

# Artificial Neural Network (ANN) Method for the Integration of Solar and Wind Hybrid Energy Sources into Telecommunication Systems

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**Abstract:** *In order to sustain monetary growth, the introduction of renewable energy into the electricity grid is crucial especially for many foreign African locations. Thus, in order to reap sustainable strength, these foreign locations may also outfit their airport electrical equipment with advanced synthetic intelligence technologies. For a distributive hybrid solar strength grid, the paper attempts to propose an actual-time energy management algorithm. It continues with the combining of photovoltaic and wind energy for network simulation. As a function of the number of wind aero-mills and photovoltaic solar panels, a multi-goal approach is proposed to optimize the spectral efficiency of the location and the energy performance. For the MATLAB software simulation, radio criteria for Cell Wireless Interoperability Medium Access (WiMAX) technologies are taken into account. The obtained effects are much mitigated however theoretically encouraging for the mixing of green energy integration into the modern telecommunication structures.*

**Keywords:** Artificial neural network (ANN), Green energy, multi-objective problem, Power generation optimization, Theoretical formulation, Solar & Wind radiation prediction.

## I. INTRODUCTION

The mobile cellular systems operate in a limited spectrum and time slot [1], [2] with a pace of an increasing growth of customers, translating a high power consumption but also are source of CO<sub>2</sub> emission. In [3], it has been pointed out that the Information Communication and Technology (ICT) industries consumed about 3% of the global energy and causing around 2% of the CO<sub>2</sub> emissions globally. In this regard, the ICT industries are facing an increase in associated energy consumption of 16 - 20% per year. The power consumption distribution has shown that the power consumption for the core network (RAN) is approximately around 30%, the baseband processing unit about 10-15% and the cooling system about 15%. The number of base stations in 2015 was approximated to 6 million all over the world, which is expected to double in 2020 [4]. It is imperative that the reduction in energy consumption of the current wireless system is therefore necessary for the future ones [4], not only but also the global warming is a real challenge. In [5], it was underlined a low electrification rate in the regions of Central Africa, estimated in the order of 13%, moreover, the reference [6] indicated that the Sub-Saharan Africa has an electrification rate of 7% in its rural areas.

The industrialized countries, like Finland, France and Germany, had established a road map for electricity with universal access for all at a 100% penetration rate at the horizon 2030 with the integration of renewable energy in the domestic consumption [7]. Many forums have focused on the hybrid electric generation from renewable energies in order to raise the level of electricity for the universal access. Particularly, the International Energy Agency (IEA)[8], estimated that the solar energy rate would represent about 11% of the total energy generated by the year-2050. Furthermore, the global energy vision 2100, led by the German Advisory Council on Global Change, indicated that solar energy generation will contribute nearly 20% in 2050, and 60% in the 2100 with respect to the produced world energy [9].

Subsequently, on the basis that all the mobile operators must use the green energy to supply the telecommunications on the continent, undeniably it will remarkably be a great amount of green injected daily into many African nation electric grid. When referring to the statistics provided in 2015 by the Togolese Authority of Regulation of Telecommunication and Post services (ARTP), these reports indicated a number of 858 GSM sites and 1080 BTS for 3Generation. Assuming, a 1000 GSM sites with an average power consumption of 4 kW per site that will approximate a demand of 40 00kW or 4 MW. In 2015, at Kumasi airport, the entire electrical system failed to respond, including all the tarmac (runway) lighting system, when a commercial plane was about to land. The diesel generator also failed to start. The blackout lasted about 5 to 6mn. Such a problem may result in voltage drop and the power quality, thus power stability management. The paper seeks to suggest an real-time energy control tool for a distributive hybrid renewable power grid while thinking about a telecommunication tool positioned in a few important regions together with an airport. The contribution of this paper is residing inside the proposition of strength control on a distributive hybrid grid using an artificial neural community (ANN). The relaxation of the paper is hooked up as follows, section 2 formulates the mathematical derivation of the power overall performance as a feature of the massive form of wind aerogenerators and the photovoltaic panels. Section three explains the synoptic block diagram of the implanted manipulate tool primarily based mostly on the artificial neural network and the simulation parameters. The subsequent phase makes a robust element of the presentation of the consequences and the evaluation. The remaining section (5) closes the paper with a succinct end.

## II. THE MODEL

The system consists of one macro-cell, pico-cells, three relays, and fem to-cells.

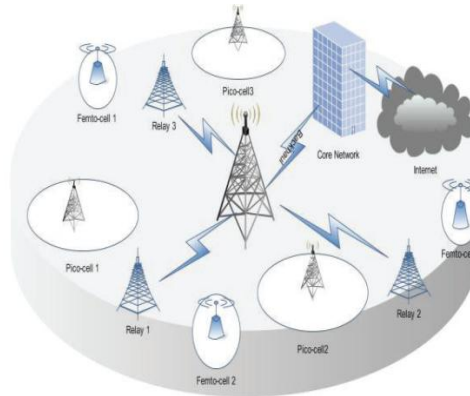


Fig. 1: the descriptive system of the study

The transmitters  $K$  are empowered by a micro-grid and the renewable energy sources are used to reduce the emission of the dioxide of carbon. It is assumed that each transmitter serves  $N$  users.

The power consumption of an active node,  $P_K$  for the downlink service can be expressed as:

$$P_{i,k} = P_{Ti,k} + P_o - P_g \quad (1)$$

$P_{Ti,k}$  is the downlink transmission dependent,  $P_o$  is the uplink transmission dependent that includes the data processing, the non-transmission, cooling, lighting, etc... and,  $P_g$ , the green injected power, into the system, that aims at reducing the dioxide of carbon emission. The transmitted power for the downlink service,  $P_{Ti,k}$  to a user attached to the cell  $k$ , is formulated as:

$$P_{Ti,k} = P_{i,k} - P_o - P_g \quad (2)$$

$P_{gr}$  the injected green power in the system to the total required power of the system,  $P_{TO}$ , comes as:

$$P_{TO} + S_o(k_o \cdot C_{cst}) + (1 - s_o)[(1 - k_o)(m \cdot P_{PV} + n \cdot G_V)] \quad (3)$$

The total injected green power  $P_{gr}$  is calculated as:  $P_{gr} = m \cdot P_{pv} + N \cdot P_w$  (4)

With, the number of solar panels; and  $n$ , the number of wind generators

For the photovoltaic power,  $P_{PV}$ , is computed as;

$$P_{PV} = \eta_{ref} \times A \times G_{ref} \quad (5)$$

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The energy produced by the solar panel is given as

$$E_{PV} = P_{PV} * I_T * k \quad (6)$$

where the indice of the clarity  $k = [0.3: 0.85]$ ,  $P_{PV}$ , Power peak of the panel in kWc,  $I_T$ , total irradiation on the panel surface kWh/m<sup>2</sup>/day.

For the wind power,  $P_W$ , is specified as:

$$P_W = \frac{1}{2} C_p \cdot \rho \cdot A \cdot V^3 \quad (7)$$

Where

$C_p$  : 22/7,  $\rho$  density  $A$ , is the cross-sectional area,  $V$ , the wind speed;

$$\eta_{SEk}(i) = \log_2(1 + \gamma_{i,kpt}) \quad (8)$$

The total spectral efficiency  $\eta_{Ai,k}$ , is expressed as:

$$\eta_{Ai,k,DI} = \sum_{k=1}^K \sum_{i=1}^N \eta_{SE_{i,k}}(i) \quad (9)$$

A scheduling monotonic rate is assumed:

$$\eta_{Ai,k,DI} = \frac{\sum_{k=1}^K \sum_{i=1}^N \eta_{SE_{i,k}}(i)}{T_{max}} \quad (10)$$

Where the  $T_{max}$  is the total transmission time to serve all users.

The green telecommunications' metric,  $\rho_{green}$ , is defined as:

$$\rho_g = \frac{\sum_i \eta_{Ai,k}}{\sum_i F_{i,k} P_{i,k}} \quad (11)$$

$F_{i,k}$  is the associated rate of dioxide of carbon emission of the energy source.

The total cost of the energy is given as:

$$TC = \sum_t^N C_{Ct} * C_{at} + f_{oct} * C_{at} + V_{ct} * P_t + C_e * T_{GHG} \quad (12)$$

$C_c$  : the investment capital of the technology

$C_a$  : the size of the installed power

$V_c$  : the cost of maintenance and operational parameters involved,

$F_{oc}$  : the fixed cost ;

$C_e$  : the external cost due to the CO<sub>2</sub> emission,

$T_{GHG}$  : the total rate of the CO<sub>2</sub> emission associated to the power generation

In multi-transmitter system, the total transmitted power is given as:

$$\sum_{k=1}^K \sum_{i=1}^M P_{Ti,k} = P_{TO} - P_g - \sum_1^K P_{o,k} \quad (13)$$

$P_{o,k}$  the power of other low consumption nodes which is neglected for the simplification purpose, and  $P_{TO} = \sum P_{i,k}$

The energy efficiency of the system is calculated by

$$\gamma_{SSDI} = \frac{\rho_g \cdot \sum_i F_{i,k} P_{i,k}}{S_o(k_o \cdot C_{cst})(1 - S_o)([(1 - k_o)(m \cdot P_{PV} + n \cdot G_W)] - N_s)} \quad (14)$$

$F_{i,k}$  is the factor of emission of the power technology used,

$P_{i,k}$ , the power consumption at a node.

$m$ : the number of solar panels

$n$ : the number of wind generators

$N_B$ : the number of battery

The optimization problem consists to maximize the spectral efficiency (SE),  $\eta_{Ai,k}$  and the energy efficiency (EE),  $\gamma_{EE,DI}$

, for the cell,  $k$ , which is given as:

$$Max(\eta_{EE,DI}, \eta_{Ai,k}) \quad (15)$$

Subject to

$$\sum_{i=1}^N P_{i,k} \leq P_{TO}^{max} \quad (16)$$

$$1 \leq m \leq max \quad (17)$$

$$1 \leq n \leq max \quad (18)$$

$$1 \leq N_B \leq max \quad (19)$$

The number of solar panel (m) and aero-generators (n) needed could be obtained by the minimization of the Root Mean Square error function as

$$\epsilon(c, m, n) = \left(\frac{1}{l}\right) \sum_{i=1}^l [\gamma_i - P_{TO-i}]^2 \quad (20)$$

Where  $\gamma_i$  is the measured value,  $l$  is the volume of the measurement sample set, and  $P_{TO-i}$  the theoretical power generated. Which implies that, all the partial derivatives of the  $err(c, m, n)$  function must equal to zero.

$$\Rightarrow \begin{cases} \frac{\partial err}{\partial c} = 0 \\ \frac{\partial err}{\partial m} = 0 \\ \frac{\partial err}{\partial n} = 0 \end{cases} \quad (21)$$

This can be written in square matrix as:

$$W \times \bar{y} := \begin{bmatrix} C_1 & 1 \\ C_2 & 1 \\ \vdots & \vdots \\ C_m & 1 \end{bmatrix} \times \begin{bmatrix} m \\ n \end{bmatrix} \quad (22)$$

The optimal correction coefficients C, m and n fulfilling the least square conditions are obtained from the least-squares solutions that are given as:

$$\bar{C}_{LS} = [W^T W]^{-1} W^T Y \quad (23)$$

### III. METHODOLOGY

#### A. Radio Parameters and Block Diagram

The radio system parameters for the simulation are given in Table 1. The system modeling has consisted in implementing the cascaded artificial neural networks as shown in Fig. 2. The use of the artificial neural network aims at predicting in prior the global solar irradiation, same as for the wind speed. The Data collection has consisted in gathering the recorded daily irradiation, and wind speed from the NASA database. Some of these data were used for the training stage. The first artificial neural network captures the global solar irradiation for the optimization of the photovoltaic energy. The second artificial neural network predicts the wind speed for the optimal wind energy production. The third artificial neural network select the best among the available energy sources including the energy storage device on the distributive bus of the micro-grid. The system parameters for the simulation are given in the table 1. The path loss for a link between a macrocell and the user equipment and the user transmission power is modeled with a random noise. The required number of solar panels and the number of aero-generators (Wind turbines) for the considered mobile WiMAX system could be obtained by a regression algorithm in addition the total power budget of the facility has to be considered. This is not presented in this current work. With the knowledge of the average wind speed at Lome-site, which is around 4m / s. This implies that the selection of a small wind turbine will be appropriate.

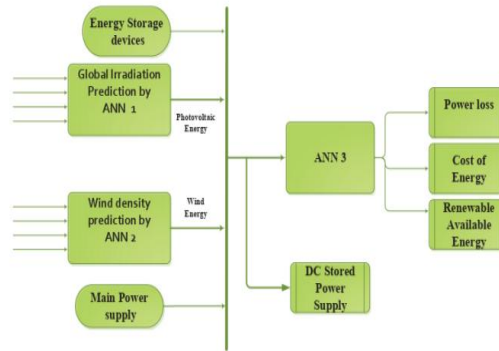


Fig. 2: The cascaded ANN system

Description	Symbol	Mobile WiMAX
Number of Users	N	150 1500
constant related to the cell-size distribution	a	0.6
User density	$\mu = u$	0.95
BS density	$\lambda_b$	0.15
Femto-cell density	$\lambda_f$	0.55
Pico-cell density	$\lambda_p$	0.25
BS-User density	$d=b/u$	
variance of AWGN channel	D	25
environment fading	h	1
Operating frequency	f	20GHz
The circuit power of Transceivers	$P_c$	100
The non-transmission power consumption	$P_o$	
digital signal processor	$P_{dsp}$	100
signal generator	$P_{gen}$	384
AC-DC converter	$P_{conv}$	100
backhaul link equipment,	$P_{link}$	80
Air-Conditionner	$P_{cool}$	690

Table-1 Simulation Parameters

#### IV. RESULTS

This section presents the results and their respective analysis. The predicted responses of the various ANNs are illustrated.

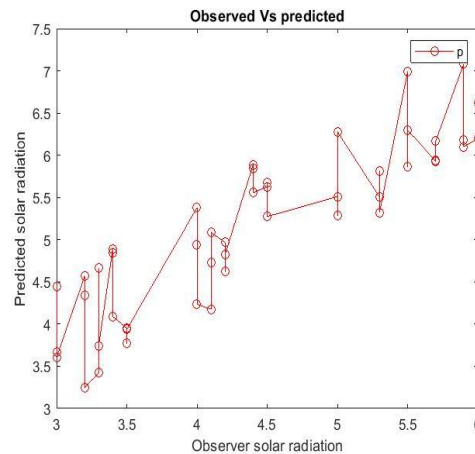


Fig 3: Predicted global solar irradiation using ANN1

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The Fig. 3 provide the output of the global solar irradiation for a selected area. It will be added that the optimal production of the solar photovoltaic energy will definitely require accurate data and an assisted supervision system. The output of the second neural network is showing that the global solar irradiation is in the range of 3.5 to 7kWh/m<sup>2</sup>/jr. The Fig. 4 may indicate that for the wind speed below 2m/s, the ANN2-multiayer perceptron layer configuration may give a high prediction, however for wind speed above 6m/s the predicted value may be lower than the observed value on the site. For wind speed in between 2m/s and 6m/s, the graph may point out that a strong agreement with the predicted data against the observed data is achieved.

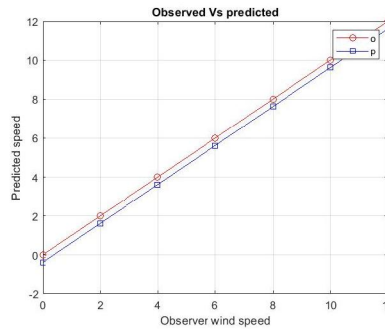


Fig 4: Predicted wind speed using ANN2

The artificial neural network 3 provides information about the system energy efficiency and spectral efficiency of a fixed-mobile WiMAX station with the single input and single output (SISO) antenna configuration. It is assumed to serve a delicate area, in this study an airport was considered. Three data services were considered, the system energy efficiency against the signal to noise ratio and the nodes respectively in the Fig. 5. The analysis (energy efficiency against the snr) is indicating that the energy efficiency is improved as the number of nodes increases. It reaches a maximum point but a compromise should be made, whatever the kind of data services. However, increasing the transmitting power of the macro-cell BS will not necessarily improve the area spectral efficiency, but when using more small cells deployment this could be achieved. In addition, the small cells (fem to, pico –cells) are very low power consumption devices, energy harvesting in the environment could be therefore very beneficial but their number under a given macrocell should be chosen with caution. In Fig. 8 indicates the injected green energy as function of the number of the small cells. The optimal value of the spectral efficiency is subject to the number of small cells under the macro-cell base station.

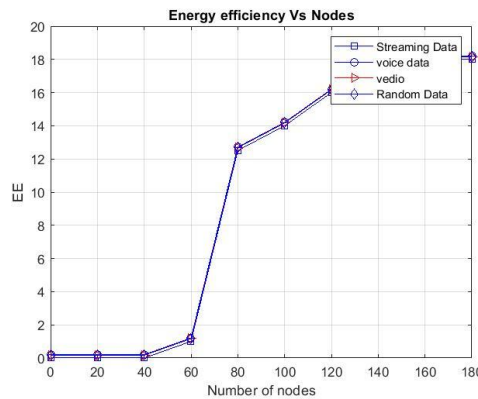


Fig 5: Comparison between energy and nodes

**Energy efficiency VS Nodes Old Data.**

S No.	Number of nodes	Energy Efficiency Streaming data	Energy Efficiency Voice data	Energy Efficiency Video	Energy Efficiency Random data
1.	0	0	0	0	0
2.	20	0	0	0	0



3.	40	0	0	0	0
4.	60	1	1.2	1.3	1
5.	80	12.3	12.4	12.4	12.3
6.	100	13.5	13.3	13.4	13.5
7.	120	13.8	13.9	13.7	13.8
8.	140	14.5	14.4	14.3	14.6
9.	160	15.5	15.6	15.7	15.9

**Energy efficiency VS Nodes New Data.**

S No.	Number of nodes	Energy Efficiency Streaming data	Energy Efficiency Voice data	Energy Efficiency Video	Energy Efficiency Random data
1.	0	0	0	0	0
2.	20	0	0	0	0
3.	40	0	0	0	0
4.	60	1.7	1.8	1.6	1.7
5.	80	12.3	12.4	12.4	12.3
6.	100	14.1	14.2	14	14.2
7.	120	16.1	16.2	16.1	16
8.	140	17.2	17	17.1	17.2
9.	160	17.5	17.4	17.6	17.4
10.	180	18.1	18	18.2	18.1

**V. CONCLUSION**

The integration of renewable electricity into the energy grid is crucial nowadays, particularly for African countries blessed with abundant natural electricity resources. Predicted global solar irradiation ranges between 3.5 to 7, and predicted wind speed ranges from 2m/s to 6m/s; notably, the observed wind speed exceeds the predictions. This bodes well for solar energy in African regions. Moreover, many coastal locations worldwide can benefit by equipping their airports with advanced artificial intelligence technology for electrical systems. This paper explores and formulates the incorporation of green energy into the telecommunication system with power control based on an Artificial Neural Network (ANN). The paper's contribution lies in providing power control for a distributive hybrid grid using an (ANN). The study underscores the significance of a heterogeneous network and suggests that increasing the macro-cell base station transmitting power will not necessarily enhance the system's spectral performance. The green metric is derived as a function of the injected green power and the availability of green energy. Various techniques, including the Pareto approach and dual Lagrange, can be employed to address the multi-objective problem. Further validation of this study can be accomplished using on-site statistics, and dynamic monitoring of the number of solar panels and wind aerogenerators will be essential. Such data can be made available with the installation of a sophisticated artificial intelligence system. In future research, the power control algorithm may consider the power system's quality and stability in real-time monitoring. The system's voltage drop and electricity loss will also be investigated. The dynamic nature of this field necessitates continuous improvement and exploration of advanced technologies for sustainable and efficient energy integration.

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