An Autoregressive Model of Electromagnetic Disturbances in An Autonomous Electric Vehicle's Route

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***Abstract*—Electromagnetic Interference (EMI) can cause a malfunction of on-board electronic circuits in an autonomous electric vehicle (AEV) and supporting electronic devices located in the environment of autonomous electric vehicleAEVs as well. In order to navigate an AEV safely, it is important to have electromagnetic field characteristic in the environment. As the details about the electromagnetic field's characteristics are elusive, there's a requirement to create a model for it. This paper presents a model of electromagnetic field characteristic that is generated by using autoregression in order to estimate potential EMI. The EMI estimation is based on electromagnetic characteristic in an environment. Unlike other applications that use time history of data to build a model, we presents X-Y plane of electromagnetic field strength (E-field) real data in a previous route to estimate the future data in a new route. To obtain historical data for auto-regression process, E-Field measurement was conducted along a circular route in a campus near Jakarta. This surrounding environment represents a typical area of suburbs. The input variables for auto-regression process are the first 27 correlated data of 155 measured data. The result shows that the use by using of 13 predictor coefficient produces a variance of prediction error with an improvement from maximum prediction error of 15.1257 to prediction error of 0.1862.**

Keywords*—autoregressive model, electromagnetic field, electromagnetic interference, electric vehicles, random process.

I. INTRODUCTION

Electromagnetic field can interfere electronic circuits. It cause a malfunction of electronic devices in the automotive research area [1]. In commercial automotive industries, it is reported in [2] that there is strong indication of malfunctions of electronic devices caused by EMI. Since AEVs are predicted as the future transportation [3], it is necessary to consider the effect of EMI to electronic control and navigation devices in the vehicles. A common and powerful tool for navigation of vehicles is a GPS receiver. A study of the performance of GPS receivers has been made comprehensively in [4]. However, since a GPS receiver can be affected by EMI [5], an AEV may take a wrong direction if the supporting GPS fails to provide correct data. The sources of electromagnetic field are not only on-board electrical or electronic devices but also transmitter stations in the environment as it is indicated in [6]. Accordingly it is essential to have a characteristic of electromagnetic field in the environment of AEVs. Based on the existing map of electromagnetic field characteristic, one can determine which routes are dangerous for AEVs. This kind of map can be used to try out path-planning algorithms of an electric vehicle before it starts travelling. Unfortunately, there is scarce information available in the map depicting electromagnetic field characteristics. Even Although some experiments have been conducted to investigate the characteristic of electromagnetic field, however the area of measurement is limited. In the previous research [7] and [8], the measurement was conducted only in a campus area. Another measurement of the experiment in [9] was conducted also in a relative particular area. In addition, the characteristic in this area can change with the time.

In order to provide a map of electromagnetic characteristic independently from the real environment, we needs to simulate and create a model of a electromagnetic field characteristic. A powerful tool for modeling is autoregression. Autoregression estimates the current values from the existing previous values of electromagnetic field strength in dBm . In the research area of telecommunication, this method is used for estimating the rain attenuation on multiple short radio links [10]. In biomedical applications, autoregressive modeling is used to analyses cardiovascular response signals [11]. It is reported in [12] that by using autoregressive modelling, the power spectrum in the spectral analysis of heart rate variability can be more easily interpreted than using the discrete Fourier transform. Such an autoregressive model of electromagnetic field is useful in evaluating the effectiveness of path-planning method of an EV, by which excessive electromagnetic field must be avoided. The limits and frequencies of electromagnetic field that are harmful for on-board electronic devices are determined in [13].

This paper presents an autoregressive model of an electromagnetic field characteristic. Commonly, autoregressive modeling is used for analyzing electric or electromagnetic responses use time history of previous data to predict future data. In our work, it is a huge time consuming to observe and to collect data in a relative wide area. There is an alternative way to model a random process

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using spatial autoregression [14]. Accordingly, we use spatial previous measured data in a circular route to estimate the future data for another route. The input data for the model are obtained by observing electromagnetic field in a typical area of suburbs as it is discussed in [15].

First of all, the characteristic of electromagnetic field in an environment along a circular route was observed by conducting a field measurement. Once measurement data are provided then we select data for autoregressive model by examining auto-correlation of the measurement data. The selected data for the autoregressive process are the data that correspond with positive result of the autocorrelation process before it indicates a negative result. Based on these data, the autoregressive model is examined. The number of the predictor coefficients are selected when the variance of prediction error is minimum or near to zero. It is also important to consider that the higher is the number of the predictor coefficient, the higher is the computational cost of autoregressive process. In this work, the order of the autoregression model is selected if the variance of predicted error is already below 0.2. We assume that electromagnetic field strength on every point along the route is normally distributed. Furthermore, a Gaussian random value is added to the prediction function to complete the model since the characteristic of electromagnetic field is a random process.

Next chapter describes the methodology of obtaining the autoregressive model. The results are discussed and analyzed in chapter three and all are concluded in chapter four.

II. Methods

This chapter describes the methodology of the research. It includes electromagnetic field observation and data collection, autocorrelation of the data, autoregressive modeling and creation of random generator.

A. Electromagnetic Field Observation

The observation of electromagnetic field is made along a circular route in The Sience and Technology Area, National Research and Innovation Agency, South East of Jakarta. The observation area represents a typical suburbs. The area is quite spacious and surrounded by small to medium buildings and high vegetation. The method of the measurement is described comprehensively in [15].

The measurement was made by using a handheld field meter Narda NBM 550 that is equipped with an isotropic probe and an integrated Garmin GPS receiver. The measurable frequency range is between 150 kHz and 6 GHz. The electric field's actual value and the geographic coordinate are recorded every second (1 second sampling time) simultaneously. The frequency of measured electric field is 2172 MHz. Measurement of electric field is done 6 times along the circular track uninterruptedly, with 480 - 500 measurement points per circular track. The average of about 9 (nine) neighboring measured electric fields in a location was calculated to obtain the local mean of E-Field.

Fig. 1 shows the characteristic of the electromagnetic field. The horizontal axis in the top figure in Fig.1 represents the measurement distance from a reference point while the horizontal axis of the bottom one shows the consecutive points (index) when the measurement was done. The reference point is the location of first measurement. So, there are 155 measurement data of electrical field strength in the circular route. The distance between two measurement point is about 3 m so it make a distance of approximately 465 m. The mean of the measured electromagnetic field strengths μ_f is -25 dBm and the standard deviation σ_f is 7.6 dBm.

Furthermore, to ensure future dependency of the previous data that are used for autoregression modeling, we use autocorrelation function. Autocorrelation is the average of the product of a measured data $x(i)$ with itself advanced by a lag. The function is represented by the equation

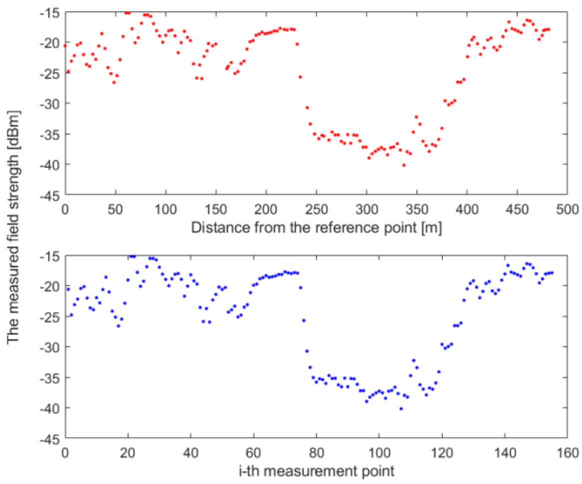

Fig. 1. The characteristic of electromagnetic field in a circular route in the campus area South of Jakarta. (index of measurement point)

$$R_{xx}(i) = \frac{1}{N} \cdot \sum_{n=1}^{N-i} x(i).x(n+i) \tag{1}$$

where $R_{xx}(i)$ is the autocorrelation value of x at a delay i, and N is the number of data points.

B. Autoregressive Modeling

An autoregressive model is a model to estimate or to predict current random process that is dependent on the previous process. The mathematical formulation of autoregression is

$$x_n = \sum_{i=1}^{M} a_i x_{n-i} + \varepsilon_n \tag{2}$$

where x_n are the current values of the process, $x_{n-1,\dots,}\ x_{n-M}$ are the previous values of the process, $a_1, \dots,\ a_M$ predictor coefficients, M *is* the model order, indicating the number of the past values used to predict the current value, and ε_n *are* the differences between the predicted and the current value.

By using the Least Square Method (LSM), the predictor coefficients can be obtained. For the clarity, let us assume that there are 5 random variables $x_1, \dots, x_5$ from the previous observation and the order M = 2. The autoregressive model is

$$\begin{bmatrix} x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} x_2 & x_1 \\ x_3 & x_2 \\ x_4 & x_3 \end{bmatrix} . \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix} \tag{3}$$

So, we have a matrix equation in the form of

$$\bar{y} = X.\bar{a} + \bar{\varepsilon} \tag{4}$$

To obtain the predictor coefficients we need to build the sum of square of errors as a function of the predictors.

$$S(\bar{a}) = \sum_{i=1}^{3} \bar{\varepsilon}_i^{\,2} = \bar{\varepsilon}^T \bar{\varepsilon} \tag{5}$$

Subtitute ε in (5) with (4)

$$S(\bar{a}) = (\bar{y} - X.\bar{a})^T (\bar{y} - X.\bar{a}) \tag{6}$$

then we obtain

$$S(\bar{a}) = \bar{y}^T \bar{y} - \bar{y}^T X.\bar{a} - \bar{a}^T X^T \bar{y} + \bar{a}^T X^T X\bar{a} \tag{7}$$

To acquire the predictor coefficients then we differentiate *S(a)* and equate to zero,

$$\partial S(\bar{a}) / \partial \bar{a} = -2X^T \bar{y} + 2X^T X\bar{a} = 0 \tag{8}$$

so we obtain the predictor coefficients

$$\bar{a} = \left(X^T X\right)^{-1} X^T \bar{y} \tag{9}$$

Once the predictor coefficients is obtained, then we can estimate x_3, x_4 and x_5. The first two variables x_1 and x_2 are assigned with their previous value.

C. Gaussian random generator

Since the presence of electromagnetic in the environment is assumed as a Gaussian random process, we need to add Gaussian random values to the model variables. The values are acquired by developing random number generator. By generating such values on a computer, we are able to simulate and evaluate the electromagnetic field characteristic.

A normalized Gaussian probability density function is defined as

$$f(x) = \frac{1}{\sqrt{2\pi}.\sigma} e^{x^2/\sigma^2} \tag{11}$$

where x is a random variable and σ^2 is the variance of x. A Gaussian random number G is obtained through the inverse of the probability distributed function

$$G = F^{-1}(x) \tag{12}$$

where

$$F(x) = \int_{-\infty}^{G} f(x) dx \tag{13}$$

The Gaussian distribution function in (13) can not be expressed in a simple function for the purpose of developing random generator. A way to obtain a random value is to use Rayleigh distribution function that is combined with uniformly distributed function. The process is described comprehensively in [16].

Finally, autoregressive model is represented by

$$x_n = \sum_{i=1}^{M} a_i x_{n-i} + G_n \tag{14}$$

$$y_n = x_n + \mu_f \tag{15}$$

Where y_n is the model variables, μ_f is the mean of measured data. G_n is a random number that is produced by the normalized Gaussian distribution function. The variance of the distributed function σ^2 is equal to the variance of measured data σ_f^2.

III. Results and Discussion

In this section the results of simulation are discussed and analyzed. The autocorrelation of the measured field strength data is presented in Fig. 2. As can be seen in the Fig. 2, the positive result of the autocorrelation of 155 data before it turns to a negative value are the correlation of the first 27 data. The 27th data corresponds with the distance of 81 meter. These data are used to examine the autoregressive process.

Next step the autoregressive process is executed. The order of the model *M* is set from 1 to 20. The variance of the prediction error which is the difference between the measured and autoregreesive output data, are shown in Fig. 4.

The variance has a maximum at *M*=2. It begins to decrease and reach a local minimum at *M*=9. After that the variance oscillates shortly before approaches to zero at *M*=13. The result shows that in a certain interval, a high order *M* of the autoregressive model does not always result in a small variance. To illustrate the similarity between the measured data and its correspondence autoregessive data with respect to the variance, we select autoregressive model with 3 different order that are represents a decreasing variance of prediction error, namely *M*=5, *M*=9 and *M*=13. The latest has the least variance. Table 1. shows the prediction coefficients $a_1,\ldots,a_M$ for each order.

The similarity between the measured data and its correspondence autoregessive model with respect to decreasing variance is illustrated in Fig. 5. The vertical axis represents the field strength and the horizontal axis is the distance from the reference. As can be seen Fig. 5, the top picture (*M*=5) shows that the autoregressive model with higher variance does not fit to measured data. Compared with the result in top picture, the result in the middle picture shows that with the lower variance the autoregressive model (M=9) begins to adapt to the measured data.

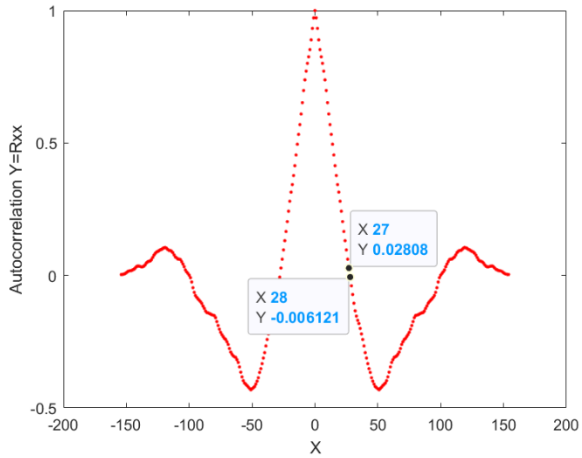

Fig. 2. The autocorrelation of observation data as the function of distances

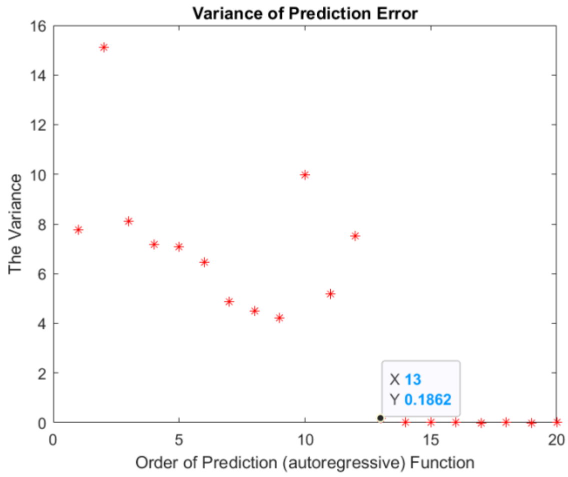

Fig. 3. The variance of prediction error.

Finally, in the bottom picture the variance of the prediction error is the lowest, so the autoregressive model (M=13) fits mostly to measured data.

The choice of the order M needs to consider that the higher number of M is, the higher is the computational cost. So we select the value of M if the variance is already below 0.2. In this case, the variance is 0.1862 at M=13.

In order to demonstrate the a random process, a normalized distributed Gaussian process is added to the model. In the previous section, the method is described. The result of the Gaussian random generator is illustrated in Fig. 5. The random generator is set to produce 1000 random values with the mean μ=0. The standard deviation σ is selected to 7.6 which represents the standard deviation of measured data σ_f .

Fig. 6 shows the results. The autoregressive model of the electromagnetic field characteristic tends to replicate the measured field characteristic.

TABLE 1. THE COEFFICIENTS OF THE AUTOREGRESSIVE MODEL

Predictor Coefficient	Order of Predictor		
	***M*=5**	***M*=9**	***M*=13**
a_1	1.5029	1.3951	1.3154
a_2	-0.9295	-0.8046	-1.0412
a_3	0.3554	0.5003	1.8755
a_4	-0.2268	-0.4199	-1.5246
a_5	0.2869	0.2003	0.1254
a_6	0	-0.0088	-0.4044
a_7	0	0.3812	0.6229
a_8	0	-0.1808	0.8504
a_9	0	-0.0837	-1.0408
a_{10}	0	0	-0.0901
a_{11}	0	0	-1.0089
a_{12}	0	0	0.9863
a_{13}	0	0	0.3025

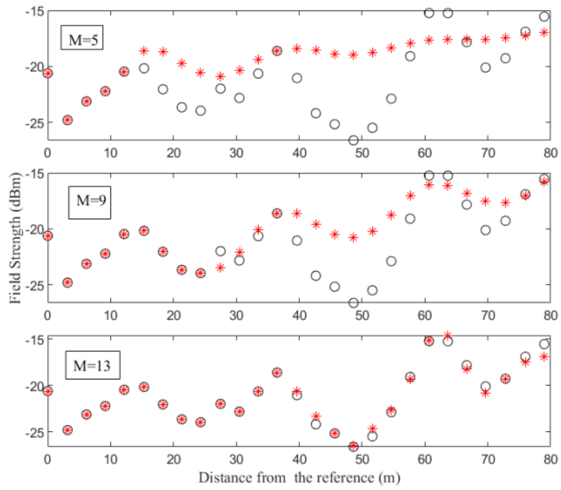

Fig. 4. The comparison of measured data (circle) with their correspondent autoregressive model (red asterix) for M = 5 (top), M=9 (middle), and M=13 (bottom).

As 3 different normalized Gaussian process are added to the autoregressive model, the result shows that 3 various simulated electromagnetic field characteristic are obtained.

To ensure that the data of the random process model are correlated, we examine the autocorrelation of the random data. Fig. 7 shows the autocorrelation of the data. The result shows that the data of the autoregressive model of the characteristic of electromagnetic field are correlated and it can represents the characteristic of electromagnetic field.

A similar result is discussed in [10], where the autoregression can be used for modeling the rain attenuation. In [10] the model is multivariat and the attenuation function has been defined (exponential function) while in this paper the model is univariate and the characteristic function has not been defined.

In addition we will verify the result of autoregressive modeling for various road sections. There are 27 data that are generated in one execution. The distance of measurement area can be approximated by 162 data since two data points represent a distance of 3 meter. So we generate 6 different simulated electromagnetic field characteristic for 6 road sections. Fig. 8 shows the simulated electromagnetic field characteristic and the measurement data for a comparison. shows the measurement EMF in 6 road sections with 27 data per section.

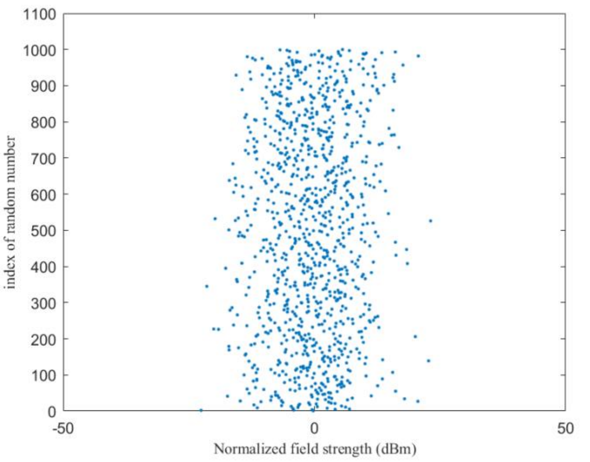

Fig. 5. The output of normal distributed Gaussian random generator.

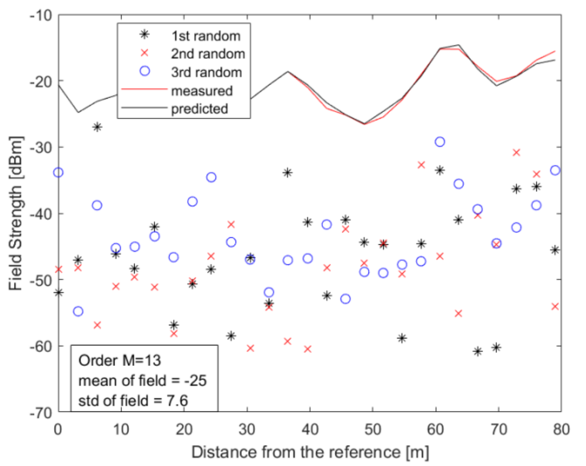

Fig. 6. The autoregressive model at M=13 is added with 3 different normal distributed Gaussian process.

The top figure shows 6 road sections represent a circular path of AEV. The 27 data of the 1st section will be used to generate the AR-model for the next 5 road sections. The bottom one shows the result of generated AR-model which uses mean μ_f from the whole measured data and G random value as generated by normalized Gaussian random generator with the standard deviation of the whole measured data.

The simulated EMF data in the 2nd - 6th sections shows a tendency to re-ensemble the first sections simulated data due to the same value of mean. The difference is only affected by G. The difference between measured and the simulated data is mainly determined by the parameters of Gaussian distribution. The simulation uses zero mean while the measured data may shifted from the ideal Gaussian form. The simulated data is not primarly a prediction of measured data but is meant to generate randomized EM source which is experienced by the EV along the route . In order to have a closer estimation of measured data instead of using only partially 27 data, it is recommended to use the next correlated data of the next section.

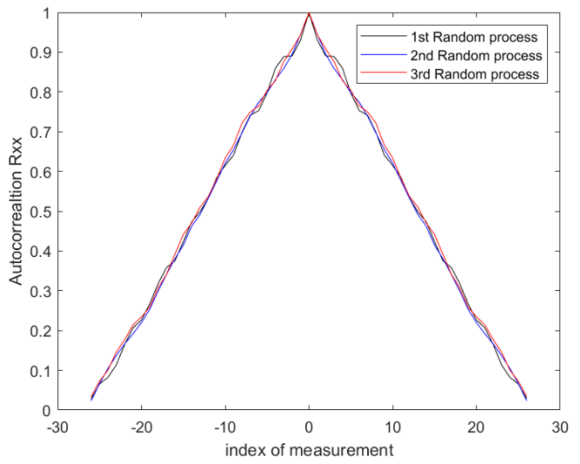

Fig. 7. The autocorrelation of each random data of simulated electromagnetic characteristic.

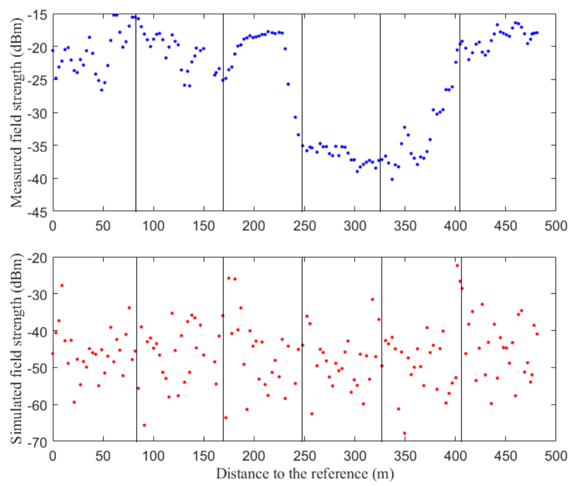

Fig. 8. Measured data (top) and simulated data (bottom) in 6 different road sections.

IV. Conclusion

To sum up, developing path-planning algorithm for a safe navigation of electric vehicles needs an existing map of electromagnetic field characteristic. Such a map is hardly any. Instead of real map, a simulation program can represent a map of electromagnetic field characteristic in a typical area. Base on data measurement in a typical area, a map can be obtained by using spatial autoregressive model including a Gaussian process. Since the number of predictor coefficients affect the computational cost, the number is selected where the variance of the prediction error already below 0.2. The results show that the data of the autoregressive model are correlated and creates various characteristic of electromagnetic field for various road section according the characteristic of a typical area. In this paper the simulated EMI data of the whole route is based on partially correlated data of the first section, for further research the use of partially corrected data of each section is necessary to have a closer estimate of the whole EM characteristics.

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