

**MACHINE LEARNING-BASED PATH LOSS MODELS FOR HETEROGENEOUS
RADIO NETWORK PLANNING IN A SMART CAMPUS**

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Matriculation Number: 16PCK01420

B.Tech. Electronic and Electrical Engineering (LAUTECH, Ogbomosho, Nigeria)

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**A DISSERTATION SUBMITTED TO THE DEPARTMENT OF ELECTRICAL AND
INFORMATION ENGINEERING, COLLEGE OF ENGINEERING IN PARTIAL
FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF
ENGINEERING (M.ENG) DEGREE IN INFORMATION AND COMMUNICATION
ENGINEERING**

July, 2018

ACCEPTANCE

This is to attest that this dissertation is accepted in partial fulfilment of the requirements for the award of **Master of Engineering (M.Eng)** degree in the Department of **Electrical and Information Engineering**, College of Engineering, Covenant University, Ota, Ogun State, Nigeria.

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DECLARATION

I, **POPOOLA, SEGUN ISAIAH** (16PCK01420), declare that this M.Eng dissertation titled “Machine Learning-Based Path Loss Models for Heterogeneous Radio Network Planning in a Smart Campus” was carried out by me under the supervision of Prof. AAA. Atayero of the Department of **Electrical and Information Engineering**, Covenant University Ota, Ogun State, Nigeria. I attest that this dissertation has not been presented either wholly or in part for the award of any degree elsewhere. All sources of scholarly information used in this dissertation are duly acknowledged.

POPOOLA, SEGUN ISAIAH

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Signature & Date

CERTIFICATION

We certify that the dissertation titled “Machine Learning-Based Path Loss Models for Heterogeneous Radio Network Planning in a Smart Campus” is an original work carried out by **POPOOLA, SEGUN ISAIAH** with Matriculation Number **16PCK01420**, in the Department of **Electrical and Information Engineering**, College of Engineering, Covenant University, Ota, Ogun State, Nigeria, under the supervision of Prof. AAA. Atayero. We have examined the work and found it acceptable for the award of **Master of Engineering (M.Eng)** degree in **Information and Communication Engineering**.

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DEDICATION

This work is dedicated to divine Trinity: the Father, the Son, and the Holy Spirit.

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LIST OF ABBREVIATIONS

3D	Three-dimensional
5G	Fifth Generation
AM	Amplitude Modulation
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
BFG	BFGS Quasi Newton
BTS	Base Transceiver Station
CDMA	Code Division Multiple Access
CGB	Conjugate Gradient with Powell/Beale Restarts
CGF	Fletcher-Powell Conjugate Gradient
CGP	Polak-Ribiere Conjugate Gradient
COST	COopération européenne dans le domaine de la recherche Scientifique et Technique
CW	Continuous Wave
DE	Differential Evolution
DCS	Digital Cellular System
DSR	Design Science Research
DTM	Digital Terrain Map
ELM	Extreme Learning Machine
GA	Genetic Algorithm

GDX	Variable Learning Rate Backpropagation
GHz	Giga Hertz
GIS	Geographic Information System
GPS	Global Positioning System
GSM	Global System for Mobile communications
HEI	Higher Education Institution
HF	High Frequency
ICT	Information and Communication Technology
IEEE	Institute of Electrical and Electronic Engineering
IoT	Internet of Things
IMT	International Mobile Telecommunications
ITU	International Telecommunication Union
ITU-R	International Telecommunication Union-Radio
LF	Low Frequency
LM	Levenberg-Marquardt
<i>logsig</i>	Logarithmic sigmoid function
LOS	Line of Sight
LRNN	Layer Recurrent Neural Network
LTE	Long Term Evolution
M2M	Machine-to-Machine
MAE	Mean Absolute Error

MATLAB	MATrix LABoratory
MHz	Mega Hertz
MLP-NN	Multi-Layer Perceptron Neural Network
MMDS	Multipoint Microwave Distribution System
MSE	Mean Square Error
N/A	Not Applicable
NLOS	Non-Line of Sight
OSS	One Step Secant
PC	Personal Computer
PCS	Personal Communication System
<i>purelin</i>	Linear activation function
QoS	Quality of Service
R	Correlation coefficient
RAM	Random Access Memory
RAN	Radio Access Network
RBF	Radial Basis Function
RMSE	Root Mean Square Error
RP	Resilient Backpropagation
RSS	Received Signal Strength
SCG	Scaled Conjugate Gradient
SED	Standard Error Deviation

SHF	Supper High Frequency
SPM	Standard Propagation Model
SUI	Stanford University Interim
SVM	Support Vector Machine
<i>tansig</i>	Hyperbolic tangent function
TETRA	TErrestrial Trunked Radio
TV	Television
UHF	Ultra-High Frequency
UMTS	Universal Mobile Telecommunications System
USB	Universal Serial Board
VHF	Very High Frequency
VLF	Very Low Frequency
WEKA	Waikato Environment for Knowledge Analysis
WiMax	Worldwide Interoperability for Microwave Access
Wi-Fi	Wireless Fidelity

ABSTRACT

An easy-to-use and accurate multi-frequency path loss model is a necessary tool for heterogeneous radio network planning and optimization towards achieving a smart campus. The learning ability in artificial intelligence may be exploited to reduce computational complexity and to improve prediction accuracy. In this research project, an optimal heterogeneous model was developed for path loss predictions in a typical university campus propagation environment using machine learning approach. Radio signal measurements were conducted within the campus of Covenant University, Ota, Nigeria to obtain the logs of signal path loss at 900, 1800, and 2100 MHz. Different path loss prediction models were developed based on Artificial Neural Network (ANN) and Support Vector Machine (SVM) learning algorithms. The prediction accuracy and generalization ability of the ANN-based model, which has seven input nodes (distance, frequency, clutter height, elevation, altitude, latitude, and longitude), single hidden layer with 43 neurons and logarithmic sigmoid (*logsig*) activation function, and a single output neuron (for path loss variable) with tangent hyperbolic sigmoid (*tansig*) activation function, was found to be the best when compared to the prediction outputs of SVM-based model, and popular empirical models (i.e. Okumura-Hata, COST 231, ECC-33, and Egli). The ANN-based path loss model was trained based on Levenberg-Marquardt learning (LM) learning algorithm. The prediction outputs of the ANN-based path loss model has the lowest Root Mean Square Error (RMSE) of 4.480 dB, Standard Error Deviation (SED) of 4.479 dB, and the highest value of correlation coefficient (R) of 0.917, relative to the measured path loss values. This finding was further validated by the results of Analysis of Variance (ANOVA) and multiple comparison post-hoc tests. In essence, ANN-based path loss model was found to be the optimal model for heterogeneous radio network planning, deployment, and optimization in a smart campus propagation environment.

Keywords: Path Loss Model; Heterogeneous Radio Network; Artificial Neural Network (ANN); Support Vector Machine (SVM); Radio Network Planning and Optimization (RNP/O); Smart Campus