excluding interference power, received power reference signal strength of the connected system; RSRQ represents the reference signal reception quality and is an indicator of the congestion level between base stations and devices. RSRQ can be expressed using RSSI, RSRP, and the amount of available resource blocks, shown in Equation $RSRQ = N \times RSRP/RSSI$. Here, N represents the number of available resource blocks, which is determined based on the bandwidth. Table I shows the number of resource blocks corresponding to different LTE system bandwidths. SINR represents the signal-to-interference plus noise ratio.

TABLE I
LTE System Bandwidths and Number of Resource Blocks

Bandwidth [MHz]	1.4	3	5	10	15	20
Number of Resource Blocks	6	15	25	50	75	100

Table II summarizes the measurement value criteria for various LTE communication logs.

TABLE II
Measurement Value Criteria for LTE Communication Indexes

value criteria	RSSI	RSRP	RSRQ	SINR
Very Strong	∼ -30 dBm	∼ -44 dBm	-3 ∼ -5 dB	20 dB
Strong	∼ -67 dBm	∼ -90 dBm	-6 ∼ -8 dB	–
Moderate	∼ -70 dBm	∼ -100 dBm	∼ -10 dB	10 dB
Weak	∼ -80 dBm	∼ -140 dBm	∼ -13 dB	–
Unavailable	-90dBm ∼	-140 dBm ∼	-19.5 dB ∼	0

IV. Proposal Method

This paper proposes a communication quality estimation method using supervised machine learning RF class analysis that considers variations in communication quality depending on the day of the week and time of day. After providing an overview of machine learning and communication quality used in this paper, the communication quality estimation method is described.

A. Overview of supervised machine learning Random Forest (RF)

Supervised Machine Learning RF is an ensemble method and uses decision trees. While decision trees are prone to overfitting, RF can reduce the effect of overfitting; in a study to predict RSRPs, RF was the best estimation method considering the computational speed [4]. Therefore, RF was employed in this paper. The procedure for RF is shown below. First, the training data set is bootstrapped and the data set is split. When splitting the data set, data duplication is allowed. Data is randomly extracted from the split data set, and a decision tree is created for each data set. Since class classification is used in this paper, multiple decision trees are created and majority voting is performed to output the results. A schematic diagram is shown in Fig 2.

B. Communication Quality

In the literature [2], throughput value was mentioned to be useful for estimating wireless communication quality. Therefore, in this paper, communication quality was defined as throughput value. Assuming the upper limit of throughput value is 100 Mbps [5], Scenario 1 and Scenario 2 were created.

Scenario 1 divides the throughput upper limit of 100 Mbps into 5 equal parts, and Scenario 2 divides it into 3 parts.

Scenario 1 is simply the throughput value divided into five equal parts of 20 Mbps each. Scenario 2 was set considering the range where message sending and video viewing are

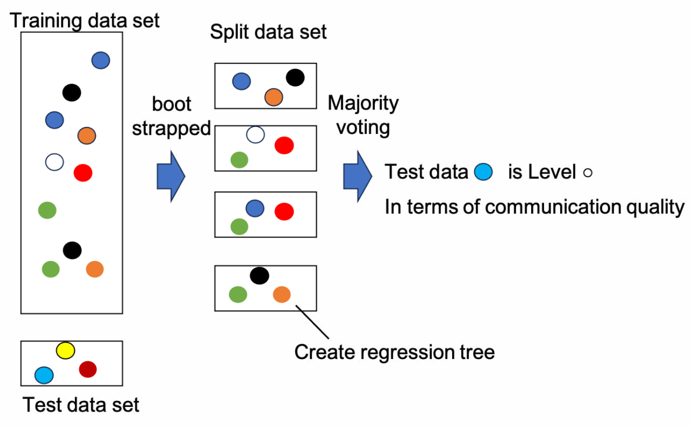

Fig. 2. Schematic diagram of Random Forest.

TABLE III
COMMUNICATION QUALITY LEVELS (SCENARIO 1)

Throughput Value	Communication Quality Level
0 ～ 20 Mbps	1
20 ～ 40 Mbps	2
40 ～ 60 Mbps	3
60 ～ 80 Mbps	4
80 Mbps ～	5

possible at Level 1, real-time online gaming with a small number of users is possible at Level 2, and real-time online gaming with a large number of users is possible at Level 3. The throughput levels for Scenario 1 and Scenario 2 are shown in Tables III and IV, respectively.

C. Communication Quality Estimation Method

First, throughput values collected from devices were converted to communication quality levels. Next, using the timestamps of the LTE communication log data collected from devices, we created three flags: day-of-week flag, time-of-day flag, and weekday/holiday flag ("time stamp flags"), and by associating the throughput values with the timestamps of the LTE communication logs, we created a data set (communication quality level, used band, RSRP, RSRQ, SINR, and time stamp flags) by associating throughput values with timestamps of LTE communication logs. Communication quality levels were entered as monitoring data, and LTE communication log data, day-of-week flag, holiday/day-of-week flag, and time slot flag were entered as explanatory variables. The model outputs the communication quality level estimated from the

TABLE IV
COMMUNICATION QUALITY LEVELS (SCENARIO 2)

Throughput Value	Communication Quality Level
0 ～ 30 Mbps	1
30 ～ 70 Mbps	2
70 Mbps ～	3

TABLE V
INPUT PARAMETERS FROM LTE COMMUNICATION LOGS

Input Item	**Parameter**
Band	1, 3, 42
RSSI	Measured value by the device
RSRP	Measured value by the device
RSRQ	Measured value by the device
SINR	Measured value by the device
Day-of-week flag	Assign a number to each day of the week
Holiday/Weekday flag	1 for weekday, 0 for Saturday/Sunday/holiday
Time slot flag	Divide a day into 3-hour slots

TABLE VI
MEASUREMENT SPECIFICATIONS

Device	FCNT-SD01
LTE Log Acquisition App	FCNT-SD01 5G-monitor
Device Connection PC	MacBook Air Retina
Device Connection PC OS	Ubuntu Desktop 22.04 LTS
iperf3 Server OS	Ubuntu Server 18.04.5 LTS

LTE communication logs. The input parameters are shown in Table V.

V. MEASUREMENT EXPERIMENT

To evaluate the proposed method using measurement results in a real environment, a measurement experiment using a mobile terminal was conducted. Only LTE communication was used in this measurement.

A. Measurement Overview

Table VI shows the measurement specifications. LTE communication measurements were taken near Keio Meidaimae Station in Setagaya-ku, Tokyo, using FCNT's FCNT-SD01 terminal; LTE communication logs were obtained with the device's built-in measurement application 5G-monitor. Downlink UDP throughput values were collected by using iperf3 and connecting the PC to the device via wired tethering. For this measurement, a MacBook Air with Ubuntu Desktop 22.04 LTS was used as the PC. iperf3 server was a server installed in the laboratory with Ubuntu Server 18.04.5 LTS. Ubuntu was selected for both the client and server because iperf3 is prone to bugs when measured on an OS other than Linux. The actual measurement environment is shown in Figure 3.

TABLE VII
MACHINE LEARNING PARAMETERS

Library	Scikit-learn
Number of Data Points	8910
Test Data to Training Data Ratio	2:8
n_estimators	300
max_features	sqrt
max_depth	None

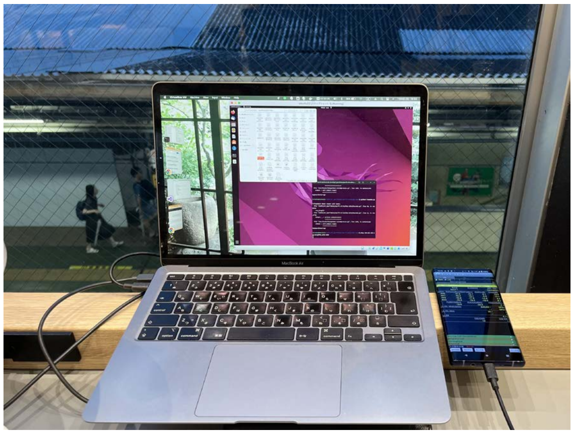

Fig. 3. Measurement Environment.

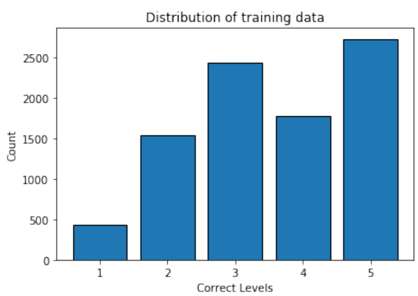

Fig. 4. Distribution of Communication Quality 5 Levels in Training Data.

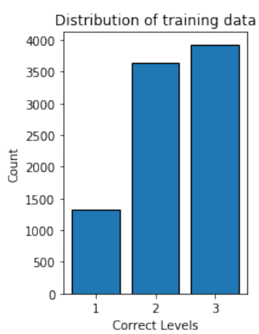

Fig. 5. Distribution of Communication Quality 3 Levels in Training Data.

TABLE VIII
MATCHING RATE OF COMMUNICATION QUALITY LEVELS

Scenario	Matching Rate
Scenario 1 (Without Timestamp Flag)	48.9%
Scenario 1 (With Timestamp Flag)	54.9%
Scenario 2 (Without Timestamp Flag)	66.3%
Scenario 2 (With Timestamp Flag)	71.3%

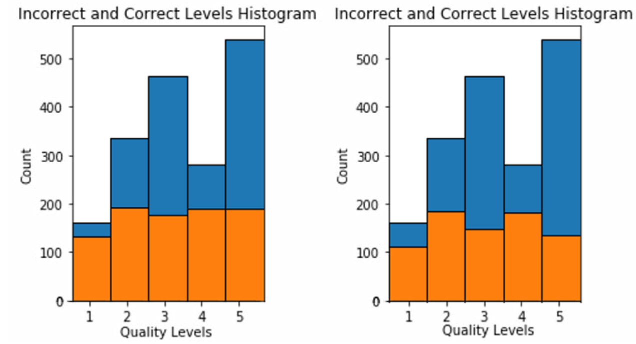

Fig. 6. Number of Correct and Incorrect Predictions for Each Level in Scenario 1.
(Left: Without Time stamp Flag, Right: With Time stamp Flag)

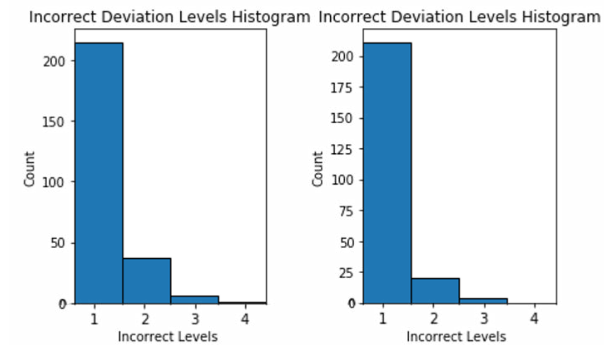

Fig. 7. Difference in Levels When Predictions are Incorrect in Scenario 1.
(Left: Without Time stamp Flag, Right: With Time stamp Flag)

VI. EVALUATION

This chapter describes the matching rate between the communication quality level estimated by the proposed method and the communication quality level calculated from the actual throughput obtained from the measurement experiments. The machine learning parameters used for the evaluation are shown in VII. The dataset consists of 8910 data points, divided into an 80:20 ratio for training and testing. We employed the Scikit-learn library in Python to train the Random Forest model with 300 decision trees, using sqrt for the number of features considered at each split and setting max_depth to None. Figure 4 shows the distribution of communication quality levels during Scenario 1 on the data set used for training. Figure 5 also represents the distribution of communication quality levels in Scenario 2. Table VIII shows the matching rates between the actual communication quality levels in Scenario 1 and Scenario 2 and the estimated levels obtained through the learning process. The results are compared with and without the addition of the timestamp flag as an input parameter, and show an improvement in accuracy of about 5-6 points for both scenarios compared to the case where the timestamp flag is not added. The evaluation of each scenario is shown below.

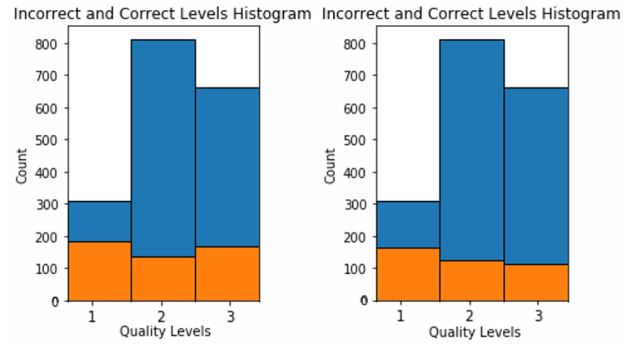

Fig. 8. Number of Correct and Incorrect Predictions for Each Level in Scenario 2.
(Left: Without Time stamp Flag, Right: With Time stamp Flag)

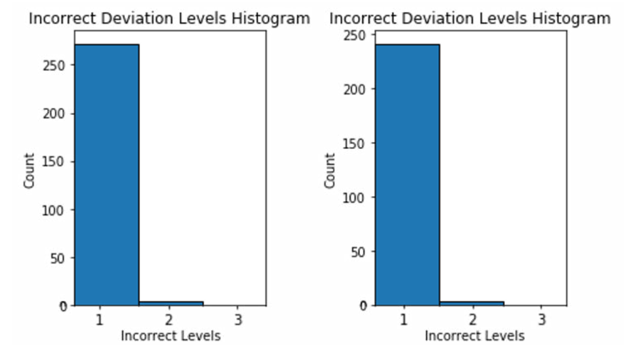

Fig. 9. Difference in Levels When Predictions are Incorrect in Scenario 2.
(Left: Without Time stamp Flag, Right: With Time stamp Flag)

A. Evaluation in Scenario 1

Figure 6 shows the number of correct and incorrect responses for each level in Scenario 1 with the test data. The vertical axis represents the number and the horizontal axis represents the communication quality level. The blue graph shows the number of correct answers and the orange graph shows the number of incorrect answers. If the estimated communication quality level matches the communication quality level calculated from the measured test data, it is counted as the number of correct answers for the calculated communication quality level. The histogram on the left is the histogram without the Time stamp flag as an input parameter, and the histogram on the right is the histogram with the Time stamp flag as an input parameter. It can be seen that the percentage of correct answers improves in Level 3 and Level 5, which are the volume layers of the data. However, the percentage of correct answers for levels 2 and 4 has not changed much. We believe that this is due to the biased number of data in the training data set and can be resolved by preparing a sufficient training data set.

Next, Fig 7 shows how much difference there is in the communication quality levels when there are errors in the estimated communication quality levels. Figure 7 shows the number of pieces on the vertical axis and the difference between the estimated communication quality level and the communication quality level calculated from the measurements on the horizontal axis. As can be seen, most of the errors are mistaken for adjacent levels.

B. Evaluation in Scenario 2

In Scenario 2, reducing the number of communication quality levels from 5 to 3 has resulted in an accuracy of 71%, which is higher than Scenario 1's accuracy. Additionally, introducing the time stamp flag has further improved accuracy by about 5 percentage points.

Figure 8 shows the number of correct and incorrect predictions for each level in Scenario 2, similar to Scenario 1. Focusing on level 3, an improvement in accuracy can be observed.

Also, Figure 9 demonstrates the difference in levels when predictions are incorrect. It can be seen that most of the errors involve confusing levels that are adjacent to each other. This is because Scenario 2 has fewer divisions in communication quality levels, and it is evident that significant misclassification of communication quality has not occurred.

VII. Conclusion

this paper proposes an estimation method of communication quality that takes into account time variability at a certain point in time by linking LTE communication logs to day-of-week and time-of-day data. The proposed method uses downlink UDP throughput values collected by fixed-point measurements and LTE communication log data such as band, RSSI, RSRP, RSRQ, and SINR. The collected data were integrated using timestamps, and a time stamp flag was added to the data to create a data set. LTE communication indexes linking to day-of-week and time-of-day data were used as explanatory variables, and throughput values were used as supervised data. Supervised machine learning random forest class analysis was employed to predict the communication quality level. The proposed method improved the accuracy of communication quality estimation by approximately 5-6% compared to the case where the time stamp flag is not added.

Future issues include verification of whether similar results can be obtained from data sets of multiple locations, establishment of a method for selecting hyper parameters to achieve higher accuracy, creation of appropriate splitting scenarios for optimal communication quality levels for service providers, and verification of estimation accuracy when latency and other factors are included as determinants of communication quality. The results of this study include the verification of the estimation accuracy in the case of including latency and other factors that determine communication quality.

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