Proposal of a new index for predicting communication performance for intra-EMC

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Abstract: We propose a new index for predicting the optimum layout of noise sources, that is designed to improve the communication performance of digital wireless equipment. In our previous studies, we developed a design method for optimizing the layout of a noise source using the correlation between the magnetic field distribution of the noise source and that of the antenna. However, this method does not allow easy comparison between different items of equipment. In this paper, we quantitatively and visually propose a new index that can predict the signal bit error rate by using the antenna interference power, obtained from the weighted magnetic field product that has been calculated from the magnetic field distributions of the noise source and the antenna. We have confirmed that the optimal layout of the noise source can be predicted using our proposal method in digital wireless equipment to minimize intra-EMC. We have further discovered a new index in which the optimal layout of the noise source can be found in contour formatted figures with good visibility.

Keywords: intra-EMC, bit error rate, magnetic distribution, digital wireless equipment

Classification: Electromagnetic Compatibility (EMC)

References


1 Introduction

The noise generated by digital circuits in digital wireless equipment is increasingly leaking into the receiver circuit, causing a loss of receiver sensitivity. Since downsizing has resulted in digital wireless equipment antennas being placed ever closer to noise sources, a significant amount of noise is delivered through the propagation channel created between the communication antenna and the noise source. However, there have hitherto been no effective solutions, making it necessary to develop a new design method to solve each individual coupling problem.

In our previous studies, we proposed a design method for estimating the optimal layout of a noise source that can be calculated according to the correlation between the magnetic distribution of the noise source and that of the antenna, and demonstrated the effectiveness of this proposed design method [1, 2]. However, this conventional method cannot be used effectively to compare different layouts and designs, because it is limited to a relative evaluation.

In this paper, we propose a new evaluation index for predicting the optimal layout of noise sources based on signal bit error rate and for minimizing the intra-EMC problem in any item of digital wireless equipment. This is done by quantifying the antenna interference power using a weighted magnetic field product that is calculated from the magnetic field distribution of the noise source and that of the antenna. We have been able to predict the optimal layout of noise sources by evaluating signal bit error rate both quantitatively and visually. We have further discovered that the optimal layout of the noise source can be predicted by using our proposed method in digital wireless equipment for intra-EMC problems.

2 Design process to minimize intra-EMC problems

We can evaluate the communication quality of digital wireless systems by using the carrier-to-noise ratio (CNR). When tackling the intra-EMC problem, in addition to taking into account the noise in the receiver, it should be remembered that the noise generated from digital circuits in digital equipment mixes into the receiving circuit by way of its own antenna. This noise is defined as the antenna interference power $P_a$. If the noise $N$ in the receiver and the antenna interference power $P_a$ are uncorrelated, the carrier-to-noise ratio (CNR') can be expressed as Eq. (1).

The antenna interference power $P_a$ can be expressed using Eq. (2), where $P_n$ is the radiation power of the noise source and $S_{21}$ is the electromagnetic coupling between the antenna and the noise source. In most cases, the electromagnetic coupling can be easily measured as the S-parameter by connecting both ports to a network analyzer, since a feeding port is present in the antenna. However, it is difficult to take measurements between the noise source and the antenna in this case, because the noise source has no specified feeding port. On another front, the radiation noise arises from the signal current. In this paper, we focus on the magnetic field generated by current as a solution to the intra-EMC problem.

\[
CNR' = \frac{C}{N + P_a} \tag{1}
\]

\[
P_a = P_n \cdot S_{21} \tag{2}
\]
Based on the considerations mentioned above, we propose the weighted magnetic field product $T_w$ as a new index for estimating the coupling characteristic ($S_{21}$) between a noise source and an antenna. $T_w$ is a quantitative index that takes the polarization of the noise source into consideration. It is defined in Eq. (3), in which the magnetic field product $(T_x, T_y, T_z)$ of each polarization is calculated using Eq. (4a), Eq. (4b) and Eq. (4c), and is weighted by the sum of squares of amplitude for each noise source polarization shown by Eq. (5a), Eq. (5b) and Eq. (5c). Therefore, since the weighted magnetic field product $T_w$ is an index that is weighted by the average power of the noise source of each polarization, it can take into consideration the influence of the dominant polarization of the noise source.

$$T_w = \frac{n_x^2}{n_x^2 + n_y^2 + n_z^2} T_x + \frac{n_y^2}{n_x^2 + n_y^2 + n_z^2} T_y + \frac{n_z^2}{n_x^2 + n_y^2 + n_z^2} T_z \quad (3)$$

$$T_x = \frac{1}{N} \sum_{i=1}^{N} (|H_{axi}| \times |H_{nxi}|) \quad (4a)$$

$$T_y = \frac{1}{N} \sum_{i=1}^{N} (|H_{ayi}| \times |H_{nyi}|) \quad (4b)$$

$$T_z = \frac{1}{N} \sum_{i=1}^{N} (|H_{azi}| \times |H_{nzi}|) \quad (4c)$$

$$n_x^2 = \frac{1}{N} \sum_{i=1}^{N} |H_{axi}|^2 \quad (5a)$$

$$n_y^2 = \frac{1}{N} \sum_{i=1}^{N} |H_{ayi}|^2 \quad (5b)$$

$$n_z^2 = \frac{1}{N} \sum_{i=1}^{N} |H_{azi}|^2 \quad (5c)$$

Next, the electromagnetic coupling $S_{21}$ ($T_w$) between an antenna and a noise source is defined as a linear function of $T_w$ as described in Eq. (6) where $S_{21}$ ($T_w$) is in units of decibels. $K$ is calculated from $S_{21}$ ($T_w$) as shown in Eq. (7). Based on the above, we can calculate the antenna interference power $P_a$ as denoted by Eq. (8).

$$P_a = K T_w \quad (6)$$

$$K = 10 \log \left( \frac{1}{T_w} \right) \quad (7)$$

Here, we will describe how to determine $a$ and $b$ in Eq. (6). Figs. 1(a) and (b) show the evaluation model we used to evaluate the proposed design approach. It emulates a cellphone 50 mm wide and 180 mm long. The monopole antenna is connected to the upper part of the substrate. The loop antenna that models the noise source is $d$ in length and 5 mm in height. For evaluation at 900 MHz, the length of the antenna is assumed to be 83 mm. In the evaluation model, the noise source is vertically arranged and thus parallel to the monopole antenna shown in Fig. 1(a). We call this the vertical model. In Fig. 1(b), the noise source is horizontally arranged and thus perpendicular to the monopole antenna shown. We call this the horizontal model. In this evaluation, the center position of the loop antenna $P(N_x, N_y)$ is employed as the variable parameter.

Fig. 1(c) shows the relationship between the weighted magnetic field product $T_w$ and the coupling characteristic ($S_{21}$) while changing the location of the noise source.
source. In Fig. 1(c), ■ denotes the vertical model when \( d = 15 \) mm, ▲ denotes the horizontal model when \( d = 15 \) mm, × denotes the vertical model when \( d = 7.5 \) mm, and ● denotes the horizontal model when \( d = 7.5 \) mm in Figs. 1(a) and (b). The broken line is the straight line obtained by linear approximation from both the vertical model and the horizontal model. The results in Fig. 1(c) confirm that the \( S_{21} \) is proportional to \( T_w \) in the four cases, regardless of the polarization or size of the noise source. As shown in Eq. (6), \( S_{21}'(T_w) \) is the value obtained from the linear approximation relationship between \( T_w \) and \( S_{21} \) using Fig. 1(c). When extracted from Fig. 1(c), \( a \) is determined to be 58.3 and \( b \) is determined to be −54.3 in Eq. (6). We can thus quantitatively estimate the \( S_{21} \) by using the proportional relationship between the two parameters.

\[
S_{21}'(T_w) = a \cdot T_w + b \tag{6}
\]

\[
K = 10^{S_{21}'(T_w) / 10} \tag{7}
\]

\[
P_a' = P_n \cdot K \tag{8}
\]

3 Evaluation using a TEG to simulate a cellphone

Fig. 2(a) shows the BER characteristic of the wireless equipment. △ denotes the measured results for radio sensitivity, and the broken line indicates the BER characteristics estimated from Eq. (9) using the measured results with no antenna interference power, where \( \gamma \) is CNR and \( \text{erfc} \) is the complementary error function.

\[
P = \text{erfc}\sqrt{\frac{\gamma}{2}} \tag{9}
\]

The BER characteristics with no antenna interference power in Fig. 2(a) confirm that the CNR is about 10 dB when \( \text{BER} = 10^{-3} \). Here, to predict the BER degradation in the presence of antenna interference, we try to estimate the BER characteristics from the measured results obtained in this study. In Fig. 2(a), □ denotes the measured results for radio sensitivity when \( P_n = -115.5 \) dBm. Here, \( P_n \)
is $-82.5 \text{ dBm}$ and the $S_{21}$ is $-33.0 \text{ dB}$. The calculations show an approximately 3-dB degradation in the CNR when the antenna interference from the noise source is present at $\text{BER} = 10^{-3}$, as shown in Fig. 2(a). This means that the CNR needs to be increased to be able to equalize the BER characteristics with no antenna interference power. Since $T_w$ was calculated from the two magnetic field distributions to be 0.32, $S_{21}(Tw)$ is determined to be $-35.6 \text{ dB}$ due to the proportional relationship between $T_w$ and $S_{21}$, as shown in Fig. 1(c). The antenna interference power $P_a$ is therefore found to be $-118.1 \text{ dBm}$. We understand that about a 2-dB degradation in the CNR can be predicted using our proposed method when $\text{BER} = 10^{-3}$, as shown in Fig. 2(a). This fact confirms the validity of our proposed method.

Fig. 2(b) shows the BER characteristics of the vertical model while varying the location of the noise source $N_y$ at $N_x = 37.5 \text{ mm}$. Fig. 2(c) shows them for the horizontal model. It is feasible to estimate the optimal position of a noise source as when the BER curve with antenna interference power is closest to the BER curve with no antenna interference power (Noiseless). From Fig. 2(b) and (c), we can see that $N_y = 15 \text{ mm}$ is the most suitable position for the vertical model, whereas for the horizontal model, any location except for $N_y = 165 \text{ mm}$ is a suitable position. We conclude from the above investigations that the prediction of the optimal layout is feasible using the proposed method, without any knowledge of the coupling characteristics ($S_{21}$).
4  A proposal for communication quality achievement rate

We propose the communication quality achievement rate $\alpha$ as a new index for quantitatively determining the optimal positioning of the noise source. $\alpha$ is defined as the ratio of the area $S'$ that meets the predetermined signal bit error rate for the area $S$ of the entire substrate as shown in Eq. (10), when the CNR is given. For example, Fig. 3 shows the change in the distribution of signal bit error rate when the CNR is set to 10 dB. Fig. 3(a) depicts the vertical model and Fig. 3(b) depicts the horizontal model.

$$\alpha = \frac{S'}{S} \times 100 \quad [\%]$$  \hspace{1cm} (10)

In the vertical model shown in Fig. 3(a), we found that the distribution of the signal bit error rate is concentrated near the antenna element and the center part of the substrate. On the other hand, in the horizontal model as shown in Fig. 3(b), we found that the distribution of signal bit error rate is the broadest at the upper part of the substrate. Moreover, if we define a range in which signal bit error rate is $5 \times 10^{-3}$ or less for $S'$ in Eq. (10), the $\alpha$ of the vertical model is about 10% or less, since $\alpha$ for the horizontal model is about 95%. This indicates that there is greater design freedom when the noise source is horizontally arranged than when it is vertically arranged. This allows us to use $\alpha$ to quantitatively judge the optimal layout of the noise source.

![Fig. 3. Distribution of the bit error rate](image)

5  Conclusion

We have proposed a new index that can be used to judge the optimal layout of a noise source based on the evaluation of the BER characteristics using the weighted magnetic field product. The effectiveness of the proposed method was assessed using a TEG to simulate a cellphone. We confirmed that our proposed method can be employed to estimate the signal bit error rate. It is clear that we can successfully predict the optimal layout of noise sources in digital wireless equipment so as to minimize intra-EMC problems.
Planar scanning measurement of monostatic/bistatic RCS by near-field far-field transformation based on fast multipole method

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Abstract: Radar cross section (RCS) is one of important EM properties of radar targets. Its measurement requires long distance to obtain far-field characteristics in higher frequency range such as X-band. Planar scanning near-field measurement combined with near-field far-field (NF-FF) transformation is realized by simple measurement system. However, scan area truncation of planar scanning often cause intolerable error for predicted RCS. In this paper, the accuracy of NF-FF transformation technique based on fast multipole method (FMM) with scan area of planar scanning is investigated.

Keywords: RCS, near-field far-field transformation, fast multipole method

Classification: Antennas and Propagation

References

1 Introduction

Radar cross section (RCS) is one of important characteristics of radar for vehicles or aircrafts. Its measurement often requires long measurement range and huge equipment. Near-field far-field (NF-FF) transformation is a powerful approach to avoid the requirement. Falconer proposed a transformation technique for monostatic RCS measurement [1]. It enables us to predict target’s monostatic RCS from only monostatic near-field (NF) measurement. However, the method is based on physical optics, so this assumption fails for some structures such as corner reflector. In such case, NF-FF transformation for antenna measurement is effective. For accurate monostatic/bistatic RCS measurement of arbitrary structure, the antenna under test (AUT) is replaced with the target illuminated by plane wave and scattered EM field is measured. An NF-FF transformation technique is proposed in ref. [2] which is based on fast multipole method (FMM) and predicts far-field of AUT by solving integral equation. This method is valid for arbitrary NF measurement grids and probes. In addition, it is more robust for NF scan area truncation relatively to conventional method [3]. Here, the planar scanning is quite convenient measurement system in terms of measurement equipment in actual measurement situation. However, the scan area truncation often introduces intolerable error. In this paper, we investigates accuracy of planar scanning measurement for RCS with scan area.

2 Planar scanning for RCS measurement

Fig. 1(a) shows the measurement system of planar scanning. Tx antenna transmits the incident wave and Rx antenna receives the scattered field on planar surface. The analysis of error for planar NF-FF transformation technique was described [4]. Planar scan area truncation causes two effects of the error. One of which is occurred outside of the reliable region. In this criteria, the calculated far-field is valid only in angular region \([-\theta_s, \theta_s]\) defined by target and scan area edge (see Fig. 1(b))

\[
\theta_s = \tan^{-1}\left(\frac{L_s - d}{2x_0}\right). \tag{1}
\]

The other error occurs even inside the reliable region and is caused by zero assumption outside the scan area. This assumption exists in conventional method [3] and FMM based NF-FF transformation we employ is free for this error. In this paper, we investigate this error inside the reliable region and show the accuracy of planar scanning measurement with FMM based NF-FF transformation.

3 Numerical study

3.1 Method

In this paper, FMM based NF-FF transformation technique is used. So we explain this technique briefly. The Rx probe’s output voltage \(U\) located on \(r_M\) is represented by FMM formulation as

\[
U(r_M) = -j \frac{\omega \mu}{4\pi} \oint T_L(\hat{k}, \hat{r}_M) \tilde{w}^{*}(\hat{k}) \cdot (\hat{t} - \hat{k}) \cdot \hat{J}(\hat{k}) d\hat{k}^2 \tag{2}
\]
where $\hat{\mathbf{J}}(\hat{k})$ is the spectral representation of current density. $\hat{\mathbf{w}}^{\text{r}}(\hat{k})$ is determined from probe’s directivity and antenna factor. $T_L(\hat{k}, \hat{r}_M)$ is the translation operator of FMM and calculated by

$$T_L(\hat{k}, \hat{r}_M) = -\frac{j k}{4\pi} \sum_{l=0}^{L} (-j)^l (2l + 1) h_{l}^{(2)}(k r_M) P_l(\hat{k} \cdot \hat{r}_M)$$

where $L$ is the multipole order. $h_{l}^{(2)}$ is the spherical Hankel function of second kind and $P_l$ Legendre polynomial. In eq. (2), $(\hat{I} - \hat{k} k) \cdot \hat{\mathbf{J}}(\hat{k})$ is thought to be outgoing plane wave from the target and the translation operator translate it to incoming plane wave to the probe. So the equation represents the probe’s output voltage by superposition of incoming plane wave weighted by probe’s directivity $\hat{\mathbf{w}}^{\text{r}}(\hat{k})$.

By solving linear equation formulated from eq. (2), the plane wave coefficient $(\hat{I} - \hat{k} k) \cdot \hat{\mathbf{J}}(\hat{k})$ is calculated and electric far-field is directly determined by the equation as

$$E(\mathbf{r}) = -j \frac{\omega_0}{4\pi} e^{j k r} \cdot (\hat{I} - \hat{r} \hat{r}) \cdot \hat{\mathbf{J}}(\hat{r}).$$

It is noted that there is no assumption of NF outside the measured region in this method.

### 3.2 Numerical results

In order to investigate the accuracy of planar scanning RCS measurement, monostatic RCS of $2\lambda \times 2\lambda$ perfect electric conductor (PEC) plate is obtained by the FMM based NF-FF transformation. The NF of PEC plate is calculated by using FDTD method. After that, the calculated NF data is applied to FMM based NF-FF transformation to calculate the monostatic RCS. Observed frequency is 3 [GHz]. The PEC plate is located on $yz$ plane and square scan plane is placed at $x_0 = 2.7\lambda$. Sampling interval $\Delta = 1/5\lambda$. The incident wave is $-x$ directed and $z$ polarized plane wave.

The result is compared with numerical solution (reference) and the transformation result by conventional transformation technique [3]. The numerical solution is calculated from electric/magnetic current on the surface enclosing the target by using FDTD method. The conventional method is that modal coefficients are calculated from 2-D Fourier transform of the electric field on the scan plane.
\[
\tilde{T}_i(k_x, k_z) = \frac{e^{-jkx_0}}{2\pi} \int_{-\infty}^{\infty} E(x_0, y, z) e^{-jky} e^{-jkz} dydz \tag{5}
\]

where \( \alpha = \sqrt{k^2 - k_x^2 - k_z^2} \). \( k \) is the wavenumber. It is noted that the effect of probe is ignored here for simplicity. Electric field in far region is calculated simply from the modal coefficients in Eq. (5). In practice, integration in eq. (5) is done in finite scan area and electric field outside the area is assumed to be zero. That introduce the truncation error inside the reliable region described in previous section.

Fig. 2 shows the error of predicted monostatic RCS for different scan length \( L_s \). The error is calculated from below equation

\[
\Delta \sigma[\text{dB}] = \sigma_i[\text{dBsm}] - \sigma_m[\text{dBsm}] \tag{6}
\]

where \( \sigma_m \) is predicted RCS by the transformation techniques and \( \sigma_r \) is reference value. The errors of two transformation techniques are shown. In this case, monostatic RCS is inside the reliable region for all scan length, therefore, \( \Delta \sigma \) is the error inside the reliable region. As we can see, error of conventional method grows larger along the scan area reduction. The error of FMM based NF-FF transformation fall into \( \pm 1.0 \) [dB] for all scan length while that of conventional method exceed when \( L_s/\lambda \leq 3 \). From these results, we can conclude that FMM based NF-FF transformation is more robust for scan area truncation than conventional method.

![Fig. 2. Monostatic RCS error of two transformation techniques. The x-axis indicates the length of scan area \( L_s \) and y-axis the error in [dB].](image)

### 4 Experimental study

In this section, the FMM based NF-FF transformation is applied to the actual measured NF data. Measured target is dihedral corner reflector made by bending square copper plate with \( 5\lambda \) side length. The target’s corner is located along \( z \) axis (see Fig. 1(a)). Incident wave is transmitted to the target by a ridged horn antenna. Scattered NF is measured by \( \lambda/2 \) dipole probe. The NF is measured on \( 5\lambda \times 5\lambda \) scan plane, the measured interval \( \Delta = 1/3\lambda \). Scan plane is placed at \( x_0 = 2.7\lambda \). Fig. 3(a) shows the result of bistatic RCS in \( \theta = \pi/2 \) cut. Incident wave is \(-x\) directed and \( z \) polarized. In this figure, reference value is numerical solution calculated in the same way as previous section. As we can see, predicted result by the transformation technique shows good agreement with reference inside the reliable region (between
dotted lines in Fig. 3(a)). Fig. 3(b) shows the monostatic RCS result for different incident angles $\theta$ at $\phi = 0$ cut. The result is calculated by using planar near-fields of different incident angles. Predicted RCS indicates high accuracy for $0–9^\circ$ incident angles.

![Graphs showing RCS data](image)

(a) Bistatic RCS in the case of $-x$ directed and $z$ polarized incident wave. (b) Monostatic RCS.

**Fig. 3.** Measured RCS of dihedral corner reflector.

## 5 Conclusion

We have investigated the accuracy between the FMM based NF-FF transformation and conventional method with planar scanning to measure RCS by numerically. We have shown the robustness of FMM based NF-FF transformation technique against the scan area truncation. Also, we transformed measured NF data using FMM based NF-FF transform method. Transformed results are good agreement with reference value. By using FMM based NF-FF transformation, RCS inside reliable region is measured accurately.
Assessment of measurement uncertainty for verification of compliance with guidelines for human exposure to EMFs from AM broadcasting transmitters

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Abstract: In this paper we analyze the uncertainty in measurement when assessing the exposure levels of the general public to RF electromagnetic fields (EMFs) from AM broadcasting transmitters. The purpose of measurement was to evaluate whether human exposure levels are in compliance (or not) with protection guidelines. Six sources of uncertainty were selected, and in order to allow for the propagation characteristics of the middle frequency range, the uncertainties of both the electric and magnetic fields were evaluated. Estimated uncertainties were identical to ±2.34 dB.

Keywords: uncertainty, AM broadcasting transmitter, electromagnetic fields (EMFs), human exposure level

Classification: Electromagnetic Compatibility (EMC)

References

1 Introduction

The middle frequency (MF) band (0.3~3 MHz), including AM broadcasting signals, has different propagation features compared with those of the ultra-high-frequency (UHF) band (0.3~3 GHz) which includes the signal range radiated from mobile base stations and also from television broadcasting transmitters in many countries. For the general public, the field region around mobile base stations is regarded as radiating far-field, but AM transmitters is as reactive, or reactive-radiating near-field owing to the relatively long wavelengths of the MF-band. So, for AM transmitters the uncertainties in measurement of both the electric and magnetic field strengths should be estimated and a method of estimating and expressing uncertainty when evaluating the levels of human exposure to EMFs from mobile base stations has been proposed [1, 2].

The sources of uncertainty are classified into two groups based on their method of evaluation. Type A sources of uncertainty were selected to include the power drift, body influence, mismatch with transmitting antenna, and spatial averaging, whereas Type B sources were selected to include calibration, isotropy and linearity of receiving probe and power chain.

2 Evaluation of Type A standard uncertainty

The in situ measurement procedure used to estimate each of the standard uncertainties of Type A followed the Korean standard [3]. In our measurement, we used the NARDA EHP-200A as the main receiver.

2.1 Power drift

In order to obtain the uncertainty value of power drift, thirty repeated measurements were performed around twenty AM transmitters. At each measurement position, we assumed the spatial average of the electric and magnetic field strengths at three heights (1.1 m, 1.5 m, and 1.7 m) with root-mean-square mode over one or six min [3, 4, 5]. After completing the measurements, the arithmetic means of each averaged value for the electric and magnetic fields, and then the standard deviations, were calculated by (1) and (2), respectively.

\[
\bar{q} = \frac{1}{N} \sum_{k=1}^{N} q_k
\]

(1)

\[
s(q_k) = \frac{1}{\sqrt{N-1}} \sqrt{\frac{1}{N} \sum_{k=1}^{N} (q_k - \bar{q})^2}
\]

(2)


where N is 30 and $q_k$ is the spatially averaged field values of electric or magnetic field strength obtained from 30 repeated measurements. The calculated standard deviations of the power drift were in a range from 0.02 dB to 0.82 dB for the electric field, and 0.04 dB to 0.80 for the magnetic field for twenty transmitters as shown in Fig. 1.

Letting the probability function for the standard uncertainty of power drift by student-$t$ distribution [6] and assuming the two-sided confidence level of 95%, we can get the $t$-factor: $t_r = t_{0.05} = 2.05$ (degree of freedom (DoF) = 29). Using these confidence level parameters, DoF, and $t$-factor, we obtain the standard uncertainty of power drift as

$$u_{pd} = t_r \times \frac{s(q_k)}{\sqrt{N}} \quad (3)$$

![Fig. 1. Deviations and standard uncertainties caused by power drift. (a) For electric field. (b) For magnetic field. Experimental data were obtained from thirty repeated measurements around AM broadcasting transmitters.](image)

2.2 Body influence

In order to estimate the effect of a nearby human body, which should be kept some distance away from the receiver, we considered the differences in the spatial average electric and magnetic field strengths, when an experimenter was 1.0 m, 2.0 m, or 3.0 m from the probe around 20 AM transmitters.

With 95% confidence level and probability function of student $t$-distribution (DoF = 19), we got $t_r = 2.09$. Thus, the standard uncertainty for each case of distance differences can be calculated by (1). In applied equation $q_k$ denotes the differences between spatially averaged field values electric or magnetic field strength of 1.0 m and 2.0 m apart from probe, 1.0 m and 3.0 m, and 2.0 m and 3.0 m of each transmitter, respectively.

The ranges of standard uncertainties were from 0.03 dB to 0.04 dB for both the electric and magnetic fields. Therefore, we estimate the standard uncertainty of the influence of a nearby body to be 0.04 dB.
2.3 Noise
This source of uncertainty elates to the amount of signal strength when the AM transmitter is off. These kinds of sources are well defined. However, measurement in the off state was impossible in our in situ measurement, so, the standard uncertainty of noise was neglected as in zero [2].

2.4 Mismatch in receiving probe and AM transmitter’s antenna
As mentioned in [2], this source of uncertainty reflects the directional mismatch between transmitting and receiving antennas. However, the configuration of the AM transmitter antenna is a monopole type with horizontally isotropic characteristics, so this type of uncertainty can be negligible under the condition of line-of-sight (LOS).

2.5 Spatial averaging
As explained in detail in [2] for UHF frequencies, the transmitted EMFs are affected by spatial variations known as small-scale fading due to multipath propagation, and an appropriate correlation distance between adjacent measurement points has been proposed [7]; however, such a distance in the MF-band is very long, so it is very difficult to apply it for AM broadcasting signals. Conceptually, the greater number of points we selected, the more exact exposure level we could get. For this reason we selected 10 cm as the appropriate distance since the size of the probe was 10 cm. The number of measurement points was either three or nine. We measured and compared the spatially averaged values of thirty-five, nine, and three points around the twenty target transmitters.

For the 35 points, there were 5 points at each height (i.e., 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, and 1.7 m). For nine points, the three points at the each height. Three points were located at the center of each of the heights (1.1 m, 1.5 m, 1.7 m).

The distribution of the difference of the spatially averaged values between the different numbers of points for twenty transmitters are in a range from 0.01 dB to 0.61 dB in electric field and 0.01 dB to 0.93 dB in magnetic field strengths. Applying the confidence level of 95% and assuming that the probability function has the form of the student-\(t\) distribution (DoF = 19, this is equal to the number of transmitters) with \(t_c = 2.09\). Thus we can write the expression for the standard uncertainty by (1). In applied equation \(q_k\) is the difference between the spatially averaged field values of thirty-five, nine, and three points of each transmitter. The standard uncertainty for spatial averaging of the AM broadcasting signal was estimated to be 0.07 dB and 0.09 dB for the electric and magnetic fields, respectively.

3 Evaluation of Type B standard uncertainty
Evaluation of Type B sources of uncertainty is obtained from reliable information such as calibration sheets [8].
4 Evaluation of combined and expanded uncertainty

The combined uncertainty value is same as root-sum-square of those of all standard uncertainty sources \((u_k)\) as shown in (4). In our calculation all of the individual standard uncertainty sources are considered to be uncorrelated \((c_k = 1.0)\). The calculated combined uncertainty is 1.19 dB in electric field and 1.20 dB in magnetic field.

\[
u_c = \sqrt{\sum_{k=1}^{N} c_k^2 u_k^2}
\]  \hspace{1cm} (4)

4.1 Expanded uncertainty

The expanded uncertainty or overall uncertainty is the final form of uncertainty which is calculated with the combined uncertainty and coverage factor \((k)\).

\[
U = k \ast u_c
\]  \hspace{1cm} (5)

In addition, expanded uncertainty is the kind of uncertainty, which also has DoF. The effective degree of freedom (eDoF) of expanded uncertainty can be calculated by the Welch-Satterthwaite equation \[1\]. The calculated values for the electric and magnetic fields were 6,929 and 6,897, respectively.

The value of \(t_{0.025}\) for one-sided confidence level of 95\% and eDoF = 6,929 and 6,897 is nearly equal to 1.96. Thus we selected 1.96 as the coverage factor. Therefore, the expanded uncertainty was estimated to be 2.34 dB. Table I summarizes all of the individual standard uncertainties, combined uncertainty, and expanded uncertainty.

<table>
<thead>
<tr>
<th>Type</th>
<th>Uncertainty source</th>
<th>Uncertainty value [dB]</th>
<th>Probability function</th>
<th>Divisor</th>
<th>DoF</th>
<th>Standard uncertainty [dB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Power drift</td>
<td>0.62/0.62</td>
<td>Student-t</td>
<td>2.05</td>
<td>29</td>
<td>0.30/0.30</td>
</tr>
<tr>
<td></td>
<td>Body influence</td>
<td>0.08/0.09</td>
<td>Student-t</td>
<td>2.09</td>
<td>19</td>
<td>0.04/0.04</td>
</tr>
<tr>
<td></td>
<td>Spatial averaging</td>
<td>0.15/0.20</td>
<td>Student-t</td>
<td>2.09</td>
<td>19</td>
<td>0.07/0.09</td>
</tr>
<tr>
<td>B</td>
<td>Calibration</td>
<td>1.32</td>
<td>Normal</td>
<td>2.00</td>
<td>∞</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>Isotropy</td>
<td>1.00</td>
<td>Normal</td>
<td>2.00</td>
<td>∞</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>Linearity</td>
<td>1.60</td>
<td>Normal</td>
<td>2.00</td>
<td>∞</td>
<td>0.80</td>
</tr>
</tbody>
</table>

Combined uncertainty: Root sum square of all standard uncertainties: 1.19/1.20

Expanded uncertainty: \(k = 1.96/1.96\) \(6,929/6,897\) 2.34/2.34

5 Conclusion

In this paper, we proposed a method and procedure to estimate the measurement uncertainty for evaluating human exposure levels to EMFs from AM broadcasting...
transmitters. Compared with UHF frequency signals, the MF band (includes AM broadcasting) signals have different propagation characteristic. So, in order to estimate the uncertainty both the electric and magnetic field strengths should be considered.

Compared with the measurement uncertainty of the RF-EMFs radiated from a mobile base station, that of AM broadcasting transmitter is relatively small. The AM transmitter transmits stable signals, in contrast to mobile base stations, which are subject to fluctuation by traffic. The expanded uncertainty of AM broadcasting transmitter was determined to be ±2.34 dB for both the electric and magnetic field strengths.

Acknowledgments

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A simple three level downlink packet scheduling to improve throughput in LTE network

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Abstract: In this paper, a three level scheduling scheme is proposed for Long Term Evolution (LTE) network to enhance the cell throughput while maintaining fairness among User Equipments (UE). At initial level, the users with good channel conditions are scheduled that result in increase in cell throughput. At next level, the users with maximum delay requirements are allocated and at last level the users with long buffer queue are scheduled to maintain fairness among users. The proposed scheme is compared with traditional scheduling algorithms and validated by means of simulation results.

Keywords: LTE, scheduling, QoS, throughput, fairness, delay
Classification: Wireless Communication Technologies

References

1 Introduction

Designing an efficient scheduler is a primary issue for the effective use of limited radio resources. In Long Term Evolution (LTE), the basic unit of resource allocation is named as Resource Block (RB) that can be modulated independently [1]. The important characteristic related to any scheduling algorithm is to guarantee that the necessary Quality of Service (QoS) should be met for a bearer. Many scheduling methods are found in literature for accommodating real time and non real time services [2]. Major studies put forth a balance between user and network related issues in designing an algorithm to get adept results. The main performance metrics for scheduling can be the throughput and level of fairness. In literature, few algorithms focus on achieving fairness among the users and others try to improve the spectral efficiency [3]. Selected algorithms use delay value as a weighting parameter for scheduling in order to satisfy the real time services, but fails to guarantee non real time services [4, 5, 6].

This paper proposes a three level scheduling algorithm to enhance the cell throughput while maintaining satisfied level of fairness and average user delay among users. The performance of the proposed algorithm is compared with the existing algorithms like Proportional Fairness (PF), Modified Largest Weighted Delay First (MLWDF), Exponential rule (EXP rule) and Logarithmic rule (LOG rule).

2 System description

A single cell downlink LTE system is considered with $K$ active users served by one evolved Node B (eNB). LTE system uses Orthogonal Frequency Division Multiple Access (OFDMA) technology in the downlink, which is highly flexible regarding radio resource management and it has the capability to exploit multi user diversity. The system consists of $N$ RBs which is determined by the transmission bandwidth $B$ [1]. The scheduling period spans for two RBs and is termed as one Transmission Time Interval (TTI) and it lasts for $1$ ms duration. The radio interface in LTE uses one common shared channel that is shared by all users in the cell. Each User Equipment (UE) sends its channel quality report as a Channel Quality Indicator (CQI) value, by calculating its own experienced Signal to Noise Ratio (SNR), through a feedback channel. This value helps the eNB to choose appropriate Modulation and Coding Scheme (MCS) for that particular UE to achieve minimal bit error rate.

3 Proposed scheduling scheme

The proposed scheduling algorithm improves the aggregate cell throughput while maintaining fairness among UEs. This algorithm works in three levels and at each level it selects the users based on the priority metric and allocates radio resources according to the user’s demand.

Level 1: The initial level of this algorithm is to choose users with good channel conditions, to increase the overall cell throughput. Among $k \in \{1,2 \ldots K\}$ users, the users having the throughput priority metric $T_k > T_{th}$ are chosen for allocation, where $T_k$ is the throughput priority metric of $k^{th}$ user and $T_{th}$ is the predefined
threshold value of that metric. Threshold value is set based on the network operator’s targeted data rate requirements to maximize system throughput.

Let $\mu_{k,n}$ be the data rate achieved by the $k^{th}$ user, $k \in \{1, 2 \ldots K\}$ on $n^{th}$ RB, $n \in \{1, 2 \ldots N\}$ that can be given as,

$$\mu_{k,n} = w \log_2(1 + p_{k,n}\gamma_{k,n})$$  \hspace{1cm} (1)

where, $w$ is the bandwidth of the system, $p_{k,n}$ is the transmitted power of $k^{th}$ user on $n^{th}$ RB and $\gamma_{k,n}$ is the signal-to-noise ratio achieved by $k^{th}$ user on $n^{th}$ RB.

The average data rate achieved by $k^{th}$ user is given as

$$\mu_{k,\text{avg}} = \frac{1}{N} \sum_{n=1}^{N} x_{k,n}\mu_{k,n}, \quad x_{k,n} \in \{0, 1\}$$  \hspace{1cm} (2)

where $\mu_{k,n}$ is the data rate achieved by $k^{th}$ user in $n^{th}$ RB and the value of $x_{k,n}$ is one if the $k^{th}$ user is scheduled in $n^{th}$ RB, otherwise it is zero.

The throughput priority metric is given as,

$$T_k = \frac{\mu_{k,n}}{\mu_{k,\text{avg}}}$$  \hspace{1cm} (3)

The set $\zeta_{\max} = \{1, 2 \ldots K\}$ of users who satisfies $T_k > T_{th}$ are chosen for allocation in descending order of $T_k$. Set $\zeta_1 \in \zeta_{\max}$ with $T_k < T_{th}$, $\forall k \in \zeta_{\max}$ are considered for further allocation in the same TTI, if it has available resources.

**Level 2:** After allocating users with good channel quality, the proposed algorithm schedules the users having delay priority metric greater than the threshold value. That is, in set $\zeta_1$, the users having $D_k > D_{th}$ are considered for further allocation in descending order of $D_k$. When the packet enters into the buffer of the Medium Access Control (MAC) layer, it is time stamped. The Head of Line (HoL) delay value of a particular packet is measured based on its time stamped value and recent packet processing time. That is,

$$T_{i,\text{HoL}}^i = T_c - T_{is}^i$$  \hspace{1cm} (4)

where $T_{is}^i$ is the time stamped value of $i^{th}$ packet, $i \in \{1, 2 \ldots I\}$ and $T_c$ is the current processing time of a packet. Every packet in the buffer will have its own delay budget parameter. The time difference between the packet delay budget parameter ($T_{db}^i$) and its HoL ($T_{HoL}^i$) delay value is considered as its theoretical departure time ($T_d^i$).

$$T_d^i = T_{db}^i - T_{HoL}^i$$  \hspace{1cm} (5)

This value is used in the calculation of delay priority metric and is given as,

$$D_k = \frac{1}{T_d^i + \frac{L_k^i}{r_k}}$$  \hspace{1cm} (6)

where $L_k^i$ is the size of the $i^{th}$ packet of $k^{th}$ user and $r_k$ is the data rate of that user.

The set $\zeta_0 \in \zeta_1$ with $D_k < D_{th} \forall k \in \zeta_{\max}$ are considered for further allocation in the same TTI, if it has available resources.

**Level 3:** After allocating users who have delay requirements, the proposed algorithm schedules the users from set $\zeta_0$ based on buffer priority metric. When the packets enter to the MAC layer they are classified according to the type of service
and placed in a queue. The number of queues depends on the number of services. Let the system has $J$ queues. The buffer priority metric can be given as

$$B_k = \frac{S_{jR,i,k}}{S_{TB} \times N_K}$$ \hspace{1cm} (7)

where $S_{jR,i,k}$ is the size of the $j$th queue excluding the $i$th packet of the $k$th user, $S_{TB}$ is the transport block size and $N_K$ is the number of active users. Next instance of scheduling begins from the first level.

4 Simulation results

The performance of the proposed scheduling scheme is examined in terms of cell throughput, fairness index and average delay using an open source simulator, LTEsim [7]. A single cell scenario is considered with a fixed eNB at the center where the users (in the range of 10–60) are uniformly distributed inside the cell. It is assumed that users are moving with a speed of 30 kmph and when they reach cell boundary, new direction is taken towards eNB. It is also assumed that at any instance of time 40% of users receive video service, 40% of users receive VoIP service and 20% of users receive BE service. The buffer at eNB is considered as infinite. The performance is evaluated by varying the number of users. Video flows with source rate of 128 kbps are produced by H.264 trace based coder. Whereas VoIP flows with source rate of 8 kbps are generated by G.729 audio coder. Finally, BE traffic is generated by ideal source that always has packet to send. The main parameters used for performance analysis are given in Table I.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth</td>
<td>10 MHz</td>
</tr>
<tr>
<td>Carrier frequency</td>
<td>2 GHz</td>
</tr>
<tr>
<td>Frame structure</td>
<td>FDD</td>
</tr>
<tr>
<td>Channel model</td>
<td>6-Ray Typical Urban (TU)</td>
</tr>
<tr>
<td>Path loss</td>
<td>$128.1 + 37.6 \log r$ (dB)</td>
</tr>
<tr>
<td>Penetration loss</td>
<td>20 dB</td>
</tr>
<tr>
<td>eNB transmission power</td>
<td>43 dBm</td>
</tr>
<tr>
<td>eNB coverage area</td>
<td>1 km</td>
</tr>
<tr>
<td>Speed of UE</td>
<td>30 kmph</td>
</tr>
<tr>
<td>$T_{th}$ and $D_{th}$ value used</td>
<td>2 and 5.5</td>
</tr>
<tr>
<td>Maximum delay</td>
<td>0.1 s</td>
</tr>
<tr>
<td>Simulation duration</td>
<td>100 s</td>
</tr>
<tr>
<td>Modulation scheme</td>
<td>QPSK (1/2, 2/3 and 3/4)</td>
</tr>
<tr>
<td></td>
<td>16 QAM (1/2, 2/3 and 3/4)</td>
</tr>
<tr>
<td></td>
<td>64 QAM (2/3 and 3/4)</td>
</tr>
<tr>
<td>Traffic model</td>
<td>Video - Trace based (H264)</td>
</tr>
<tr>
<td></td>
<td>VoIP - G.729 voice flows</td>
</tr>
<tr>
<td></td>
<td>BE - Infinite buffer</td>
</tr>
</tbody>
</table>
The performance of the proposed algorithm is compared with four existing scheduling algorithms: PF, MLWDF, EXP rule and LOG rule. Fig. 1 shows the aggregate throughput with respect to the different number of users. As LTE uses shared channel for downlink, the aggregate cell throughput decreases as the number of users increases. The decrease in the throughput is also due to many reasons like the type of service of users, increase in control overhead due to retransmission etc. It is verified by taking random services (i.e., at any instance of time for the chosen number of users, the type of service being served is not fixed) to users for proposed algorithm in the simulation. At initial level, the proposed algorithm increases the throughput by assigning resources to the users that are in good channel condition by using throughput priority metric. However, by providing lower bound to that value, and by giving preference to users with delay sensitive applications, real time users are satisfied at second level. At last level, the users with long buffer queues are scheduled to maintain fairness among users. It is noted from the Fig. 1 that the proposed algorithm outperforms other scheduling algorithm in terms of aggregate cell throughput, while maintaining same level of fairness and average user delay as existing algorithms as shown in Fig. 2. The proposed algorithm provides 11% increase in throughput when compared with the EXP rule algorithm, which performs well among existing algorithms.

Fig. 1. Aggregate cell throughput for different number of users

(a) Fairness index  
(b) Average delay

Fig. 2. Fairness index and average delay for different number of users
5 Conclusion

A three level scheduling algorithm for the downlink LTE system is proposed to improve the aggregate cell throughput. At initial level, the users with good channel conditions are scheduled which results in an increase in the cell throughput. At next level, the users with highest delay requirements are allocated and at last level the users with long buffer queue are scheduled to maintain fairness among users. This algorithm can be used in urban areas that is characterized by high population density, where accommodating more number of users in a given spectrum is very much essential. From the simulation results, it is confirmed that the proposed algorithm outperforms other existing algorithms and provide 11% increase in cell throughput while maintaining same level of fairness and average user delay among users.
Generating a network reliability formula by using binary decision diagrams

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Abstract: Evaluating network reliability is essential for network management. In the case that the failure probabilities of nodes and links change in an evaluation, iterative calculation of the reliability is required. In large networks, however, this calculation takes considerable time; thus, iterative calculation cannot be done within a practical amount of time. In this paper, we present a method for generating network reliability formulas that is based on the reliability calculation method with binary decision diagrams (BDD). We show that the time taken to calculate reliability can be reduced by the formula expression in some orders of magnitude compared with the conventional BDD calculation method, which excludes the overhead of formula generation.

Keywords: reliability, formulation, BDD

Classification: Fundamental Theories for Communications

References


1 Introduction

Reliability, which is the probability that the facilities in a network can communicate with each other, is a fundamental performance measure in communication networks. In network management, a network is often expressed by a graph. Facilities, such as routers and servers, are expressed as nodes, and cables and fibers are expressed as links in the graph. The probability that facilities communicate normally is considered in the graph as the probability that corresponding nodes and links have a “success” status, where the nodes and links do not fail in connection.
We call this probability the “success probability.” The reliability among \( k \) facilities such as servers is calculated as the probability that any set of corresponding nodes can establish a path with nodes and links that have a success status. There have been several methods proposed for calculating network reliability [1, 2, 3]. Methods that use the binary decision diagram (BDD) are very efficient [3].

Network reliability is evaluated in network planning. For example, we can examine node-pair reliability, that is, reliability with \( k = 2 \), for all node pairs in a candidate network topology by giving success probabilities to all nodes and links, and find which node pair is likely disconnected. In the case that the type of nodes and links should also be determined, we should iteratively evaluate the reliability for each node pair by giving the success probabilities corresponding to the candidate type of nodes and links. In large networks, however, calculating reliability requires considerable time since the conventional method needs to consider success and failure cases for each node and link with a given success probability for each. Calculation for a node pair is required for each pattern of success probabilities; thus, calculation for all the node pairs cannot be done in a practical amount of time.

However, reliability should become a function of success probability. If a formula that expresses the network reliability of a node pair is derived once, we can calculate the reliability only by substituting the success probability with the obtained formula, not by considering success or failure for all nodes and links.

In this paper, we propose a method for generating a network reliability formula by using BDD. Section 2 explains BDD, and the generation method is discussed in Section 3. Section 4 shows the simulation results, and we conclude the paper in Section 5.

### 2 Reliability calculation with BDD

In this section, we give a brief summary of BDD. Here, we assume \( k = 2 \) and only consider link failure for simplicity. However, the method can be generalized.

In the network in Fig. 1(a), the Boolean function of the set of required links for connection between \( s \) and \( t \) is

![Network and BDD](image-url)
where \( x_i \) is a Boolean variable that is 1 if \( e_i \) is a success link and 0 if not. The Boolean function for connectivity between \( s \) and \( t \) in network \( G \) can be derived by the recursive procedure [3]. By encoding AND and OR in the procedure by BDD operation [3], the Boolean function can be expressed by a BDD graph (see Fig. 1(b)). In the graph, the edges are directed from top to bottom. The solid and dashed edges from vertex \( x_i \) express \( x_i = 1 \) and \( x_i = 0 \), respectively. The terminal vertices 1 and 0 express if the boolean function is TRUE(1) or FALSE(0), respectively, with the set of \( x_i \), which leads to the vertices.

With BDD graph \( f \), the reliability can be calculated as

\[
\text{Prob}(f) = P(\bar{x}) \cdot \text{Prob}(f_{e=1}) + (1 - P(\bar{x})) \cdot \text{Prob}(f_{e=0}),
\]

where \( \bar{x} \) is the variable of the top vertice in \( f \), \( P(\bar{x}) \) is the success probability of the corresponding link, and \( f_{e=1} \) (\( f_{e=0} \)) is the BDD graph connected to the solid (dashed) edge from vertex \( \bar{x} \). \( \text{Prob}(f) \) is 1 (0) if \( f \) is the terminal vertice 1 (0). \( \text{Prob}(f) \) calculates the reliability by considering the combination of success \([P(\bar{x})]\) and failure \([1 - P(\bar{x})]\) patterns for each link, where redundant calculations are eliminated [3]. In addition, overlapping subgraphs are collected in one subgraph in BDD, and a hash table can be used to reduce the calculation [3]. Calculating reliability with BDD, however, still requires considerable recursive calls and takes more time as the size of a BDD graph grows because of network largeness or complexity.

### 3 Formula generation with BDD

The calculation of reliability with BDD is executed with the success probability \( P(\bar{x}) \) for each link, and the value is output. Since the BDD calculation method requires only simple multiplication and summation between the probabilities and the redundant calculations are omitted, we can efficiently obtain a formula expression of the reliability by giving the success probabilities as symbols, not as values, and outputting the character string that represents the arithmetic operation between the symbols.

Algorithm 1 shows the procedure. Here, quotation marks are used around words to express that the words are returned as the character string. With BDD in Fig. 1(b), for example, \( \text{REL}(f) \) outputs the following formula. \( p_1 \times (p_2 \times (p_4 + (1 - p_4) \times p_5) + (1 - p_2) \times (p_3 \times (p_4 + (1 - p_4) \times p_5) + (1 - p_3) \times p_6)) + (1 - p_1) \times (p_2 \times (p_3 \times (p_4 + (1 - p_4) \times p_5) + (1 - p_3) \times p_5)), \) which represents the network reliability formula.

With the tools for symbolic mathematics, SymPy [4] for example, the output formula can be simplified. By using simplification method \( \text{expand()} \) in SymPy, the formula previously noted is simplified as \( 2p_1p_2p_3p_4p_5 - p_1p_2p_3p_4 - p_1p_2p_4p_5 - p_1p_5p_4p_5 + p_1p_3p_5 + p_1p_4 - p_2p_3p_4p_5 + p_2p_3p_4 + p_2p_5 \), where the multiplication symbols are omitted.
Algorithm 1 REL($f$)

Input BDD graph $f$
Initialize hash table $H$
if $f$ is terminal node 1 then
    return “1”
ext if $f$ is terminal node 0 then
    return “0”
ext if $f$ is in $H$ then
    return $H(f)$
else
    \( \tilde{x} \leftarrow \) variable of top vertice in $f$
    \( \tilde{p} \leftarrow \) symbol of success probability of link corresponding to $\tilde{x}$
    \( f_{\tilde{x}=1} \leftarrow \) BDD graph connected to solid edge from vertice $\tilde{x}$
    \( f_{\tilde{x}=0} \leftarrow \) BDD graph connected to dashed edge from vertice $\tilde{x}$
    \( C_1 = \text{REL}(f_{\tilde{x}=1}) \)
    \( C_2 = \text{REL}(f_{\tilde{x}=0}) \)
    if $C_1 = “1”$ and $C_2 = “0”$ then
        return $\tilde{p}$
ext if $C_1 = “1”$ then
        \( C_r \leftarrow \text{connected symbols with } [\tilde{p}, “+”(1-”, \tilde{p}, “)\times(”, C_2, “)] \)
ext if $C_2 = “0”$ then
        \( C_r \leftarrow \text{connected symbols with } [\tilde{p}, “\times(”, C_1, “)] \)
ext
        \( C_r \leftarrow \text{connected symbols with } [\tilde{p}, “\times(”, C_1, “), “+”(1-”, \tilde{p}, “)\times(”, C_2, “)] \)
end if
\( H(f) \leftarrow C_r \)
return $C_r$
end if

When most of the success probability is given as a value and we want to express only the rest as symbols, the formula can be simplified further with the tools by substituting the known values with the corresponding symbols. For example, by giving $p_2, p_3, p_4, \text{ and } p_5$ as 0.9 and assuming $p_1$ as a variable, the formula previously noted becomes $0.1062p_1 + 0.8829$.

4 Simulation results

We compared the calculation times between the conventional BDD method and proposed method. For the evaluation, we used a $3 \times 3$ grid network (see Fig. 2).

Table I shows the evaluation results of the computation time, where “gen.” is the time taken to generate the formula and “cal.” is the time taken to calculate the reliability for all node pairs. For one node pair, the reliability is calculated once with the given success probabilities. BDD (conv.) is the conventional BDD method. formula (naive) is the formulation without any simplification, formula (simplified) is that with simplification of the whole formula, and formula (partial) is the formulation where the success probabilities of $e_1, e_3, e_7, \text{ and } e_9$ are given as the
symbolic variables and those of the rest as values. The computation was executed on Python 2.7.6 on CentOS 6.6 with 6 GB of memory × 6 and a 1.9-GHz CPU × 2. In formula (simplified) and formula (partial), the simplification of the formula was processed by SymPy [4]. Although the generation of the formula in formula (naive) requires the same time as the calculation in BDD (conv.) and that in formula (simplified) and formula (partial) take more time due to the simplification procedure, the time taken to calculate reliability was one to two orders of magnitude lower. Since generating a formula is needed only once, calculation with the formula is effective when the iterative calculation of the reliability is required.

We also compared the calculation time of the reliability between BDD (conv.) and formula (partial), where the network was a 5 × 5 grid and the success probabilities of seven links in the left top of the grid were only given as symbolic objects in formula (partial). The calculation time in BDD (conv.) for all node pairs was 1.46 × 10 (sec). In comparison, the generation time of the formula and the calculation time for all node pairs in formula (partial) were 1.13 × 10 (sec) and 6.14 × 10 (sec), respectively. If the number of the types of the link is four, the combinations of the types of seven links is 47 = 16,384. Thus, the total time needed to evaluate the reliabilities is about 66 (hours) in BDD (conv.), whereas that in formula (partial) is about 3 (hours). As the number of the combinations of the types increases, formula (partial) becomes more efficient since the calculation time in formula (partial) is negligible.

5 Conclusion

We proposed a method for generating a network reliability formula by using BDD. Although generating a formula requires overhead, the calculation time of the reliability can be reduced some orders of magnitude compared with the conventional BDD method.
Deriving maximum effective area throughput of dynamically reconfigurable QoE-oriented WLAN

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Abstract: Aiming for satisfying the requirement on quality of experience (QoE) for many important applications, we proposed a QoE-oriented WLAN which employs channel access permission control and dynamic network reconfiguration. For practical system deployment, it is important to assess the upper performance limit of the system. This letter introduces a metric “effective area throughput” (EAT): it is the area throughput summed up among the applications which achieve the throughput for satisfying their QoE requirements. This letter then derives the maximum expected EAT of the QoE-oriented WLAN based on a random sampling method. Through numerical evaluation, it is confirmed that the proposed derivation method provides a valid expected EAT for WLAN with several tens of nodes in a tractable computational complexity. It is also confirmed that the QoE-oriented WLAN has potential to increase the EAT compared with the conventional WLAN.

Keywords: effective area throughput, channel access control, dynamic network reconfiguration, wireless LAN, performance assessment

Classification: Terrestrial Wireless Communication/Broadcasting Technologies

References

QoE-oriented wireless LAN with dynamic network reconfiguration,” submitted to IEICE Trans. Commun.


1 Introduction

With the widespread use of IEEE 802.11 wireless local area network (WLAN) [1], a number of nodes generate a variety of application traffic flows, which sometimes cause severe network congestion. In such a case, most of applications may not work regardless of their importance, because the transmission opportunity is evenly offered to each node in IEEE 802.11 WLAN. Consequently, it provides insufficient quality of service (QoS) or quality of experience (QoE). QoE is generally calculated from several QoS factors such as throughput, delay and packet loss probability, for each application.

To overcome this problem, we have proposed a QoE-oriented WLAN [2, 3, 4]. It predicts which application can satisfy its QoE requirement by considering several factors such as the transmission data rate available at each station (STA), the offered load, packet size, priority, and current status of QoE satisfaction of each running application [5, 6]. According to the result of this prediction, it performs channel access permission control, change of associating access point (AP) of STAs, and change of operating frequency channel for avoiding overload on each channel and load balancing among basic service sets (BSSs).

From a viewpoint of system deployment, it is important to assess the upper limit of the number of operatable applications of the system. A desirable way may be to analytically predict whether or not each application can satisfy the QoE requirement by using some numerical models, e.g., models presented in [7, 8] for estimating mean opinion score (MOS). QoE is generally affected by several QoS factors such as throughput, transmission delay, and packet loss probability [8]. However, it is hard to precisely predict all factors which affect MOS in a complex network.
Therefore, we take more simple approach which is an approximative assessment of the upper performance limit of the system. We focus on throughput of running applications and consider whether or not throughput of each application can achieve satisfactory level for fulfilling its QoE requirements. This is because other QoS factors, which affect QoE such as transmission delay and packet loss probability, are expected to become good if all applications can achieve enough throughput.

In this letter, we introduce a metric “effective area throughput” (EAT): it is the area throughput summed up among the applications which satisfy the throughput requirements. In the previous research [5], we have established an analytical method using Iwami’s throughput estimation algorithm [9] to derive the expected EAT of the QoE-oriented WLAN without dynamic network reconfiguration.

The maximum expected EAT considering dynamic network reconfiguration can be assessed by checking all possible topology patterns, whereas the number of possible topology patterns increases exponentially as the number of nodes increases. Subsequently, it is intractable to check all patterns when a number of nodes exist. In this letter, therefore, we propose a method for deriving the maximum expected EAT using random sampling of network topology in order to assess the upper performance limit of the QoE-oriented WLAN with dynamic network reconfiguration.

The rest of this letter is organized as follows. In Sect. 2, we introduce an analytical method to derive the expected EAT. In Sect. 3, we evaluate the convergence performance. Finally, concluding remarks are given in Sect. 4.

2 Derivation of expected effective area throughput

2.1 Algorithm for network without dynamic network reconfiguration [5]

This subsection briefly introduces our developed analytical method to derive the expected EAT of the QoE-oriented WLAN without dynamic network reconfiguration. We assume that there are one target BSS for estimating EAT and several other BSSs as interference sources. The expected EAT of the target BSS is calculated as follows.

**Step a-1:** Initialize a set of transmission nodes $S$ as empty, and a priority counter $i$ as 1.

**Step a-2:** Add the node with the $i$-th high-priority into $S$. Here, the priority of each node is given according to a pre-determined channel access policy.

**Step a-3:** Estimate the throughput of each node in $S$ by Iwami’s throughput estimation algorithm [9]. This algorithm analytically estimates achievable throughput from application offered load, packet size, and transmission data rate of every node including nodes in other BSSs. It should be noted that all nodes in other BSSs or in the conventional WLAN will transmit their application data because they are uncontrollable.

**Step a-4:** Check the estimated throughput of each node in the target BSS whether or not it satisfies its throughput requirement to satisfy its QoE requirement. If any node in $S$ fails to satisfy its throughput requirement, the newly added node is excluded from $S$.
2.2 Proposed algorithm considering dynamic network reconfiguration

The maximum expected EAT considering dynamic network reconfiguration can be derived by checking all topology patterns. However, the number of topology patterns increases exponentially as the number of nodes increases. Specifically, the number of possible topology patterns is \( (M^N \times L^{P_{L-M}}) \), where \( M \) is the number of APs, \( N \) is the number of STAs, \( L \) is the number of available channels, and \( P \) denotes the permutations. Thus, it is intractable to check all patterns in a complex situation. Therefore, we adopt a random sampling approach. The procedure of the proposed algorithm is the following:

**Step b-1:** Set the maximum expected EAT \( E_{\text{MAX}} \) as 0.

**Step b-2:** Calculate the EAT \( E_{\text{cur}} \) for a randomly determined topology.

- **Step b-2-1:** Determine an associating AP of each STA in the proposed WLAN randomly.
- **Step b-2-2:** Determine operating frequency channel of each BSS in the proposed WLAN randomly. Note that each BSS is assigned different and non-overlapping channel (e.g., 1, 7, 13 ch).
- **Step b-2-3:** Determine the expected transmission data rate of each link. It is obtained from received signal strength indication (RSSI) which is calculated by transmission power and path-loss between each STA and its associating AP.
- **Step b-2-4:** Calculate the EAT \( E_{\text{cur, ch}} \) of each channel by the algorithm described in Sect. 2.1.
- **Step b-2-5:** Sum up \( E_{\text{cur, ch}} \).

**Step b-3:** If \( E_{\text{cur}} \) is larger than \( E_{\text{MAX}} \), update \( E_{\text{MAX}} \) with the \( E_{\text{cur}} \).

**Step b-4:** Iterate Steps b-2 and b-3 until \( E_{\text{MAX}} \) converges.

3 Convergence performance evaluation

In this section, we evaluate the convergence performance of the proposed random sampling approach to confirm the validity of this approach.

3.1 Scenario parameters

For evaluating the impact of the number of nodes on the convergence performance (the required sampling size and the processing time), we assume two scenarios with different number of nodes. We consider that there are two target BSSs (BSS 1, 2).

The first scenario (Scenario 1) consists of 4 APs and 14 STAs including conventional WLANs as interference sources. The second scenario (Scenario 2) consists of 5 APs and 51 STAs. The throughput requirement is set to 98% of the offered load as in [5]. We derive the maximum expected EAT with different ten initial random seeds for evaluating the convergence performance. We also measure the processing time using a computer with an Intel® Core™2 Quad 2.66 GHz CPU and

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1Note that each AP in the proposed WLAN shall use different independent channel.
4 GB memory. In addition, we compare the maximum expected EAT with the results of system level simulations in order to validate the converged value. The scenario configurations are shown in Table I.

### 3.2 Evaluation results

The evaluation results of Scenario 1 and Scenario 2 are shown in Fig. 1. The legends “seed N” are the results of the maximum expected EAT of the proposed QoE-oriented WLAN with initial random seed N, and “SIM” show the simulation result, respectively. In this simulation, the dynamic network reconfiguration control is performed as explained in [3, 4].

As shown in the results of Scenario 1 with a small number of nodes, the maximum expected EAT of the QoE-oriented WLAN converge to the same value within 10 samples, and it well agrees with the simulation result. This is because the number of topology patterns of this scenario is not so large, and there are enough

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**Table I.** Scenario configurations.

### Table I-a. Basic scenario configuration.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLAN mode</td>
<td>IEEE 802.11g ERP-OFDM (DCF)</td>
<td></td>
</tr>
<tr>
<td>RTS/CTS</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>Target BSS</td>
<td>BSS 1, 2</td>
<td>BSS 1, 2</td>
</tr>
<tr>
<td>Interference BSS</td>
<td>BSS 3, 4</td>
<td>BSS 3, 4, 5</td>
</tr>
<tr>
<td>Maximum transmission data rate</td>
<td>12 Mb/s</td>
<td>36 Mb/s</td>
</tr>
<tr>
<td>Required RSSI for each data rate</td>
<td>Based on minimum sensitivity standardised by IEEE 802.11g OFDM [1]</td>
<td></td>
</tr>
</tbody>
</table>

### Table I-b. The number of traffic flows in each BSS.

<table>
<thead>
<tr>
<th>BSS</th>
<th>App type</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSS 1 + BSS 2</td>
<td>Monitoring sensor</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>File download 1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>File download 2</td>
<td>2</td>
<td>26</td>
</tr>
<tr>
<td>BSS 3</td>
<td>File download 2</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>BSS 4</td>
<td>File download 2</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>BSS 5</td>
<td>File download 2</td>
<td>-</td>
<td>6</td>
</tr>
</tbody>
</table>

### Table I-c. Traffic configuration.

<table>
<thead>
<tr>
<th>Application</th>
<th>DL/UL</th>
<th>Priority</th>
<th>Offered load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monitoring sensor</td>
<td>UL</td>
<td>High</td>
<td>1.44 Mb/s, 1440 Byte(packet)</td>
</tr>
<tr>
<td>File download 1</td>
<td>DL</td>
<td>Mid</td>
<td>500 kb/s, 1472 Byte(packet)</td>
</tr>
<tr>
<td>File download 2</td>
<td>DL</td>
<td>Low</td>
<td>1 Mb/s, 1472 Byte(packet)</td>
</tr>
</tbody>
</table>

### Table I-d. Simulation configuration.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial channel of BSS 1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Initial channel of BSS 2</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>Channel of BSS 3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Channel of BSS 4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Channel of BSS 5</td>
<td>-</td>
<td>7</td>
</tr>
<tr>
<td>Simulation area</td>
<td>40 m × 20 m</td>
<td></td>
</tr>
<tr>
<td>Initial associating AP</td>
<td>AP with the maximum RSSI</td>
<td></td>
</tr>
</tbody>
</table>
wireless resources to satisfy QoE requirements of all applications, which means that there are multiple patterns to achieve the best EAT. In this scenario, the processing time is about 1.5 seconds per sample.

In Scenario 2 which has more nodes than in Scenario 1, the maximum expected EAT reaches near the exact value within around 10 samples, and converges to the same value in around 60 samples even though the number of possible topology patterns is relatively huge. This is because there are few variations in node’s property (i.e., transmission data rate and application type), and the number of practical combinations is reduced. In this scenario, the processing time is about 3 seconds per sample. This result indicates that we can assess the upper performance limit of the QoE-oriented WLAN with several tens of nodes in a tractable computational complexity. Note that the derived expected value of Scenario 2 is better than the simulation result. This is because the dynamic network reconfiguration control employed in this simulation is not optimal, and it can be improved.

Fig. 1 also shows the maximum expected EAT when target BSSs (BSS 1 and BSS 2) operate as the proposed WLAN and the conventional WLAN (“CONV” in this figure). It is confirmed that the proposed QoE-oriented WLAN has potential to increase the EAT compared with the conventional WLAN.

4 Conclusion

In this letter, we proposed a derivation method of the maximum expected EAT based on a random sampling approach, in order to assess the upper limit of the performance of the WLAN with dynamic network reconfiguration. Through the evaluation of convergence performance, it was confirmed that the proposed deviation method provides valid expected EAT of the WLAN with several tens of nodes in a tractable computational complexity. In addition, it was confirmed that the proposed QoE-oriented WLAN can increase the EAT compared with the conventional WLAN.

Acknowledgments

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