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Optimization of RF-EMF exposure to public in Tanzania using Artificial Neural Network and multi linear regression models

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ABSTRACT

Technology development has triggered the demand for the use of radio frequency electromagnetic fields (RF-EMF). The growing demand for mobile communication, digital industrial evolutions and social services have forced service providers to expand the wireless network technology with additional installation of base stations. The increase in the use of RF-EMF for communication such as television (TV), radio, wireless services, internet and cellular communication have also increased the exposure levels of human to RF-EMF. However, exposure RF-EMF can have advance health effect to human and environmental radiation pollutions. RF - EMF exposure is higher in areas where people are highly concentrated such as hospitals, market places, schools, universities, colleges, shopping malls, than in any other region. Therefore, it is important to be concerned about the RF-EMF exposure to public in order to ensure that the exposure is under the allowable limits. In this study, power density values are measured at different locations in Dodoma, Dar es Salaam and Mwanza where the population density is too high, to examine their power density levels. An Artificial Neural Network (ANN) and Multi Linear Regression (MLR) models are developed to estimate the total power density values of different locations from RF-EMF exposure sources. The results show that both models are significant with coefficient of determination $R^2 = 0.999$ for MLR and $R^2 = 0.966$ for ANN model. The results of these models show how the study are of significance and valuable for monitoring and evaluating, hence the optimization of exposure dose from RF-EMF sources is adhered.

1. Introduction

Radiofrequency electromagnetic fields (RF-EMF) are a type of non-ionizing radiation (NIR) found on the electromagnetic spectrum, shown in Fig. 1, covering the range of frequencies below 300 GHz. RF-EMF are invisible waves and have been used for many years to transmit information between an antenna and a device without the use of wires. They can also be used in products that serve to heat things.

RF-EMF is a type of electromagnetic (EM) waves. EM waves are defined as a propagating couple of an electric and magnetic field components (Beckers et al., 2017). Many every day devices use RF-EMF to transmit information wirelessly. RF-EMF are generated by a large number of equipment used in medicine (e.g. magnetic resonance imaging), industry (e.g. heating and welding), domestic appliances (e.g. Wi-Fi, hairdryers, micro-oven), security and navigation (e.g. radar and RFID) and in telecommunications (e.g. radio transmitter, TV broadcasting, Base transceiver station (BTS)) (Balmori, 2022; Röösli et al., 2021). The 5G (5th Generation) mobile technology uses more frequencies within the RF-EMF range, and is likely increasing the number of transmitting sources (Di Ciaula, 2018).

The rapid advancements in science and technology have led to the invention and widespread use of numerous electronic devices, which in turn has significantly increased our exposure to electromagnetic waves in daily life. In modern society, the explosive use of various electronic devices has continuously heightened the chances of electromagnetic wave exposure. Furthermore, the development of wireless communication technologies, including computers and smartphones, has become indispensable for modern living.

Consequently, all living organisms on Earth are now experiencing environmental changes and levels of exposure to electromagnetic waves that are unprecedented in history (Kim et al., 2019). A six years predictions by Al-Falahy and Alani (2024) showed that global mobile data traffic (GMDT) will also increase as shown in Fig. 2 which implies the increase in the radiation level of electromagnetic waves as well as its

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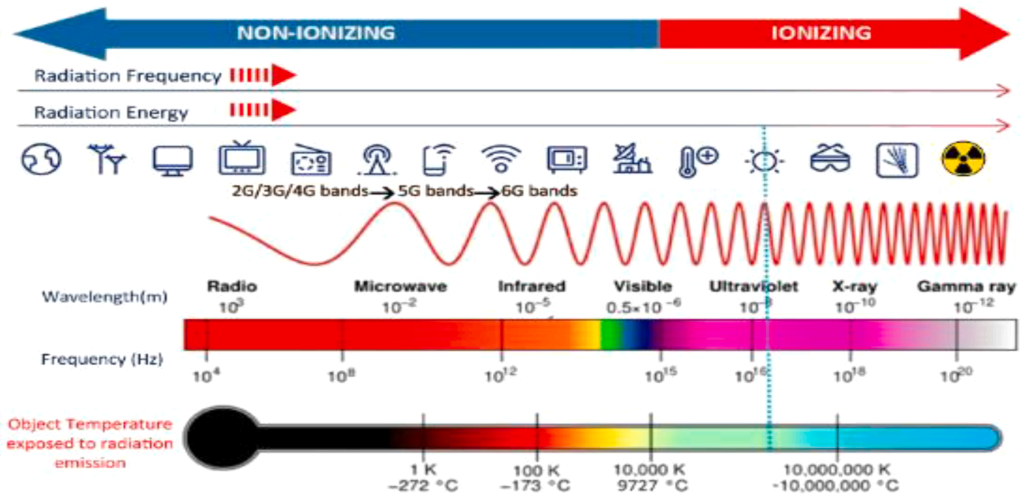

Fig. 1. Ionizing and non-ionizing radiation spectrum (Yong et al., 2015).

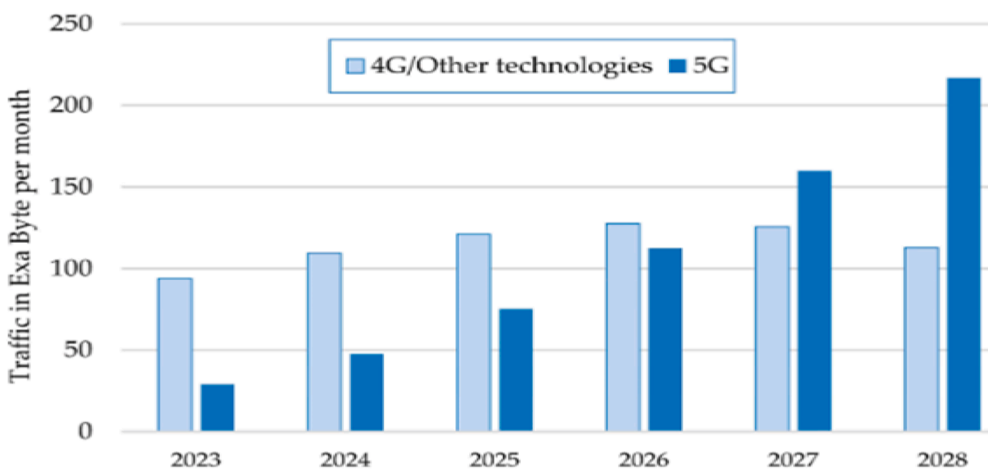

Fig. 2. GMDT growth forecast (Al-Falahy and Alani, 2024).

exposure. Tinker et al. (2022) grouped RF-EMR exposures to humans into three categories: *occupational exposures* - incurred by workers as a result of their working activities involving NIR sources, *medical exposures* - incurred by patients as part of their medical treatment and *public exposures* - cover all exposures of people other than occupational and medical exposures of patients. In public or general exposure, individuals of all ages and of differing health statuses with different education level and knowledge are exposed to RF-EMF (Nyakyi et al., 2024).

RF-EMF exposures to humans may have probable health effects (Levitt et al., 2022). Although, Kim et al. (2019) argued that the effect of RF-EMR on living creatures has been controversial due to studies with contradicting results, Kim et al. (2019) cited many studies with controversies regarding health effects due to RF-EMF exposure. Many studies focused on cancer (Morgan et al., 2015), genetic damage (Kim et al., 2008; Ruediger, 2009), neurological disease (Jiang et al., 2016; Kim et al., 2017), reproductive disorders (Altun et al., 2018; Falzone et al., 2011), immune dysfunction (Kazemi et al., 2015; Ohtani et al., 2015), kidney damage (Kuybulu et al., 2016; Türedi et al., 2017), as well as electromagnetic hypersensitivity (Gruber et al., 2018), and cognitive effects (Son et al., 2018). Blackman (2009), Uche and Naidenko (2021) showed that health risk assessment of non-ionizing radiation generated science and policy debates for decades, particularly around the health effects of RF-EMR used for wireless communications. Blackman and Uche & Naidenko cited some biological effects of electromagnetic fields reported by researches such as harm to fatal growth and development (Azimzadeh and Jelodar, 2020; Erkut et al., 2016; Falcioni et al., 2018; Azimzadeh and Jelodar, 2020; Erkut et al., 2016; Falcioni et al., 2018), changes in heart rate variability (Szmigielski et al., 1998; Wallace et al., 2020), changes in brain activity (Volkow et al., 2011; Wallace and Selmaoui, 2019), and elevated risk of several cancers (Luo et al., 2019; 2020; Sadetzki et al., 2008). Therefore, it is very essential to measure and assess the environmental level of RF-EMF as its exposure has detrimental effects on human health (Balmori, 2022; Gautam et al., 2022; Olorunsola et al., 2021).

As studies have shown that exposure to RF-EMF has health effects, it is therefore necessary that people or the population are protected from unnecessary exposure. According to the International Commission on Radiation Protection (ICRP), radiation protection involves the use of three techniques, and these are justification of practices, optimization of protection and the use of dose limits/levels (Osibote, 2020). The principle of *limitation* requires that the exposure to any individual from NIR sources other than medical exposure of patients should not exceed the appropriate recommended limits (International Commission on Non-Ionizing Radiation Protection, 2020). The principle of *justification* requires that any decision that alters the radiation exposure situation should do better than harm (Michael Moores, 2021). The principle of *optimization* requires that all exposures should be kept as low as reasonably achievable (ALARA), taking into account economic and societal factors, and with restrictions on individual exposure to limit imbalances in dose distribution (Hansson, 2013).

Table 1
ICNIRP safety limits for different frequency bands (Ahlbom, 2001).

Sources	Frequency Band (MHz)	Power Density (W/m^2)
FM Radio	87–108	2.08
VHF Band TV	174–230	2.08
GSM 900	930–960	4.46
GSM 1800	1805–1880	8.57
UMTS	2110–2170	9.63
W-LAN	2400–2483.5	9.08

To ensure humans are protected from radiation exposure, organizations, both international and country-wise, have been established that set regulations, standards, guidelines and limitations of exposure. International Commission on Non-Ionizing Radiation Protection (ICNIRP) is recognized by the World Health Organization in this respect (Foster et al., 2018). ICNIRP has set threshold values for power density, expressed in W/m^2, for radiation from different sources as indicated in Table 1, which countries can customize accordingly.

Thus, we can say that RF-EMF is very useful in our daily life as it provides or facilitates the delivery of different services which are very important in human life. It promotes economic growth of the counties. Unfortunately, exposure to RF-EMF radiation has health effects to humans. In this respect, EMF has both benefits and effects and therefore it is very important to optimize it to ensure it is used with less effects.

1.1. Statement of the problem

The growing demand for mobile communication has led the operators to expand the telecommunication infrastructure in different areas in countries like Tanzania. Base transceiver stations (BTS), radio transmitters and television transmitters, High Voltage Power Transmission Lines (HVPTL) as well as millimetre antennas are installed even within the vicinity of our premises (Nyakyi et al., 2013). People are also owning and using devices producing radiation like microwave oven, mobile phones, hair driers, CTR TVs etc (Nyakyi et al., 2024). This shows that humans are exposed to RF-EMF and can possibly be affected by radiation from those sources. Joseph et al. (2012) did an assessment of RF exposures from emerging Wireless Communication Technologies at 311 locations, 68 indoor and 243 outdoor, spread over 35 areas in Belgium, The Netherlands, and Sweden by performing narrowband spectrum analyser measurements. Exposure ratios for maximal electric field values, with respect to ICNIRP reference levels, range from 0.5 % (WiMAX) to 9.3 % (GSM900). Exposure ratios for total field values were seen to vary from 3.1 % for rural environments to 9.4 % for residential environments (Joseph et al., 2012). Kurnaz (2016) measured electric field strength (E) levels on Ondokuz Mayıs University's Kurupelit Campus and Faculty of Medicine Hospital in Samsun, Turkey between years 2013 and 2015 and the results showed that the measured E levels are far below the limits that are determined by ICNIRP. Then, Kurnaz (2016) proposed new models to estimate main distribution of total Frei et al. (2009) developed a multivariable regression model (MRM) to predict personal mean RF-EMF exposure when being at home by collecting personal RF-EMF exposure measurements of 166 volunteers from Basel, Switzerland. The predictors identified were propagation model, housing characteristics, ownership of communication devices (wireless LAN, mobile and cordless phones) and behavioural aspects such as amount of time spent in public transports (Frei et al., 2009).

As RF-EMF radiation is very beneficial, it is essential to optimize it to ensure it has less effects to human health. This means optimization of EMF protection will predict and assist on the technique for reducing the exposure doses as low as possible, while taking into consideration social and economic balances.

1.2. Objective of the study

The objective of this research was to study the optimization of RF-EMF radiation exposure to the public using Artificial Neural Network and multi linear regression model in order to predict the radiation dose in the environment. TV broadcasting stations, Radio transmitters, Base Transceivers Stations (common name is cellular towers), Universal Mobile Telecommunications Service (UMTS) and Wireless Local Area Network (W-LAN) are radiation sources covered by this research. The research is of great importance as it ensures the environment are safe when exposed to radiation i.e. the public can absorb minimum dose.

1.3. Optimization of radiation dose

The optimization of RF-EMF radiation dose can be viewed as a process of balancing risks against benefits. Optimization examines the procedural and operational practices while the public is exposed to RF-EMF radiation during their daily operations and plays an important role in reducing the dose to the environment (Seeram et al., 2013). Optimization may involve reducing or minimizing exposure factors such as Exposure Index (EI), Specific Absorption Rate (SAR), EMF strength, Power Density radiated, transmission time reduction, beamforming technique and data usage reduction by RF-EMF sources (Ajibare and Ramotsoela, 2021; Vermeeren et al., 2015).

Several works in the literature have investigated the optimization of

Fig. 3. Narda 3006 SRM with probe and wooden tripod stand.

RF-EMF using different factors. Ajibare and Ramotsoela (2021) investigated the effect of minimizing the exposure index and SAR induced in fifth generation wireless networks and its impact on the quality of service of the users in the network by proposing a power control algorithm that solves an optimization problem. Plets et al. (2014) presented a study on whole-body and localized SAR and dose prediction by considering absorbed doses, measured SAR values and time duration of the exposure. Plets et al. concluded that SAR is lowered when more base stations with lower transmit power are installed. (Stephan et al., 2014) minimized EMF exposure by considering quality of services (QoS) and network capacity, taking into consideration the impact of user distance from the access points (AP) and inter-site distances on the RF-EMF sources. Stephan et al. concluded that the transmitting power decreases when the RF-EMF source brings access points closer to the user. When dealing with wireless networks, user EMF exposure can be reduced by introducing efficient power control and handover management (Tesanovic et al., 2014). Another scholar, (Sambo et al., 2014), proposed a user scheduling/power allocation scheme to minimize the EMF exposure of users subject to transmitting a target number of bits.

Since the RF-EMF sources are of many benefits and the development of any country depends on it for economic growth, hence the installation of RF-EMF infrastructure should be given the attention to foreseen the hazards viz the profits. The current study considered the effects of power density in the general public (environments) by involving the following RF-EMF sources: FM transmitters, TV broadcasting, Cellular towers (GSM), UMTS and Wireless-LAN.

2. Materials and methods

2.1. Data collection

To measure the power density level, the study employed the Narda 3006 Selective Radiation Meter (SRM) equipment as shown in Fig. 3. This equipment is connected with isotropic antenna, which is capable of receiving signals from all directions. The isotropic antenna has a range of 27 MHz to 3 GHz for FM transmitters, TV broadcasting, Cellular towers (GSM), UMTS and Wireless-LAN. The SRM equipment and the antenna were connected by a 1.5 m long coaxial cable, with the antenna fixed at the height of 1.5 m above the ground using a tripod stand. The tripod stand is of a wooden material to help avoid the tripod from being a conductor and hence prevent duplication of signals received. The measurements were divided into several frequency bands based on services/sources shown in Table 1. The measured data were transferred to the computer via SRM software tool. While taking measurements, the study observed both the national and international standards. The SRM equipment incorporates the ICNIRP Safety Restriction Standards. During measurement, the specifications from SRM equipment were selected and used for the given study. Resolution bandwidth (RBW) settings used were 200 kHz for FM, GSM, UMTS and W-LAN. Readings of power densities, both actual and maximum values, were captured after every 6 min in different locations.

2.2. Site selection

The sites for measurements were chosen by considering areas with high population and possibility of high level of RF-EMF radiations such as shopping malls, crowded residential areas, colleges, bus terminals, market places and hospitals. Measurement results presented in this study were taken from three regions in Tanzania, i.e., Dodoma, Mwanza and Dar es Salaam. The regions of study were chosen based on the physical and geographical characteristics as well as natural and vegetation cover. In Dodoma, most of the places are flat area and semi-arid, the urban is not congested with houses. Mwanza region is dominated with rocks, hills and in some places, houses are close to each other while Dar es Salaam is full of houses and having high humidity. Measurements of power density levels were taken at 150 different sites in the three regions.

2.3. EMF exposure model development

In this study, two mathematical models were developed: the multiple linear regression (MLR) and Artificial Neural Network (ANN) model and their outputs were compared. The linear model has been created based on multiple linear regression analysis, while the non-linear model has been built using Artificial Neural Networks (ANN).

2.4. Multi linear regression model

A multi linear regression (MLR) model is developed and optimised using the least square method in order to predict the total power density from the RF-EMF sources. MLR is one of the well-known techniques which can help to establish a relationship between the predictors and the target value. The total power density (TotalPD) is the dependent variable, while the individual power densities from RF-EMF radiation sources: TV band transmitter named as TVBand, FM Radio transmitter named FMRadio, BandIV (DVB-T) named as Band4V, Band V (DAB) named as Band5A, GSM, L-Band (DAB) named as LBandA, UMTS-TDD named as UT, UMTS DL named as UD, and W-LAN named as WLAN are the independent variables. Based on the sources of exposure, the multi linear model is of the form:

$$\mathrm{TotalPD} = \beta_0 + \left(\sum_{i,j=1}^{9} \beta_i \mathrm{PD_j} \right) \tag{1}$$

Where;

$\mathrm{PD}_1 = \mathrm{TVBand},\ \mathrm{PD}_2 = \mathrm{FMRadio},\ \mathrm{PD}_3 = \mathrm{Band4V},\ \mathrm{PD}_4 = \mathrm{Band5A},\ \mathrm{PD}_5 = \mathrm{GSM}, \mathrm{PD}_6 = \mathrm{LBandA},\ \mathrm{PD}_7 = \mathrm{UT},\ \mathrm{PD}_8 = \mathrm{UD},\ \mathrm{PD}_9 = \mathrm{WLAN},\ \beta_0$ is a constant value, $\beta_1, \ \ldots, \ \beta_9$ are coefficients of independent variable.

Then,

$$\begin{aligned}\sum_{i,j=1}^{9} \beta_i \mathrm{PD_j} = {} & \beta_1 \text{ x TVBand } + \beta_2 \text{ x FMRadio } + \beta_3 \text{ x Band4V} \\ & + \beta_4 \text{ x Band5A} + \beta_5 \text{ x GSM } + \beta_6 \text{ x LBandA} + \beta_7 \text{ x UT} \\ & + \beta_8 \text{ x UD} + \beta_9 \text{ x WLAN}\end{aligned} \tag{2}$$

Substituting Eq. (2) into (1) to obtain

$$\begin{aligned}\mathrm{TotalPD} = {} & \beta_0 + \beta_1 \text{ x TVBand } + \beta_2 \text{ x FMRadio } + \beta_3 \text{ x Band4V} \\ & + \beta_4 \text{ x Band5A} + \beta_5 \text{ x GSM } + \beta_6 \text{ x LBandA} + \beta_7 \text{ x UT} \\ & + \beta_8 \text{ x UD} + \beta_9 \text{ x WLAN}\end{aligned} \tag{3}$$

The MLR model then provides the predicted value of total power density as in Eq. (3).

2.5. Artificial Neural Network model

Artificial Neural Networks (ANN) are information processing systems that are based on performance characteristics of biological neural networks. ANN are developed as generalizations of mathematical models of neurons in human brain. Several ANN models have been developed for various purposes and used in different fields. The multilayer feed-forward ANN is the most commonly used, and it is used in our study. The multilayer perceptron (MLP) is an Artificial Neural Network type which uses at least one layer between the input and output layer. MLP can solve non-linear problems, and so they are the most popular type of ANN widely used.

RF-EMF Artificial Neural Network model with nine input layers, several hidden layers, and one output layer is developed in this study. The number of nodes of the input layers correspond to the number of variables describing the attributes being tested, while the number of

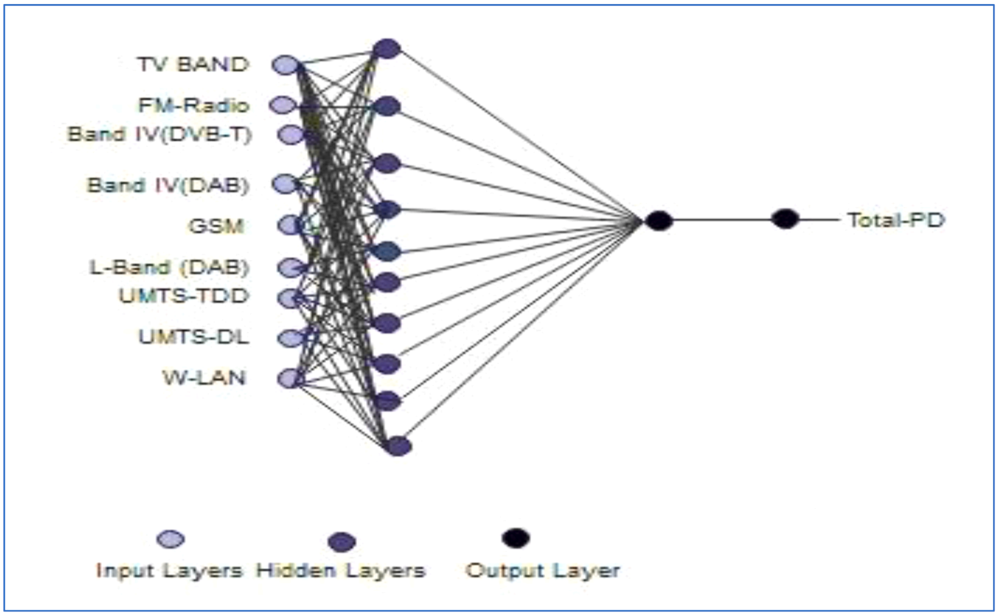

Fig. 4. The layers of Artificial Neural Network model.

neurons in the output layer equals the number of classes. In particular, our model has nine (9) inputs in the input layer which are RF-EMF sources.

The number of hidden layers and the number of neurons depend on the difficulty of the task and the amount of training data. Each neuron in the hidden layer is connected to output layer by an associated numerical weight which controls the amount of the signal that passes between them. In our model, the estimation takes place in the hidden layer and the total power density is estimated in the output layer as shown in Fig. 4. The model is verified on the basis of the determination coefficient (R^2).

Fig. 4, illustrates a multi-layer neural network used for predictive modelling based on input data from various frequency bands, highlighting its structure and the flow of information through the network. It comprises input layers, output layers, hidden layers and the connections. Input layers are represented by nodes corresponding to different frequency bands which are TV BAND, FM-Radio, Band IV(DVB-T), Band V (DAB), GSM, L-Band (DAB), UMTS-TDD, UMTS-DL and W-LAN.

An ANN Model equation is given by

$$\mathrm{Total}-\mathrm{PD}=\mathrm{f}\left(\sum_{\mathrm{i}=1}^{9}\beta_{\mathrm{i}}\ \mathrm{PD}_{\mathrm{i}}+\mathrm{K}\right) \tag{4}$$

where Total − PD, f, K, βi and PDi are the output of the neuron, activation function, bias term, weight and input value, respectively. Fig. 4 shows the hidden layers in middle section contain several interconnected nodes, they perform computations on the input data to extract patterns and features relevant for predicting the output. Also, they have number of nodes (circles) connected by lines indicating the flow of information and weights between the nodes. The output layer is a single node labeled “Total-PD”. This node aggregates the information processed by the hidden layers to produce the final prediction. The connection lines of the nodes represent the weights and biases in the neural network which are adjusted during the training process to minimize prediction errors.

3. Results and discussion

3.1. MLR model results and discussion

The MLR model was optimized using least square optimization method and the results of the model are shown in Tables 2 and 3.

Table 2
MLR model summary.

Dep. Var	Total PD	**R-squared**	0.999
Model	OLS	**Adj. R-squared**	0.999
Method	Least Squares	**No. Samples**	150

Table 3
Statistics results for MLR model.

Predictors	**coef**	**std err**	***t***	***p*>|t|**
Const	178.9026	147.774	1.211	0.228
TV BAND	1.0168	0.028	36.833	0.000
FM-Radio	0.9979	0.008	130.507	0.000
Band IV (DVB-T)	1.0103	0.057	17.687	0.000
Band V (DAB)	1.0633	0.316	3.362	0.001
GSM	1.0149	0.077	13.223	0.000
L-Band (DAB)	0.6082	0.412	1.475	0.143
UMTS-TDD	0.9762	0.149	6.573	0.000
UMTS-DL	1.0456	0.101	10.346	0.000
W-LAN	0.9916	0.061	16.179	0.000

Consider Table 3, the model identified several significant predictors, including TV Band, FM Radio, BandIV (DVB-T), BandV (DAB), GSM, UMTS-TDD, UMTS-DL, and W-LAN, all of which have *p*-values below 0.05, indicating their statistical significance. Conversely, L-Band A, with a *p*-value above 0.05, is not statistically significant in this model. Most predictors have coefficient values close to 1, suggesting they exert a similar magnitude of effect on the dependent variable. The standard errors are generally low, indicating precise estimates, except for L-Band A and Band5A, which have higher standard errors. High *t*-values for significant predictors reflect strong relationships with the dependent variable. These results imply that most predictors are important, except for L-Band A, which could be excluded in future model refinements due to its insignificance. Overall, the model seems to fit well, demonstrated by the high *t*-values and low *p*-values for most predictors.

Hence Eq. (3) can be re-written as:

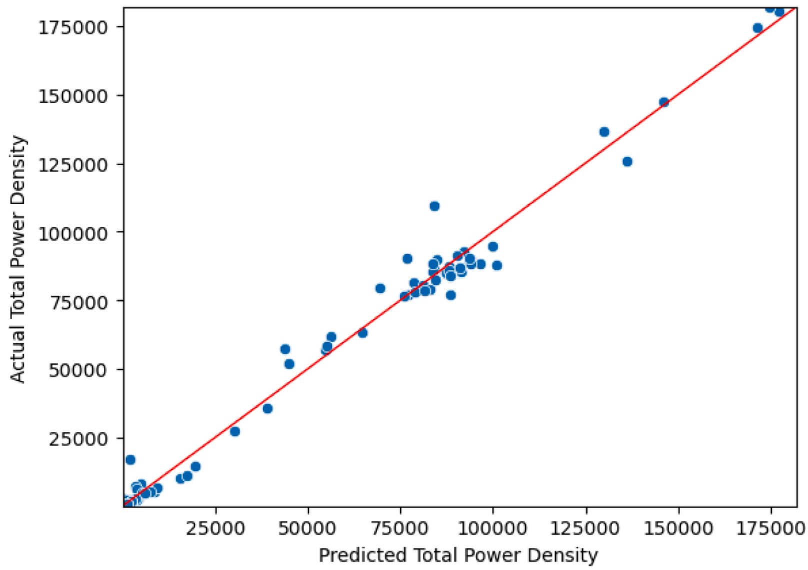

Fig. 5. Actual viz predicted total power density for MLR model.

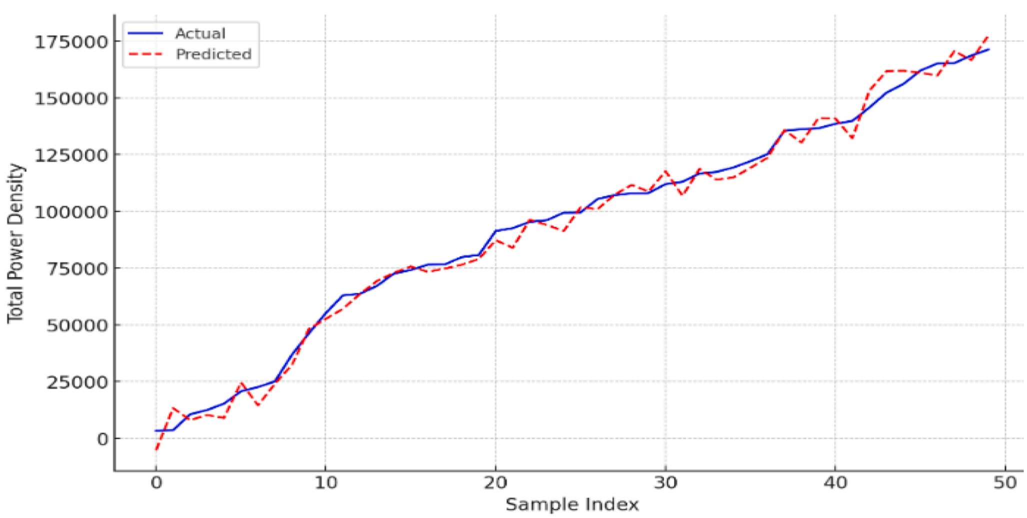

Fig. 6. Total power density level viz sample index.

$$\begin{aligned} \text{TotalPD} = {} & 178.9026 + 1.0168 \text{ x TVBand} + 0.9979 \text{ x FMRadio} \\ & + 1.0103 \text{ x Band4V} + 1.0633 \text{ x Band5A} + 1.0149 \text{ x GSM} \\ & + 0.6082 \text{ x LBandA} + 0.9762 \text{ x UT} + 1.0456 \text{ x UD} \\ & + 0.9916 \text{ x WLAN} \end{aligned} \tag{5}$$

In Eq. (5) the value of coefficients for independent variables sources are presented in Table 3.

In Fig. 5, scatter plot displays the relationship between the actual total power density and the predicted total power density from the MLR model. The blue dots represent individual data points with actual total power density on the y-axis and predicted total power density on the x-axis, where the line of perfect fit is represented by solid red line, the actual values equal to the predicted values $(Y = X)$

In analyzing the results, Fig. 6 shows both lines follow a similar upward trend, indicating that the model's predictions generally track the actual values. Where the blue line represents the actual total power density value and red dashed line represents the predicted total power density values. For the most part, the predicted values closely follow the actual values, demonstrating the model's accuracy. The predictions are fairly consistent with the actual values across the entire range of the data. The model seems to perform well both at lower and higher values of total power density.

In case of correlation, the close alignment between the two lines suggests a high correlation between the actual and predicted values, this shows that the model is effective. Across different levels of total power density, the model shows robustness as it is maintaining accuracy without significant bias toward any particular range. It may provide room for fine-turning the model to improve its predictions further since there are slight divergences at certain points. This plot is an effective way to visualize the performance of the model, demonstrating its strengths and highlighting areas for potential enhancement.

3.2. ANN model results and discussion

To develop ANN model, the datasets were divided into two subsets: the training set (a set of samples used to adjust the network weights), and the test set (a set of samples used only to assess the performance of the neural network). The ANN model was trained using selected

Table 4
ANN model results.

Model: "sequential_72"		
Layer (type)	Output Shape	Param #
Hidden (Dense)	(None, 10)	100
Output (Dense)	(None, 1)	11

Total params: 335 (1.31 KB)
Trainable params: 111 (444.00 B)
Non-trainable params: 0 (0.00 B)
Optimizer params: 224 (900.00 B)

parameters from the data set and was subsequently validated using an independent data set. The input layer is made up of 9 neurons which is the number of the independent variables, and for this particular case is the RF-EMF radiation sources. We have added a hidden layer with 10 neurons just for modeling purposes. Since there is one dependent variable, then 1 neuron is the output layer as in Fig. 4.

The ANN model result summary is shown in Table 4. The sum of squares function was used during the network training process.

To determine the accuracy of the ANN model in calculating and predicting the total power density (Total-PD), the coefficient of determination $R^2$and the mean squared error (MSE) were determined. The R^2 of the ANN model was 0.966 implying that the model is able to predict 96.6% of the dependent variable, and the MSE was 130.245. The more accurate the model, the larger the R^2 and the smaller the MSE value. The model was repeated several times to ensure that we obtain the best representation, the graph of best parameter verses accuracy is shown in Fig. 7.

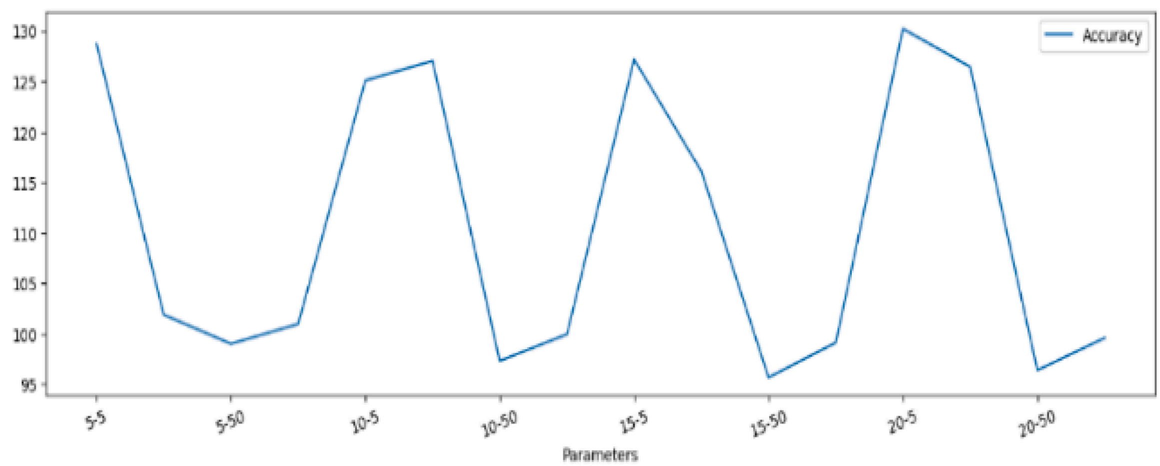

Fig. 7. Best parameters vs. accuracy.

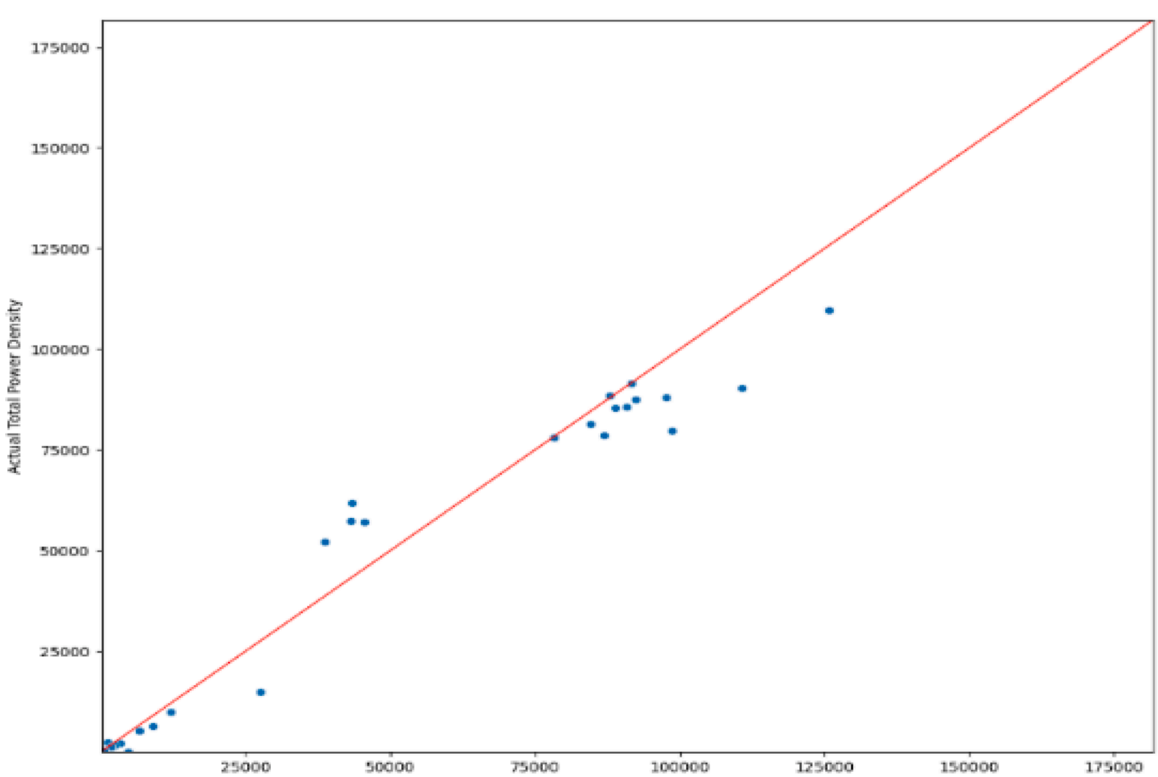

Fig. 8. Predicted total PD viz actual total PD for ANN model.

Fig. 7 is a plot which proposes that, tuning the parameters can lead to significant changes in accuracy, and there seems to be a predictable pattern to these changes. Identifying the exact nature of these parameters and their impact on the ANN model performance could help optimize for higher accuracy.

In conclusion, the graph of the actual and predicted total power density obtained through the ANN model for training datasets is presented in Fig. 8. The scatter plot displays a positive correlation between predicted and actual total power density, suggesting that the model generally predicts the power density reasonably well. The analysis indicates that the ANN model has a good overall performance with some room for improvement. Although most predictions are close to the actual values, addressing the discrepancies and outliers can help enhance the model's reliability and accuracy.

4. Conclusion and recommendations

In this study we employ machine learning process to optimize public exposure to RF-EMF radiations using least-square optimization method in MLR model and ANN model for the multilayer perceptions. The nine (9) sources of RF-EMF radiations were used as inputs to predict the total power density which was then compared with the measured total power density. The accuracy of the prediction in both models was evaluated and measured by the coefficient of determination (R^2 *value*). For the MLR model, the $R^2 = 0.999$ showing that 99.9% of the total power density could be predicted by the inputs used. The $R^2$of the ANN model was 0.966 implying that the model is able to predict 96.6% of the dependent variable. Therefore, both MLR model and ANN model can calculate and predict the total power density with high accuracy. The result of the MLR and ANN model have an acceptable prediction performance.

Measurements in all points indicate that the maximum exposure is below the national and international standards. Even if the measurement results show that the RF-EMF levels are below the permitted limits, it is important to regularly measure the radiation levels from RF-EMF sources to avoid the possible harmful effects of RF-EMF radiation on human in the long-term exposure. Effective measurement strategies should be developed to reduce the health risks of the RF-EMF radiations.

CRediT authorship contribution statement

Christina P. Nyakyi: Writing – original draft, Visualization, Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Saul C. Mpeshe:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Conceptualization. **Mussa A. Dida:** Writing – review & editing, Supervision, Resources, Project administration, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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