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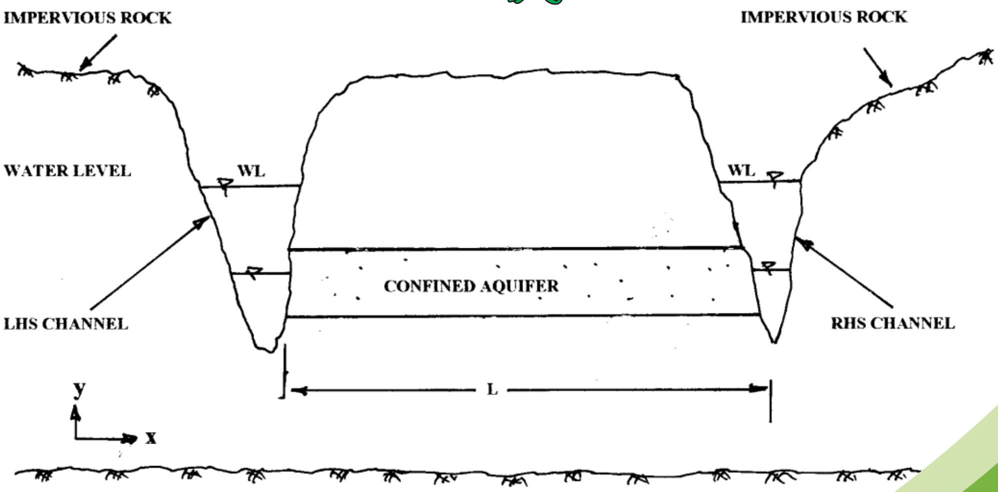

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NON-STEADY ONE-DIMENSIONAL GROUNDWATER FLOW IN CONFINED AQUIFER INDUCED BY TIME DELAYED WATER LEVEL CHANGES IN BOUNDING CHANNELS

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ABSTRACT
Unsteady state one dimensional flow of ground water induced by changes in water level in two channels bounding an isotropic homogeneous confined aquifer was studied. The water level in the two channels varies gradually with time and defined by mathematical functions with inbuilt time delay parameters. Exact solution to the problem was sought analytically, using the Laplace transform method. Results were obtained for pressure heads in error functions at various times and places in the aquifer. The equations obtained in the study were in agreement with those obtained by other researchers in previous studies. Using a numerical example, actual head values were determined for varying set values of delay parameters and these were plotted and compared.

Key words
Confined aquifer, channel water level, isotropic, transmissibility, Laplace transform, error functions, delay parameters.

INTRODUCTION
Many situations do occur in the field in which a body of water in a channel interfacing an aquifer would constitute major sources of ground water recharge and flow in the aquifer. The water level in the channel could change either rapidly or slowly, depending on the pattern of pressure force causing the change. For instance, sudden release of water from remote sources due to water leakages or flood waves caused by intense precipitation of short duration would generate large surface flow leading to rapid build-up of water level in the river channel. Similar situations would be expected to occur, from either pumping operations in irrigation fields or, rapid withdrawal of water from surface reservoirs. In some instances, there would be gradual build-up of water level in reservoirs such as during operations in pumped-storage hydropower generation plants.

On the other hand, the drying up of lakes and reservoirs adjoining an aquifer in dry regions due to high evaporation processes would also lead to slow decline in water level. On the global scale, there would be expected, gradual change in water level, resulting from freezing and de-freezing of polar ice, caused by climate change. In coastal areas adjoining permeable rocks, flood waves generated by tidal oceans would raise the water level and induce ground water flow in aquifers. Although the changes in water level discussed herein take place in remote parts of the aquifer; however, the effects are transmitted either slowly or rapidly to all parts of the aquifer system, depending on the nature of change.

The general problems of water level changes in channels, lakes and lagoons bounding confined aquifers have been studied by many hydrologists and researchers. There was also study of the groundwater flow in African Saharan aquifer system (Hammad, 1969) among many other studies in Africa. The results of the study established the pattern and general trend of ground water flow in the sub-Saharan region. Later (Marino,1974; Gill,1984), analytical solutions were derived for groundwater flow problems in confined and semi-finite aquifers due to changes in channel water levels. Thereafter (Mustafa, 1987, 2013), similar approaches were employed and in addition, there was introduced a practical dimension to the problems, by examining variations in groundwater flow induced by both surface infiltration/evaporation and changes in water level in bounding channels.

With the recent advances in the application of GIS system in watershed modelling, 3-D groundwater flow modelling gained prominence, as more information can be obtained and processed on regional scale, on the nature, pattern, distribution and trend of groundwater flow in aquifers. There was applied (Gossel et al (2004) for instance, the GIS-based groundwater flow modelling technique to study the long-term groundwater flow in the Nubian sandstone aquifer in Eastern Sahara. The results of the studies established that, the Nubian Aquifer groundwater system, had been formed largely, by infiltration, during the 20,000-5,000(BP). The studies further showed that, the aquifer system, is a fossil aquifer and had been in unsteady state condition for the past 3,000 years.

Of recent, the problem of surface and subsurface water interaction generally observed in coastal areas giving rise to moving water boundary was studied (Kong et al.,2010). In the study, a moving water boundary was simulated by a ground water and surface water 2-D model. The resulting governing equations were however not amenable to analytical solution but, were solved numerically, using finite difference methods.

On regional scale, due to its complexity, regional groundwater flow is usually studied by hydrologic mathematical catchment models. The most widely used groundwater model is, USGS finite different based MODFLOW. The versatility of the model has been enhanced greatly upon its successful integration with the Geographic Information System (GIS).

The MODFLOW-2000 successfully employed (Hashemi et al., 2012) to study ground water flow under steady state conditions, to determine the recharging system in the Gareh-Bygone Plain in southern Iran. The study used the flood water spreading system that was established to recharge the ground water. The results established that, without surface water inflow, the plain was being recharged through a fault conducting water from the upper sub-basin.

Also (Khadri and Pande, 2016) recently, the Mahesh River Basin in the Akola and Buddha districts of India was modelled, using MODFLOW model, in which, it was established that, the aquifer system was stable under the conditions prevailing at the time.

Using the similar approach (Baalousha, 2016), MODFLOW model was successfully applied, to study groundwater flow for Qatar aquifers comprising of karst limestone containing cavities, sink holes and depressions, covering the country's area of 11,586km^2. The study estimated the amount of recharge and established the trend of groundwater flow, which was observed to be decreasing over the years. The study also established that, sea water intrusion was occurring in the coastal areas and that, there was lateral flow into Qatar, through its southern border with Saudi Arabia.

In a similar study (Aniekan et al.,2014), MODFLOW model was applied to determine the mode and pattern of groundwater flow in the coastal aquifers of Akwa Ibom state, Nigeria. The study evaluated the recharge values for the six different zones studied and established that, there was high recharge occurring in the area and thus, showing high potential for ground water resources.

Most groundwater flow modelling studies are largely carried out under the steady state flow conditions. However, it is observed that, on the contrary, groundwater flow in the field is generally unsteady and transient.

Few researchers of recent (Hong Niu et.al., 2015) employed analytical methods to study the flow of ground water under unsteady steady state. The findings on the whole, showed that, when time was large enough, the flow distribution under unsteady state conditions tended to the steady state flow.

The problem presented in this study is, aimed at determining the pattern of flow resulting from time delayed water level changes taking place in two channels bounding a semi-finite artesian aquifer. A mathematical representation of the problem is shown in Fig.1 for which analytical solution was sought.

MATHEMATICAL REPRESENTATION OF THE PROBLEM

In the study presented, a situation is visualized in which, the water levels in both the LHS and RHS channels shown in Fig.1 were initially at the same level, the datum. Thereafter, both levels change gradually, as to induce ground water flow into the adjoining aquifer.

A solution is sought on the nature and distribution pattern of groundwater flow resulting from the water level changes under unsteady state conditions using boundary conditions specified by mathematical functions with inbuilt delay parameters.

The generalized ground water flow equation results from combining continuity equation (mass balance) with Darcy's law. Thus, for inhomogeneous and anisotropic confined aquifer, the continuity equation(Trescott and Larson, 1977) is,

$$-\left\{\frac{\partial}{\partial x}(q_x) + \frac{\partial}{\partial y}(q_y) + \frac{\partial}{\partial z}(q_z)\right\} + Q = S_s\frac{\partial h}{\partial t} \qquad (1)$$

Q is pumping or injection of a vol. of flux (L^3/T per vol.(L^3)) and S_s is specific storage (L^{-1}).
Combining Equation (1) with Darcy's law $\{q_x = -K_x \frac{\partial h}{\partial x}$, $q_y = -K_y \frac{\partial h}{\partial y}$ and $q_z = -K_z \frac{\partial h}{\partial z}\}$ is obtained, for homogeneous hydraulic conductivity, i.e. independent of x, y and z, anisotropic confined aquifer without pumping or recharge

$$K_x\,\partial^2h/\partial x^2 + K_y\,\partial^2h/\partial y^2 + K_z\,\partial^2h/\partial z^2 = S_s\,\partial h/\partial t \qquad (2)$$

For homogeneous and isotropic aquifer, i.e., $K_x = K_y = K_z = K$, Eq. (2) reduces to

$$\partial^2h/\partial x^2 + \partial^2h/\partial y^2 + \partial^2h/\partial z^2 = (S_s/K)\,\partial h/\partial t \qquad (3)$$

Thus, the general groundwater flow equation for homogeneous and isotropic aquifer is given by

$$K\nabla^2h = S_s\,\partial h/\partial t \qquad (4a)$$

For aquifer of constant thickness b Eq.4a is expressed as

$$b(K\nabla^2h) = b(S_s\,\partial h/\partial t) \quad \text{or}$$

$$T\nabla^2h = S\,\partial h/\partial t \;\rightarrow\; \nabla^2h = (S/T)\,\partial h/\partial t \qquad (4b)$$

Such that, T = bK and S = b S_s whereas, S is dimensionless and T(L^2/T)

∇^2 is the Laplacian operator = $\partial^2/\partial x^2 + \partial^2/\partial y^2 + \partial^2/\partial z^2$

For 3- dimensional homogeneous isotropic and uniform thickness confined aquifer, the groundwater flow equation is given by

$$\partial^2h/\partial x^2 + \partial^2h/\partial y^2 + \partial^2h/\partial z^2 = (S/T)\,\partial h/\partial t \qquad (4c)$$

If there is no flow in the vertical direction and flow is only in one dimension, the x axis, Eq.4c reduces to

$$\partial^2h/\partial x^2 = (S/T)\,\partial h/\partial t = (1/\propto)\,\partial h/\partial t \qquad (4d)$$

S is the storage coefficient, T is the transmissibility,

$\propto = T/S$, a coefficient , b is aquifer thickness and x, y, z orthogonal direction

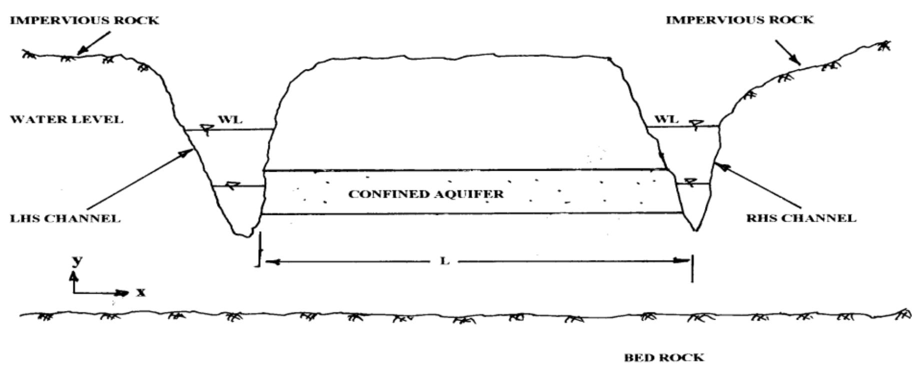

FIG.1 SCHEMATIC REPRESENTATION OF GROUNDWATER FLOW IN THE AQUIFER

Equation (4d) is a Partial Differential Equation (PDE)

In seeking solution to the PDE, the boundary conditions must be specified, in addition to the initial conditions. The following boundary and initial conditions apply herein

$h(x,0) = 0$ $\quad t \leq 0$ - (5a)

$h(0,t) = H_o[1 + \exp(\zeta t)\, \mathrm{erfc}(\sqrt{\zeta t})]$ $\quad t > 0$ - (5b)

$h(L,t) = H_o[1 + \exp(\mu t)\, \mathrm{erfc}(\sqrt{\mu t})]$ $\quad t > 0$ - (5c)

This means, the head h, in the channels at x = 0 and at x = L will change after time t > 0 while,

ζ and μ are introduced as time delay parameters.

Let us define $\theta^2 = \zeta$ and $\beta^2 = \mu$

Let solution be sought by taking the Laplace transform of Eq.4d, and Eqs.5(a-c) thus:

$L\ \{h(x,t)\} = h(x,p)$

where p is the transform time

Hence, the solution for Eq.4d is put in the form:

$h(x, p) = C_1\cosh(\varphi x) + C_2 \sinh(\varphi x)$ - (6)

where $\varphi = (p/\alpha)^{1/2}$ and C_1 and C_2 are constants

Now, from Eq. (5b): $h(0, p) = H_0 \left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\theta)}\right\}$ - (7a)

and from Eq. (5c): $h(L, p) = H_0 \left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\beta)}\right\}$ - (7b)

Putting these into Eq.6, the values of the constants are obtained as

$C_1 = H_0\left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\theta)}\right\}$ and $C_2 = H_0 \left[\left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\theta)}\right\} - \left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\beta)}\right\}\frac{\cosh(\varphi L)}{\sinh(\varphi L)}\right]$ - (8)

For brevity, let $\phi_1 = \left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\theta)}\right\}$ and

$\phi_2 = \left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\beta)}\right\}$ such that,

$C_1 = \phi_1$ and $C_2 = \left(\frac{1}{\sinh(\varphi L)}\right)\{\phi 2 - \phi 1\cosh(\varphi L)\}$

After rearranging Eq.6 after putting the values of the constants C_1 and C_2,

$h(x, p) = H_0\left\{\phi 1 \frac{\sinh \varphi(L-x)}{\sinh(\varphi L)} + \phi 2 \frac{\sinh(\varphi x)}{sinh(\varphi L)}\right\}$ - (9)

Now, using Binomial series expansion and after some algebraic rearrangement of Eq.6 gives for the term,

$\phi_1 \frac{\sinh\varphi(L-x)}{\sinh(\varphi L)} = \phi 1 \{\sum_{n=0}^{\infty}[\exp -\varphi(2nL-x)] + \sum_{n=0}^{\infty}[exp - \varphi(2nL+x)]\}$

- (10a)

And the term,

$\phi 2 \frac{\sinh(\varphi x)}{sinh(\varphi L)} = \phi 2\{\sum_{n=0}^{\infty}[\exp -\varphi(2nL+L-x)] + \sum_{n=0}^{\infty}[exp - \varphi(2nL+L+x)]\}$ - (10b)

$h(x,t) = L^{-1}\{h(x,p)\}$

For the term with ϕ_1 , the Inverse Laplace transform is

$L^{-1}\{\phi_1 \frac{\sinh\varphi(L-x)}{\sinh(\varphi L)}\}$ which is rewritten as

$L^{-1}\left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\Theta)}\right\}\{\sum_{n=0}^{\infty} [\exp -\varphi(2nL-x)] + \sum_{n=0}^{\infty} [exp - \varphi(2nL+x)]\}$

For the terms with $\frac{1}{p}$ upon inverting and replacing φ by $\sqrt{\alpha t}$, the solution is given by

$\sum_{n=0}^{\infty}\{ \text{erfc}((2nL- x)/2\sqrt{\alpha t})\} + \sum_{n=0}^{\infty} \{ \text{erfc}((2nL+x)/2\sqrt{\alpha t})\}$ - (11a)

Similarly, for the terms with $\frac{1}{\sqrt{p}(\sqrt{p}+\Theta)}$ upon inversion and replacing the values of $\Theta, \boldsymbol{\beta}$ with those of ζ and μ respectively, give

$\sum_{n=0}^{\infty} \exp [\zeta t + (2nL-x)\sqrt{\zeta/\alpha}] \sum_{n=0}^{\infty} \text{erfc} [(2nL-x)/2\sqrt{\alpha t} + \sqrt{\zeta t}]$

$+ \sum_{n=0}^{\infty} \exp [\zeta t + ((2nL+x)\sqrt{\zeta/\alpha})] \sum_{n=0}^{\infty} \text{erfc}[(2nL+x)/2\sqrt{\alpha t} + \sqrt{\zeta t}]$ - (11b)

Similar approach for the terms with ϕ_2 , taking the inverse transform:

$L^{-1}\left\{\phi 2 \frac{\sinh(\varphi x)}{sinh(\varphi L)}\right\} = L^{-1}\left\{\frac{1}{p} + \frac{1}{\sqrt{p}(\sqrt{p}+\beta)}\right\}\left\{\begin{array}{l} \sum_{n=0}^{\infty}[\exp -\varphi(2nL+L-x)] \\ + \sum_{n=0}^{\infty}[exp - \varphi(2nL+L+x)] \end{array}\right\}$

For the terms with $\frac{1}{p}$ would give

$\sum_{n=0}^{\infty} \text{erfc}[((2n+1)L-x)/2\sqrt{\alpha t}] + \sum_{n=0}^{\infty} \text{erfc}[((2n+1)L+x)/2\sqrt{\alpha t}]$ - (11c)

And for the terms with $\frac{1}{\sqrt{p}(\sqrt{p}+\beta)}$ would give

$\sum_{n=0}^{\infty}\left[\exp[\mu t + (2n+1)L - x]\sqrt{\mu/\alpha}\right] \sum_{n=0}^{\infty} \text{erfc}[((2n+1)L-x)/2\sqrt{\alpha t} + \sqrt{\mu t}]$

$+ \sum_{n=0}^{\infty}\left[\exp[\mu t + (2n+1)L + x)]\sqrt{\mu/\alpha}\right] \sum_{n=0}^{\infty} \text{erfc} [(2n+1)L+x)/2\sqrt{\alpha t} + \sqrt{\mu t})]$

- (11d)

The total solution for head h(x, t) is obtained by adding Eq.11(a-d) to give

$h(x,t)= H_0 \{\sum_{n=0}^{\infty} \text{erfc} [(2nL- x)/2\sqrt{\alpha t}] + \sum_{n=0}^{\infty} \text{erfc} [(2nL+x)/2\sqrt{\alpha t}]$

$+ \sum_{n=0}^{\infty} \exp [\zeta t + (2nL-x)\sqrt{\zeta/\alpha}] \sum_{n=0}^{\infty} \text{erfc} [(2nL-x)/2\sqrt{\alpha t} + \sqrt{\zeta t}]$

$+ \sum_{n=0}^{\infty} \exp [\zeta t + (2nL+x)\sqrt{\zeta/\alpha}] \text{erfc}\sum_{n=0}^{\infty} [(2nL+x)/2\sqrt{\alpha t} + \sqrt{\zeta t}]$

$+ \sum_{n=0}^{\infty} \text{erfc}[((2n+1)L-x)/2\sqrt{\alpha t}] + \sum_{n=0}^{\infty} \text{erfc}[((2n+1)L+x)/2\sqrt{\alpha t}]$

$+ \sum_{n=0}^{\infty}\left[\exp[\mu t + (2n+1)L - x]\sqrt{\mu/\alpha}\right] \sum_{n=0}^{\infty} \text{erfc} [((2n+1)L-x)/2\sqrt{\alpha t} + \sqrt{\mu t}]$

$+ \sum_{n=0}^{\infty}\left[\exp[\mu t + (2n+1)L + x)]\sqrt{\mu/\alpha}\right] \sum_{n=0}^{\infty} \text{erfc} [((2n+1)L+x)/2\sqrt{\alpha t} + \sqrt{\mu t}] \}$

- (12)

where,

$\text{erf}(x) = 1 - \text{erfc}(x)$ and $\text{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e - \tau \, dt$ - (13a)

where $\tau = t^2$

The values of the function can be obtained in standard mathematical handbooks.

Using Taylor series expansion and integrating the error function, gives

$\text{erf}(x) = 1 - \frac{1}{\sqrt{\pi}} e^{x2} \{1/x - 2/x^3 + (1.3)/(2^3x^5) - (1.3.5)/(2^3x^7) + \ldots\}$ - (13b)

From Abramowitz and Stegun (1992), an approximation of the function is

$\text{erf}(x) = 1 - 1/(1 + a_1x + a_2x^2 + a_3x^3 + a_4x^4)^4 + e(x)$ - (13c)

Such that, $|e(x)| \leq 5 \text{ X } 10^{-4}$

Constants a_1, a_2, a_3 and a_4 are obtained from rational fitting of weights thus:

a_1= 0.278393, a_2= 0.23030389, a_3 = 0.000972 and a_4 = 0.078108
The error function complimentary takes special values at
erfc(0) =1 ; erfc (∞) =0 and erfc(−∞) = 2

Discussion of Results

In the case the delay constants ζ and μ take zero values, that is $\zeta = \mu = 0$
Eq.12 simply reduces to

$$h(x,t)=2 H_0 \{\sum_{n=0}^{\infty} \text{erfc}\,[(2nL- x)/2\sqrt{\alpha t}\,] +\sum_{n=0}^{\infty} \text{erfc}\,[(2nL+x)/2\sqrt{\alpha t}\,] + \sum_{n=0}^{\infty} \text{erfc}\,[((2n+1)L-x)/2\sqrt{\alpha t}] + \sum_{n=0}^{\infty} \text{erfc}[((2n+1)L+x)/2\sqrt{\alpha t}]\ \} \quad - \quad (14)$$

Which means the flow is caused by head $H_o$only at both left and right-hand side boundaries, giving results similar to the ones and obtained in earlier studies (Gill ,1984 and Mustafa, 1987- 2013).

Numerical Example

A numerical example is given for the solution in which typical aquifer values and constants were assigned to parameters in Eq.12. To obtain the head distribution in the aquifer at various time intervals, the distance between the channels is set at, **L**= 1000m. Time t is practical time in days and set at, t = 1 day, 2 days, 5 days, 100, days, 200 days, . . 1000 days. The head causing flow H_o is fixed at, 10m. This value is sufficient to generate determinable flow in the aquifer system.
Using a typical aquifer parameter $\boldsymbol{\alpha}$ = 12,000m^2/day, the value for the delay constant at a start was put at ɵ = 0.000001 and then increased to 0.000005, 0.00005 and 0.005. Likewise, the other delay parameter **β** was fixed at a value 0.0001 and then increased to 0.01. Using MS- EXCEL, the various heads were calculated at distances fixed at x = 10m, 200m, 400m, 600m, . . 1000m from Eq. 12, using the approximation formula obtained for the error function given in Eqs.13 (a-c). The resulting head distributions at different places in the aquifer were evaluated and plotted in Figs.2(a-d) and shown in the Appendix.

The values of head at both left and right-hand side channels are not fixed but controlled by the delay parameters □ and **β** as reflected in spread of head. However, it would appear, that delay parameter ɵ tends to be more sensitive and defining the pattern of flow. Overall, the pattern of head distribution in the long run become uniform albeit, with varying magnitudes. The head causing flow is from both boundaries, the direction of flow determined by the delay parameters. At the initial time, the head values do not change appreciably until after considerable time interval as dictated by the delay parameters.

Conclusion

The problem of flow situation in finite artesian aquifer in which the level of water in two channels bounding an aquifer change was investigated. The change takes place gradually, over time, defined by delay parameters; for which, solutions were obtained, using Laplace transform method. Analytical solutions for the problem studied were given in error functions. A numerical example was given in which at various time intervals the head distribution in the aquifer at different places was calculated using MS-Excel computer program. These solutions would help to understand the nature of ground water flow resulting from sudden inflow of surface water, such as caused by delayed flood water, or tidal waves generated in coastal areas.

Acknowledgement

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Notations

H_0 , h = *head in aquifer* - *(L)*
α =*T/S* - *(L^2T^{-1})*
q_x , q_y , q_z = *flux* - *(LT^{-1})*
Q = *pumping or recharge flow*- *(L^3/T per vol. L^3)*
K_x , K_y , K_z , *K* = *hydraulic conductivity*- *(LT^{-1})*
T = *transmissibility* - *(L^2T^{-1})*
S_s = *Specific Coefficient (L^{-1})*
S= *Storativity of the aquifer* - *(storage coefficient; dimensionless)*
$\varphi = (p/\alpha)^{1/2}$ - *(L^{-1})*
p = *parameter in Laplace transform* - *(T^{-1})*
L = *distance separating the two bounding channels* - *(L)*
⍰, β = *time delay parameters* - *($T^{-1/2}$)*
ζ and μ = *time delay constants* - *(T^{-1})*
ϕ_1 , ϕ_2 - *(T)*
t, τ= time - (T)
C_1 and C_2 are constants in Laplace transform - (LT)

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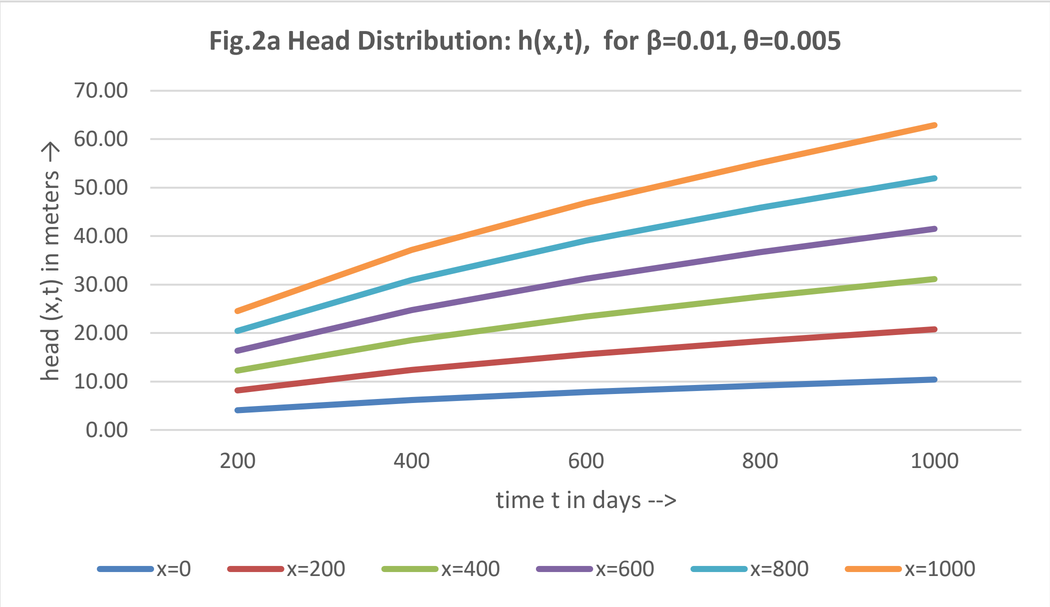
APPENDIX

Figs. 2(a-d) Showing head distribution for various values of delaying parameters θ and β



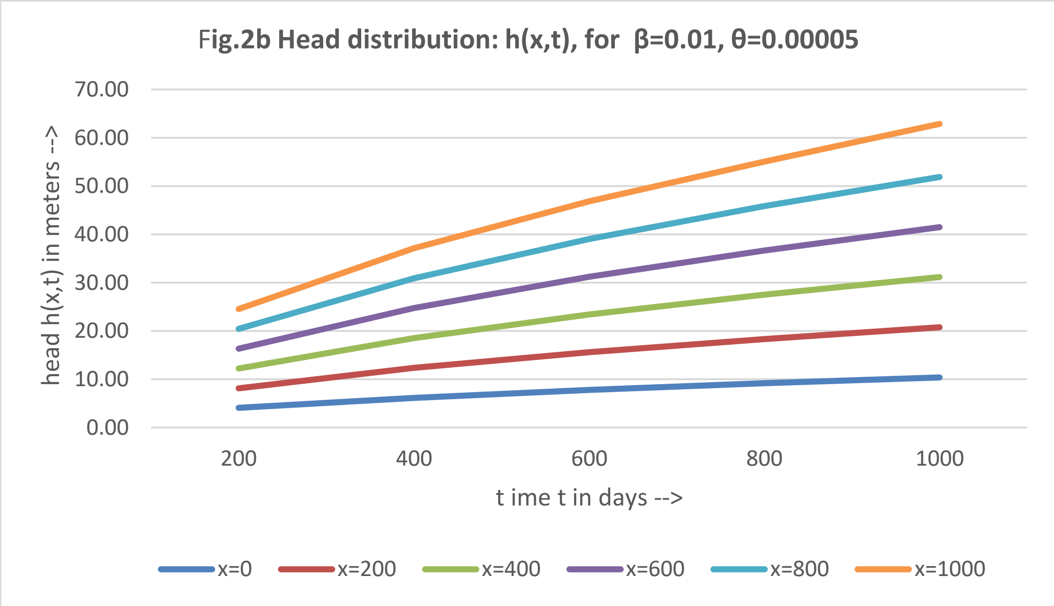


Fig.2b Head distribution: h(x,t), for β=0.01, θ=0.00005
70.00
60.00
50.00
40.00
30.00
20.00
10.00
0.00
head h(x,t) in meters -->
200
400
600
800
1000
t ime t in days -->
x=0
x=200
x=400
x=600
x=800
x=1000

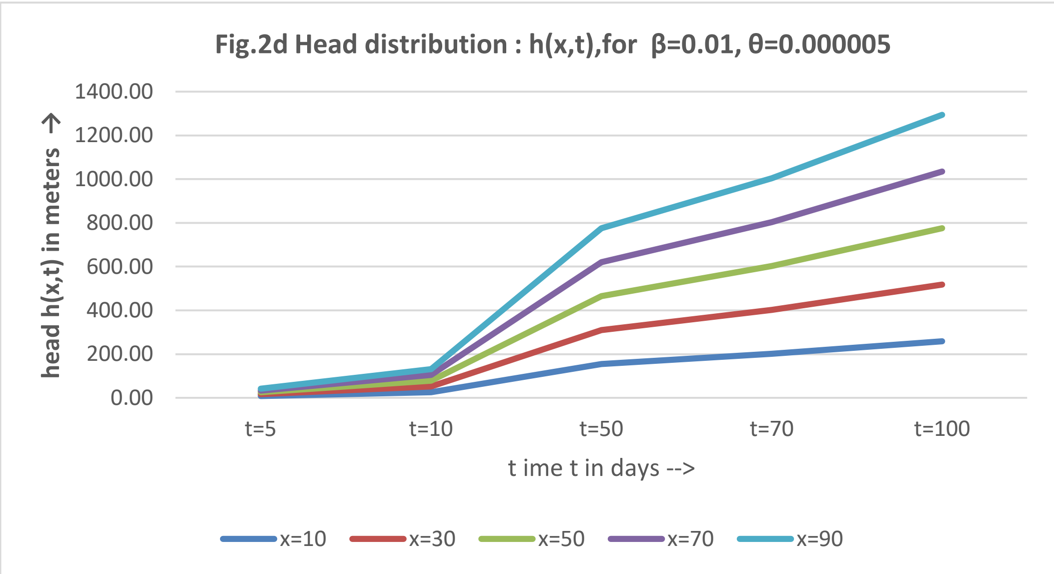


Fig.2d Head distribution : h(x,t),for β=0.01, θ=0.000005
1400.00
1200.00
1000.00
800.00
600.00
400.00
200.00
0.00
head h(x,t) in meters →
t=5
t=10
t=50
t=70
t=100
t ime t in days -->
x=10
x=30
x=50
x=70
x=90

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River Nworie in Owerri, Imo State, Nigeria: A Public Health Hazard?

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ABSTRACT

Nworie River is a river that traverses Owerri City, the capital of Imo State, Nigeria. It is of intense use by residents of Owerri and industries in its vicinity. This results in the discharge of various contaminants into it and thereby making it a health hazard, especially for people of low economic status who use it for drinking when public water supply fails. A previous study clearly established that Nworie River was facing substantial organic pollution. The purpose of this study was to reassess the pollution status of the river. During the month of May 2014, water samples were collected from Nworie River from three sites about 50 meters apart. The water was tested physically, chemically, and biologically using LaMotte pollution test kits and Carolina bacterial pollution of water kit. Of the 12 chemical parameters tested, alkalinity, carbon dioxide, and phosphorus exceeded the Mississippi Water Quality Criteria/ Environmental Protection Agency (EPA)/ WHO water quality standards while dissolved oxygen was low. Microbial pollution was evident from the coliform bacteria and *Escherichia coli* found. Based on the physical, chemical, and biological test results, the river was polluted and not potable. Dredging of the river that was started several years ago appears to have been abandoned and has rendered the water more polluted with the raking up of the pollutants that settled at the bottom of the river and may have caused the resurgence of water-borne disease agents. It is strongly recommended that the dredging be completed and the water quality improved in the interest of human health.

Keywords: River Nworie, Owerri, Nigeria, Public Health.

INTRODUCTION

Water is the driver of nature. It is the *summumbonum* of life but good quality water is essential for good health. Nworie River is a river that runs about 5km course across Owerri City, the capital of Imo State, Nigeria before emptying into another river, the Otamiri River. It is prone to intensive human and industrial uses, resulting in the discharge of a wide range of pollutants. It is used for various domestic applications by inhabitants of Owerri. When the public water supply fails, the river further serves as a source of direct drinking water, especially for the poorer segment of the population. A previous study(Okorie and Acholonu, 2008) clearly established that Nworie River was facing substantial organic pollution, as was obvious from the high values of carbon dioxide content and low dissolved oxygen of the river. Another study was subsequently conducted on Okitankwo River, a river that flows across the northern periphery of Owerri City along a course with relatively sparse human population, but active agricultural activity(Okorie, Acholonu, and Ekwuruo, 2013). The purpose of the present study was to reassess the pollution status of the River Nworie after a period of 7 years when this kind of study was conducted on the river (*loc. cit*.).

This study was also encouraged by the statements of Renn(Renn, 1968). He observed that in view of the public apprehension of the hazard of water pollution, regular water quality monitoring of inland water bodies is highly necessary. It was also carried out to include the biological profile which was not done in the previous study but recommended for subsequent investigations(Okorie and Acholonu, 2008).

Fig. 1: Map of Nigeria showing Imo State, where the study was conducted.

Fig. 2: Owerri Municipal in Imo State where River Nworie is located.

Materials and Methods

During the month of May 2014, water samples were collected from Nworie River from three sites about 50 meters apart in the vicinity of old Nekede Road. (See Figs. 3-6). The water was taken to the USA and tested in the Alcorn State University laboratory physically, chemically, and biologically. The physical parameters tested were odour, colour, and turbidity, and the chemical were alkalinity, ammonia- nitrogen, calcium, carbon dioxide, hardness, iron, magnesium, phosphorus, silica, nitrate, dissolved oxygen, and salinity using LaMotte pollution test kits (Carolina bacterial pollution of water kit 2014) supplied by Carolina Biological Supply Company and following the manufacturer's directions (loc.cit.). The number of bacteria in the water was determined by counting the number of coliform colonies on the Nutrient Agar plate and MacConkey Agar plate (See Figs. 7A and B). This was recorded in numbers per millilitre. Lauryl tryptose broth fermentation tests for gas production from lactose were also conducted as indicated by the manufacturer (See Fig. 9) to further confirm the presence of coliform bacilli in the water.

Fig. 3: Dr.Acholonu pointing at the present condition of Nworie River.The brownness of the water showed that the water turbidity was high and the River was polluted and still is polluted.

Fig. 4: A person taking sterile plastic water bottles to collect water samples from River Nworie.

Fig. 5: A person collecting water samples from River Nworie.

Fig. 6: A person closing water bottles after water samples were collected from River Nworie.

Results

The physical characteristics checked showed that the water was odourless, brownish in colour, and very turbid (not transparent) (See Fig.3). Of the parameters tested, alkalinity, carbon dioxide, and phosphorus exceeded the Mississippi Water Quality Criteria (MSWQC)/Environmental Protection Agency (EPA)/ WHO water quality standard while dissolved oxygen was low (See Table 1 and Fig.10). Microbial and/ or biotic pollution was evident from the coliform bacteria and *Escherichia coli* found. (See Figs. 7A and B).

Table 1: Parameters Tested, Average Readings for River Nworie in PPM (parts per million) and MSWQC/EPA Standards.

Parameters	Site 1	Site2	Site 3	Average	MSWQC/EPA
Chemical					
Alkalinity ppm*	52.0	52.0	24.0	42.7	3.08
Ammonia-N ppm	1.0	0.25	0.1	0.45	10.0
Calcium ppm	16.0	12.0	8.0	12	200.0
Caron Dioxide ppm*	12	14.0	11.0	12.3	10.0
Chloride ppm					230.0
Copper ppm	0.0	0.0	0.0	0.0	8.85/6.28
Hardness ppm	20.0	20.0	24.0	21.3	50.0
Iron ppm	0.0	0.0	0.0	0.0	0.2
Magnesium ppm					150.0
pH	6.5	6.5	6.5	6.5	6.5-9.0
Phosphate ppm	0.5	0.0	0.5	0.5	0.1
Silica ppm					75.0
Nitrate-N ppm	2.0	10.0	6.0	5.4	10.0
Dissolved Oxygen ppm	1.0	0.6	1.6	1.07	5.0
Physical					
Turbidity NTU					50.0
Salinity ppm	0.1	0.1	0.1	0.1	---
Surface H_20 temp°C					32.2

Lauryl Tryptose broth	Bacteria Present	Bacteria Present	Bacteria Present	Bacteria Present	
Nutrient agar	Bacteria Present	Bacteria Present	Bacteria Present	Bacteria Present	
MacConkey agar	Bacteria Present	Bacteria Present	Bacteria Present	Bacteria Present	

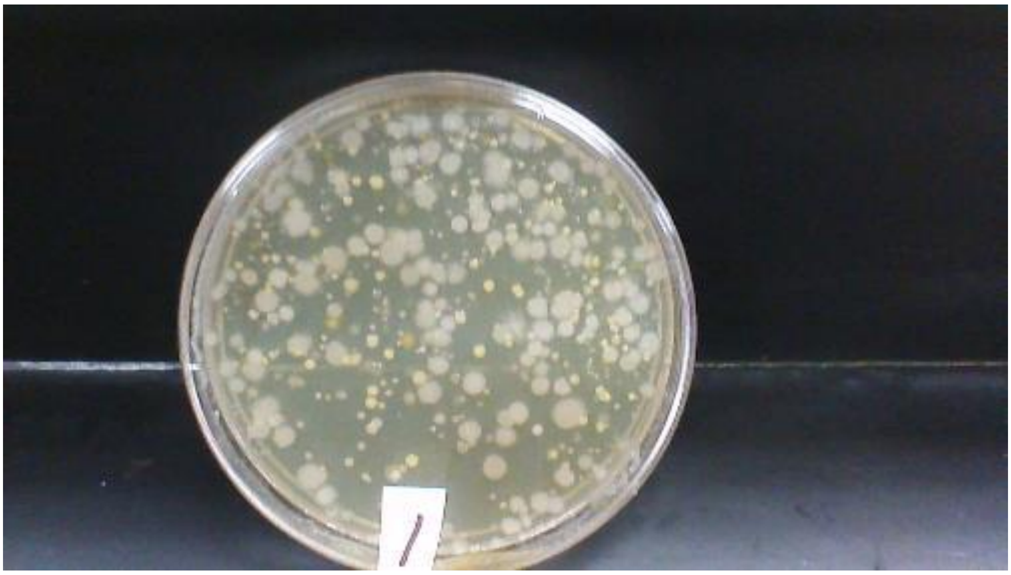

Fig. 7A: Coliform Bacterial growth in nutrient agar from collected water samples indicative of water pollution (nutrient agar plate).

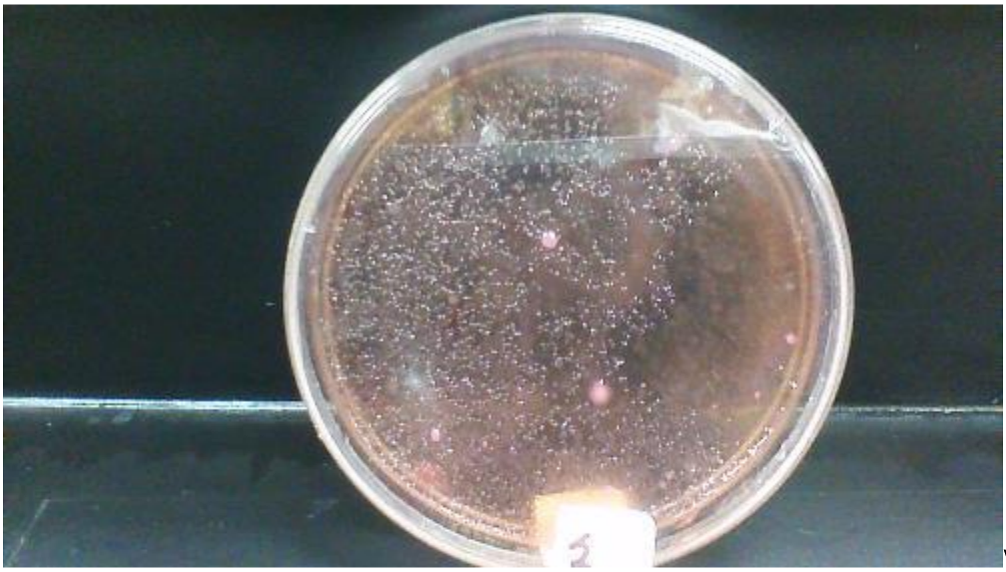

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Fig. 7B MacConkey agar plateColiform Bacterial growth from collected water samples indicative of water pollution.

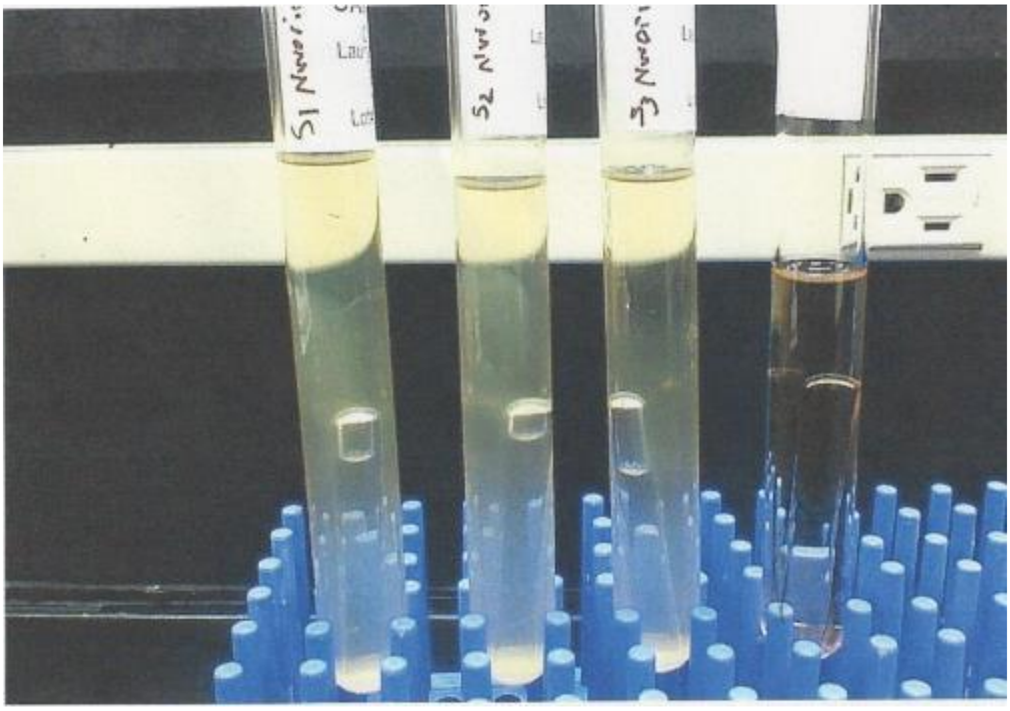
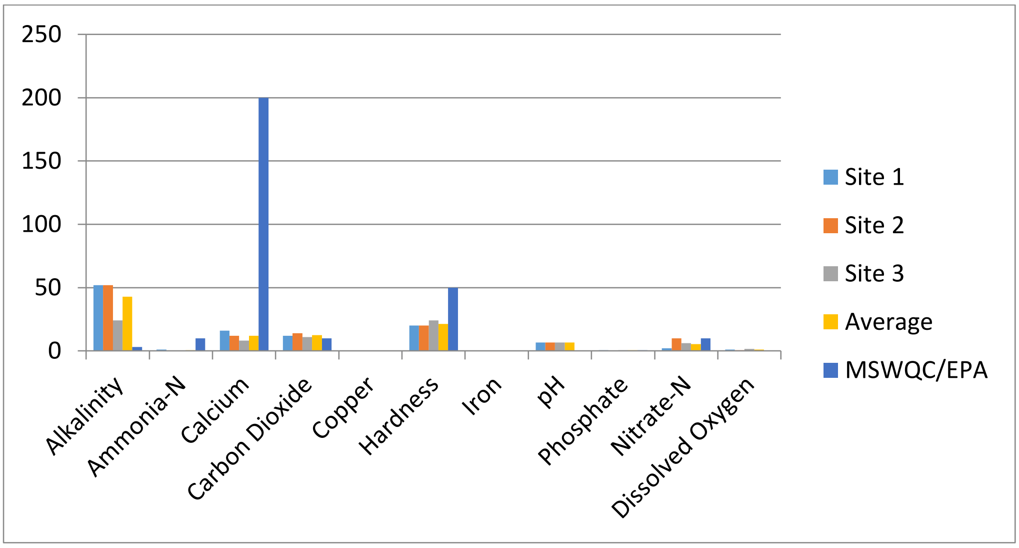


Fig. 8 Lauryl Broth Fermentation test (Gas seen insmall tubes in each vial is evidence of water contamination).

Fig. 9. Graph showing results of tests as compared with the MSWQC and EPA/WHO standards.



Discussion and Conclusion

Based on the physical, chemical, and biological test results, the river was polluted and not potable. Dredging of the river that was started several years ago (over 7 years) appears to have been abandoned and has rendered the water more polluted with the raking up of the pollutants that settled at the bottom of the river and may have caused the resurgence of water-borne disease agents. It is strongly recommended that the dredging be completed and the water quality improved. That the Nworie River in Owerri municipal was and is still polluted is evident from the brownish colour of the water and thus the high turbidity, the chemical parameters that exceeded the water quality standards, namely, alkalinity (42.7/3.08), Carbon Dioxide (12.2/10) and phosphate (0.5/0.1) coupled with the low dissolved oxygen (1.07/5.0). As observed by Wetzel and Likens[5], the measure of dissolved oxygen is one of the frequently used and the most important of all chemical methods available for the investigation of the aquatic environment. It provides valuable information about the biological and biochemical reactions going on in waters. The pollution of the water is further evident from the biological test results. The finding of coliform bacteria and *Escherichia coli* is an obvious indication that the water has human and/or animal faecal contamination and not good for drinking and could have water borne disease agents. The production of gas from the Lauryl Tryphosa broth fermentation test (Fig. 8) also confirmed the presence of coliform bacilli and water pollution.

From the aesthetic point of view, the river's condition has greatly detracted from the beauty of Owerri and reduced the recognition of infrastructural developments. The sooner something is done to improve the water quality of Nworie in Owerri capital city, the better. The dredging should be completed without further delay. The river is dying!

A contrast between the study on River Nworie and Okitankwo River shows that the latter is of better quality than River Nworie in Owerri City. With respect to the Okitankwo River, none of the chemical parameters tested exceeded the WHO/EPA standards. The river was not under any serious threats from chemical pollution when the study was conducted(Okorie, Acholonu and Ekwuruo, 2013).

A comparison between the water quality of River Nworie in 2008 and 2014 (Okorie and Acholonu, 2008) shows that the carbon dioxide content is still above the threshold set by MSWQC and/or EPA and WHO standard. Dissolved oxygen is also still lower than the norm. But the part of the study that obviously shows that the River Nworie is polluted is the biological (microbial) aspect. The finding of coliform bacteria and *Escherichia coli* (*E. coli*) shows that the river is polluted and not drinkable; that it has human and/or animal faecal contamination, among others as stated above.

Acknowledgment

Grateful acknowledgment is paid to Dr.Donzell Lee, Provost and Vice President for Academic Affairs of Alcorn State University for making available funds to procure the test supplies used in conducting this study and to Dr. Keith McGee of the Biology Department for helping through his grant from Mississippi INBRE (IDeA Network of Biomedical Research Excellence). Technical input by my student assistant Sharkiesha Jackson, is greatly appreciated. Ms. Rosie Hopkins my graduate assistant and students in the Environmental Biology Class who helped in running some of the tests are hereby recognized.

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A REVIEW OF THE DYNAMICAL SYSTEMS MODELING OF EPILEPTIC SEIZURES FOR ONSET PREDICTION

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ABSTRACT

In this review, we present a critical appraisal of works that consider epilepsy as a dynamic disease and therefore presentable from the perspective of dynamic system theory. Epilepsy is an acute brain disorder characterized by recurrent seizures where parts of the brain elicit abnormally synchronous electrical activity. The most commonly encountered forms of epilepsy are generalized absence epilepsy and temporal lobe epilepsy. The electroencephalography (EEG) which is the recording of the fluctuating electric field of the brain is the major clinical diagnostic tool for epilepsy and also a vital source of data for epilepsy research. In majority of cases accurate diagnosis of the disease can be made and seizures are controlled by the regular use of anti-epileptic drugs (AEDs). However, approximately 30% of epileptic patients suffer from medically refractory epilepsy which has defied all existing treatment protocols. Understanding the mechanisms underlying these forms of epileptic seizures and the development of alternative effective treatment strategies is a fundamental challenge in modern epilepsy research. Experimental researches show that the mechanisms involved in refractory epilepsy are so diverse and complex that it is a formidable task to obtain a single framework that categorizes all the pathophysiological changes in the properties of the epileptic brain involved.

There has evolved massive evidence that seizures do not occur abruptly as it has been earlier thought but develop over time even hours before the clinical symptoms, thus raising the hope for predictability of epileptic seizure occurrence. Thus, models of the epileptic brain can be postulated using concepts from deterministic and nondeterministic dynamical systems modelling. The main idea is that since the epileptic brain transitions into and out of seizures we can view it as a dynamical system.

The deterministic and non-deterministic models are based on seizure onset detection algorithm for the design of a closed loop seizure warning/intervention system. The major focus being the stimulation of the epileptic brain by sending electrical pulses to it in order to disrupt seizure progression once its onset has been detected.

Finally, we considered the essential issues in epileptic seizure prediction including the sceptism expressed in recent publications on the validity of nonlinear dynamical systems modelling to epileptic seizure prediction.

Key Words: Epilepsy, Electroencephalogram, Dynamical systems theory, Computational modeling, Deterministic models, Non deterministic models, Neural mass models, Adaptive Neuro-Fuzzy Inference System, Seizure prediction

LIST OF ABREVIATIONS

AED: Anti-epileptic-drug
AMPA: α-amino-3-hydroxy-5-methyl-4-isoxazolepropionic acid
EEG: Electroencephalography
GABA: γ-aminobutyric acid
IN: Interneurons
NMDA: N-methyl-D-aspartate
MAE: Mean absolute error
ODE: Ordinary differential equations
PSP: Post synaptic potential
RMSE: Root mean square error
SMC-ABC: Sequential Monte-Carlo approximate Bayesian computation
SWD: Spike-wave discharges
TCR: Thalamo-cortical relay cells
TLE: Temporal lobe epilepsy

1.0 INTRODUCTION

Epilepsy is a neurological disease characterized by recurrent and spontaneous seizures. It affects approximately 50 million people worldwide (Wendling, 2008). These seizures not only disrupt normal living but can also cause mental and physical damage and in extreme cases, even death. Ancient civilizations such as the Greeks and the Babylonians had emphasized the supernatural nature of the disease with each seizure type associated with the name of a spirit or god, usually evil. The Greeks used the term 'Saleniazetai' (i.e. moon struck) to describe people with epilepsy because they were thought to be affected by 'salene', the moon god (Sanei and Chambers, 2013).

The perception of epilepsy as a brain disorder started growing in the 18^{th} and 19^{th} centuries AD. In 1930 Hans Berger, a renowned psychiatrist, invented the human Electroencephalogram, EEG. EEG revealed the presence of electrical discharges in the brain. EEG also showed different patterns of brainwave discharges associated with different brain state or activity. The EEG also helped to locate the site of seizure discharges in the brain and expanded the possibilities of neurosurgical treatments(Sanei and Chambers, 2013).

The prevalence of epilepsy is particularly high in developing countries especially Latin America and several African countries, notably Liberia, Nigeria and the United Republic of Tanzania. In Nigeria the prevalence rate of epilepsy based on defined communities varies from 15 – 37 per 1000(Ogunrin, 2006). Attempts at treating epilepsy comprise medication, dietary therapy and surgery.

In majority of epileptic cases accurate diagnosis of the disease can be made with treatment in the form of regular use of anti-epileptic drugs (AEDs) but there are concerns about the side effects of these drugs. Quite a number of epileptic patients suffer from drug resistant epilepsy and may require surgical measures which involve excision of relatively large amount of brain tissue. Apart from the fact that surgery raises concerns about neurological disability that may result by the removal of either normal or functionally necessary tissue, there have been reported cases of seizures in quite a number of patients who had resection. In summary, refractory epilepsy has defied existing treatment protocols and currently researchers are looking for alternative therapies.

Results of research focusing on techniques that detect the onset of seizures are increasingly available in the open literature. This is of marked value to patients with epilepsy as it affords the opportunity of using drugs only on demand to reduce side effects. For patients with refractory epilepsy, this might allow them to take preparatory steps to protect themselves from injury by avoiding potentially dangerous activities like driving and operating heavy machines.

The study of mechanisms that trigger epileptic seizures is essential for its onset detection and not only for the improvement of existing therapies but also the development of new therapeutic strategies. Experimental research has identified many factors involved in the generation of epileptic seizures(Holmes *et al.*, 1997). These findings suggest that the etiologies of refractory epilepsy are so diverse and complex, that it is a formidable task to obtain a single framework that categorizes all the pathophysiological changes in genetic, molecular, cellular and neuronal network level properties of the brain involved in uncontrolled recurrent epileptic seizures.
According to a theoretical concept proposed by Mackey and Glass epilepsy may be considered a special large class of dynamical diseases i.e. diseases that unfold in time (Mackey and Glass, 1988). Epileptic seizures come and go, thus epilepsy is viewed as a dynamical disease of the brain and therefore suited to study from the perspective of dynamical systems theory.

2.0 LITERATURE REVIEW

2.1 Dynamical Systems

The term dynamics refers to a causal relationship between the present state of a system and the next. In this context a dynamical system can be described as a system that evolves in time (i.e. the values of the variables describing the state of the system depend on time).

2.2 Mathematical Theory of Dynamical Systems

We consider an example of a 1- dimensional dynamical system, defined through a system variable y.The time evolution of the system is described by $\dot{y} = \frac{dy}{dt} = f(y) + \mathrm{I}$. The function $F(y) = f(y) + \mathrm{I}$, referred to as the vector field governs the time evolution $\phi^t(y_0)$ of y for a given value of system parameter I and initial condition $y(t = 0) = 0. \phi^t(y_0)$ is referred to as the flow or trajectory of the dynamical system. A fixed point equilibrium is the value of $y = y_s$ at which the vector field $F(y_s) = 0$. In this case, there is no flow in the system, i.e. $\phi^t(y_s) = y_s$. The value of the first derivative $\lambda = \frac{\partial F}{\partial y}$ evaluated at the fixed point y_s determines the stability of the fixed point equilibrium state. For $\lambda < 0$, the fixed point is said to be a stable equilibrium point (or an attractor), whereas for $\lambda > 0$, the fixed point is unstable (or a repeller). If $\lambda = 0$, we have to employ a second derivative $\frac{d^2F}{dy^2}$ to determine the nature of the stability.

We can extend these concepts and definition for a multi-dimensional dynamical system with $y = \mathbb{R}^n$, where n is the dimension of the dynamical system. The time evolution of each system variable is governed by its own vector-field: $\dot{y}_i = F_i,\ i = 1 \ldots . n$. The flow of the system is now described in an n-dimensional phase-space $\phi^t(y_1(0), \ldots \ldots .., y_n(0))$ with axes defined by the system variables. The stability of the equilibrium states is now obtained by identifying the eigenvalues of the Jacobian matrix J with matrix elements $J_{ik} = \frac{\partial F_i}{\partial y_k}$(Strogatz, 2001).

2.3 Attractors

An attractor may be seen as a state toward which a system tends to evolve over time (Da Silva *et al.*, 2003). Dynamical systems are characterized by the presence of attracting sets, or attractors, in the phase space. An attractor can be as simple as a point in the phase space. In some cases it is a closed curve called limit cycle. However, in more complex systems, the attractor has an intricate geometric structure, called a manifold. The latter is characteristic of high-dimensional systems exhibiting what is known as chaotic dynamics. The complex manifolds are commonly called fractals, if they consist of non-integer dimensions. An attractor that is a fractal is called a strange attractor. These systems display sensitive dependence on initial conditions and as time evolves small fluctuations in some parameters may drastically change the behavior of the system. The set of all initial conditions from which trajectories evolve to a given attractor define the basin of attraction for that attractor. A complex nonlinear system may have more than one attractor, and therefore more than one basin of attraction which are separated by a closed curve referred to as the separatrix. Another important feature of dynamical systems is multi-stability, that is, multiple attractors can reside in the phase space at the same time and depending on the initial conditions the dynamical system can evolve to any of these attractors.

In general, a dynamical system has a relatively small number of parameters that can modify its overall dynamical structure, such that the system may make transition from one to another attractor. This concept is referred to as bifurcation and the precise values of the parameters for which this change occur are called bifurcation points.

2.4 Epilepsy

Epilepsy is characterized by sudden recurrent and transient disturbances of perception or behavior resulting from excessive synchronization of cortical neuronal network. Epileptic seizures are caused by parts of the brain eliciting abnormal electrical activity. The region of seizure generating tissue, or the epileptic focus, can be due to structural abnormalities that disrupt normal neural circuitry. These abnormalities may be genetic, caused by head injury, infection, stroke or tumor. In such cases when the cause is known, it is termed symptomatic epilepsy. Other classifications include idiopathic epilepsy, when there is no identifiable cause but a genetic basis is presumed. Cryptogenic epilepsy is when neither classification fits and the cause is unknown. The most common way to classify epileptic seizure is to distinguish between focal (partial) and generalized seizures (Berg *et al.*, 2010). The onset of the seizure is localized in one hemisphere of the brain for focal seizures and involves both hemispheres for generalized seizures. Focal seizures can be further divided based on the location of seizure onset and the extent to which consciousness is impaired. Awareness is not impaired for a simple partial seizure and impaired for a complex partial seizure. A seizure can start locally and eventually diverges into the entire brain; this is called a secondary generalized seizure. Generalized seizures can be further divided based on the effect that they have on the body. The different kinds of generalized seizures are absence, tonic, clonic, tonic-clonic, myoclonic and atonic seizures. All these seizures involve a loss of consciousness. This way of classification, based on clinical and electrographic observations, is in accordance with the scheme proposed by the International League Against Epilepsy (ILAE) (Baucaud, Henriksen and Rubio, 1981).

Our focus is on both focal and generalized seizures. The specific type for focal seizures will be mesial temporal lobe epilepsy (MTLE), because it is the commonest type of focal epilepsy. MTLE has its onset in the inner part of the temporal lobe of the brain. It can express itself as a simple or complex partial seizure or as a secondary generalized seizure. The specific type for generalized seizures will be absence seizures, because this seizure mostly affects children and can occur many times in just a day thereby disrupting attention in school.

2.5 Biomedical Signals

Living organisms are made up of many component systems. Each system is made up of several subsystems that carry on many physiological processes. Physiological processes are complex phenomena. They include nervous or hormonal stimulation and control, Inputs and outputs that could be in the form of physical material, neurotransmitters or information and action that could be mechanical, electrical, or biochemical. Most physiological processes are accompanied by signals (physical quantities that change with time) of several types that reflect their nature and activities: biochemical signals in the form of hormones and neurotransmitters, electrical signal in the form of potential or current, and physical signal in the form of pressure or temperature. Diseases or defects in a biological system cause alterations in its normal physiological processes, leading to pathological processes that affect the performance, health, and wellbeing of the system. A pathological process is typically associated with signals that are different in some respects from the corresponding normal signals. It requires a good understanding of a system of interest to observe the corresponding signals and assess the state of the system.

2.6 Electrical Activity of the Neuron

The human brain consists of up to 100 billion neurons which are supported structurally and metabolically by glial cells. There are many different types of neurons and are interconnected in a complex manner. Signals are received, transformed and sent between neurons using electrical and chemical transmitters. Neurons typically have three main parts, a cell body (soma), dendrites, and an axon with presynaptic terminals at the end. Several different neurotransmitters exist and their effect can be categorized into two main groups; excitatory (e.g. glutamate) and inhibitory (e.g. GABA or gamma-aminobutyric acid). Typically, a neuron has an electrical resting potential of -70mV. When this changes to become less negative this is known as depolarization, if it becomes more negative this is known as hyperpolarisation. As a neuron receives electrochemical stimuli from other neurons' synapses its membrane potential can be altered. The response at the postsynaptic terminal (commonly at the dendrite) is known as the postsynaptic potential (PSP). If the PSP causes the internal cellular voltage to increase (decrease) then this is known as an excitatory (inhibitory) PSP. If this excitatory input is sufficiently large (i.e. above a certain threshold) then this causes the neuron to fire, which is called an action potential, likewise, more inhibitory input means the cell is less likely to reach threshold and subsequently not fire. It is important to note here that there is considerable variation between neurons, neurotransmitters, receptors, and receptor mediated mechanisms.

2.7 Measurement of Neural Activity

The primary method for the study of neural activity in the clinical setting is through the use of the electroencephalogram (EEG) which records the electrical activity of the brain through the placement of recording electrodes on the scalp. The generators of this activity are thought to be predominantly cortical pyramidal cells which are aligned perpendicular to the scalp and generate extracellular currents. The recorded signal is influenced by this perpendicular current and the dipole orientation of neighbouring areas. These are effectively summed and recorded at the EEG electrode. Various factors can affect the recorded activity including cortical folding (which affects dipole orientation), the density of pyramidal cells (which varies throughout the cortex), and skull/scalp anatomy (which affects conductivity). Despite various complications affecting the EEG (as described above) it has the benefits of being noninvasive, has high temporal resolution and is relatively inexpensive.

Typically electrodes are placed centimeters apart over the entire scalp according to a standardized alignment such as the 10-20 method. It is also possible to record electrical activity by placing electrodes directly on the cortex. This requires invasive surgery to remove a section of the skull to allow access. These recordings are electrocorticograms (ECoGs) and are often placed with a finer spatial resolution on the scale of millimeters. Recent advances in technology have enabled the development of higher resolution 'microelectrodes' which record at the scale of micrometers (Stead *et al.*, 2010).

2.8 Brain Rhythms

There are five major brain waves distinguished by their frequency ranges. These waves represent normal background activities of the human brain and are associated to certain physical activities in the body. Delta (δ) rhythms have frequency in the range 0.5-4Hz and are seen during deep sleep, theta (θ) waves are seen when consciousness slips into drowsiness and have frequency range 4-7.5Hz. Waves in the frequency range 8-13Hz are often seen in a state of relaxed awareness without any attention, they are called alpha (α) rhythms. The frequency range 14-26Hz belongs to beta (β) rhythms and they occur during active thinking and attention. Waves with frequency above 30Hz are termed gamma (γ) rhythms.

2.9 Dynamical Systems and Epilepsy

From the explanation above and by a way of extension we may assume that in the epileptic brain, some neuronal networks can display different kinds of dynamical states because they possess an abnormal set of control parameters. This means the epileptic brain system possess more than one stable equilibrium state (or attractor). We can now understand how epilepsy can be viewed as a dynamical disease (Da Silva *et al.*, 2003; Milton, 2010) in the sense of transitions from a "normal" brain state attractor to a "pathological" brain state attractor in an epileptic brain network.

2.10 Generalized Absence and Temporal Lobe Epileptic Seizures

Absence seizures are generalized epileptic seizures of a brief duration (often less than twenty seconds) that start and end abruptly. During the seizure the patient has a loss of consciousness, but usually does not suffer from convulsions. These types of seizures normally occur during childhood and often disappear with adolescence. This is however not always the case. Absence seizures have a characteristic EEG pattern, namely spike and wave discharges (SPDs) (Destexhe, 2007). Intracellular recordings have shown that the 'spike' and 'wave' components are associated with neuronal firing and neuronal silence respectively(Pollen, 1964) which suggests an active role of inhibitory processes and γ-aminobutyric (GABA) receptors. Experimental models from the last decades made it possible to identify the brain structures that are involved in absence seizures. A lot of these experiments have pointed out that the thalamus plays a critical role in the generation of absence seizures.For example, some authors have shown that lesions or inactivation of the thalamus caused SWDs to disappear(Pellegrini, Musgrave and Gloor, 1979; Avoli and Gloor, 1982; Vergnes and Marescaux, 1992). In other studies, researchers show that it is possible to gradually transform spindle oscillations into SWDs (Kostopoulos *et al.*, 1981; McLachlan, Avoli and Gloor, 1984). Spindle oscillations are waxingand-waning oscillations of 7-14 Hz that are generated in the thalamic circuits. Furthermore, mice that were genetically modified so that they lacked the gene for the low-threshold $I_T$calcium current in thalamic relay cells showed a resistance to absence seizures (Kim *et al.*, 2001). This current is responsible for the bursting behavior of thalamic cells and is essential to generate absence seizures.

Just like the thalamus, experimental models have indicted the cortex in the generation of absence seizures. Gloor, Ball and Schaul, (1977) and Steriade and Contreras(1998)observed that there were no SW discharges when high doses of $GABA_A$ antagonists were injected in the thalamus but cortical injection of the same drug did lead to SW patterns. Steriade and Cotreras (1998) went further to show that the threshold for generating absence seizures was much higher in the thalamus compared with the cortex. It has also been observed by Lytton *et al.*, (1997) and Pinault *et al.*, (1998)that during a cortical seizure with SW patterns, a large fraction of the thalamic cells were completely silent.

These experimental models show that the thalamus and cortex are both actively involved in the generation of absence seizures. They also have led to more insights into the basic neuronal mechanisms of absence seizures. However, up to date there is no definite fact about the phenomenon that leads to this type of seizure.

Temporal lobe epilepsy (TLE) is the most common type of focal epilepsy. Mesial or Medial Temporal Lobe Epilepsy, MTLE has its onset in the inner aspect of the temporal lobe, namely the hippocampus or the amygdala. MTLE has a characteristic electrophysiological pattern during the onset of a seizure. Typically, there is a development of spikes with high amplitude and a low frequency. This activity is then succeeded by oscillations of low amplitude and high frequency (low voltage rapid discharges). When intracranial EEG signals are recorded during a pre-surgical evaluation, both types of signals are often observed at seizure onset (Spencer *et al.*, 1992). It is also possible that only the high-frequency oscillations develop at seizure onset(Bartolomei *et al.*, 2004). These high-frequency signals contain maximum frequencies belonging to the γ-band (30-100 Hz) and originate from epileptogenic regions. Experimental and computational studies provided new findings in the neuronal mechanisms that are responsible for these low voltage rapid discharges. First of all, inhibitory interneurons in the hippocamus or neocortex were shown to have close relations with these high-frequency oscillations (Jefferys, Traub and Whittington, 1996; Whittington *et al.*, 2000). Secondly, it was stated that two different kinds of $GABA_A$ responses (slow and fast) played an important role in the generation of γ-rhythms (Wendling *et al.*, 2000; White *et al.*, 2000). Wendling *et al.*, (2000) showed that neuronal population models could explain different rhythms of intracranial (depth) EEG signals.

2.11 Modeling Epilepsy

In modeling physiological systems a key question is: what trade off can be made to simplify the process of model development, while maintaining a certain degree of biological realism relevant to the questions of interest? Two of the most commonly employed criteria of simplification are (a) the type of the model (i.e., deterministic vs. non-deterministic) and (b) the spatial scale of the model (i.e. micro vs. macro) (Stefanescu, Shivakeshavan and Talathi, 2012).

2.11.1 Deterministic Models of epilepsy

Deterministic models for epilepsy are usually presented in the form of ordinary differential equations (ODEs). These models assume that the time evolution of system variables is completely governed by the set of ODEs. In other words, if initial conditions and the system parameters are specified, one can evaluate the state of the system at any time in future. Before a good deterministic model could be formulated the modeler usually goes through the following steps (Shayegh *et al.,* 2011) :

1. Selection of the type of EEG signals, whether scalp EEG or depth EEG
2. Deciding the kind of seizure to be modelled
3. Studying mechanism of seizure generation and the semiology of the associated signals and how to model them. Alternatively, developed physiological model(s) already at hand can also be selected.

Micro-Scale Model

On the micro-scale, modelers are concerned with questions related to the dynamical behavior of individual neurons including pathology in neuronal ion channels, contribution of neuronal morphology (dendritic tree, axonal arborization) and interaction between neurons and its surrounding environments. Many of the epilepsy models that fall under this class adopt the Hodgkin-Huxley framework of conductance-based neuronal modeling (Stefanescu, Shivakeshavan and Talathi, 2012). Network dynamics are inferred from the activity of individual neurons and the interactions between the neurons in the network.

In the Hodgkin and Huxley framework, capacitance $C_m$of a neural membrane, its potential or voltage v and the charge Q stored by the neural membrane are related through $C_m v = Q$. Taking the derivative of this expression with respect to time and assuming a constant $C_m$give $C_m \frac{dv}{dt} = \frac{dQ}{dt} = I$, where I is the current flowing through the neural membrane. In a more general approach the electrical activity of a neuron is described by the cell's membrane potential v which can vary between different part of the cell and with time. The voltage, $v = v(x, t)$ satisfy the current balance equation:

$$C_m \frac{\partial v}{\partial t} = I_{ion}(v) + I_{coupling}$$
$$= \frac{d}{4R_i} \frac{\partial^2 v}{\partial x^2} + I_{app} \qquad 2.0$$

Here $C_m \frac{\partial v}{\partial t}$ is current due to membrane's capacitive property. $I_{ion}(v)$represents the cell's intrinsic ionic currents, $I_{coupling}$ represents the inputs and interaction currents from coupling with other cells while I_{app} is the current supplied by experimentalist's electrode. The term $\frac{d}{4R_i}\frac{\partial^2 v}{\partial x^2}$represents current spread along dendritic or axonal segments due to spatial gradients in voltage ($d$is diameter, R_i is cytoplasmic resistivity). This term may be neglected by considering the case of a "point" neuron, i.e. all the membrane currents and inputs are lumped into a single "compartment" with v independent of x. This can be a good approximation when the cell is electrically compact.

Other micro-scale models focus on the role of neuronal morphology and the contributions of morphology to the increased excitability of epileptic brain networks. For example, in compartmental modeling a neuron is divided into small segments, or compartments, each of which is described by an ODE. This approach represents the highest level of detail for constructing detailed model neurons while preserving complex neuronal morphology. The above approach of conductance-based compartmental modeling can become computationally expensive, especially in simulated networks comprised of thousands of neuronal units.

Macro-Scale Model (Model of Mass Action)

Here attempt is made at modeling the aggregated activity of large populations of neurons. Neural field models and neural mass models are two main categories of mass action model. The first attempt to model the aggregated responses of populations of excitatory and inhibitory neurons was made by Wilson and Cowan, (1972) who demonstrated that many features of aggregated neuronal dynamics such as hysteresis loops and limit cycles can be captured using a pair of nonlinear differential equations, with one equation defining the proportion of excitatory cells that are active and the second defining the number of inhibitory cells that are active. Similar work was done by Lopes da Silva *et al.*, (1974) who derived a lumped parameter model to explain the alpha rhythm of the EEG, and Nunez and A.(1974) who derived the brain wave equation. These studies form the foundation of most models of mass action in the cortex.

Neural Field Models

Neural Field models include spatial components for the purpose of modeling the propagation of neural activity across the cortex. Spatial dependence is accomplished by modeling two, either discrete or continuous spatial dimensions directly in the equations for each neural population (Coombes, 2005). A third discretized depth dimension is sometimes included to model the different layers of cortex (Amari, 1977). Neural field models seem to be a natural choice to study the spread of the pathological oscillations of epilepsy as they travel across the cortex. Primary data on epilepsy is gathered by EEG, in which an array of recording electrodes is placed at spatially distinct locations over the head of the patient. Field potentials of the area of cortex underlying each electrode are recorded. What is measured by the EEG can therefore be thought of as an averaged field potential of all the neurons under each electrode.

However, neural field models are problematic to implement since their assumptions create a large disconnect with physiology. For instance, to make the models analytically tractable potential to firing rate operators are often approximated as a Heaviside function which is not at par with most experimental observations.

Neural Mass Models

Neural mass models are derived from neural field models by disregarding spatial dependence terms and thus turning partial derivatives into ordinary (time) derivatives. Neural mass models utilize a "rate to potential" transfer function, conceptually located at the synapse of an average neuron. This changes the firing rate of the afferent nucleus into a post synaptic potential and is typically modeled by a bi-exponential as in Lopes da Silva *et al.*, (1974) and Marten *et al.*, (2009)or an alpha function as in Wendling *et al.*, (2000). There is a unique transfer function for each receptor type in each neural population. The PSPs are linearly summed and transformed into a firing rate by a "potential to firing rate" operator conceptually located at the soma of the average neuron. The usual choice for this function is a sigmoid, which is more physiologically realistic than the Heaviside function that is often used in neural field formulations. The form of the "potential to rate" and "rate to potential" operators embodies the mean cellular dynamics from synapse to soma.

Epilepsy is suited to analysis using models of this type since it is a dynamical disorder of the brain characterized by hyper-synchronous neural activity across large areas of cortex, thus spatial dependencies can often safely be neglected. Also, the number of nuclei involved in modeling the cortex is relatively small (a population of pyramidal cells whose activity defines the simulated EEG, and either two or three distinct populations of interneurons) so the dimensionality of the system is sufficiently small that numerical and analytical analyses are possible.

General Principle of a Neural Mass Model

Each neural mass has average membrane potential, v. This average membrane potential can be viewed as the state variable of the neural mass. This average membrane potential is the result of the different inputs that this neural mass receives. In neural mass models these inputs represents average pulse densities. These inputs can come from other neural masses in the model or from external inputs. A neural mass itself can also give an output. This output is also an average pulse density. Average membrane potential and average pulse densities are the two main quantities in neural mass models. These two quantities are converted via two transformations: Post Synaptic Potential (PSP) and a potential-to-rate function. Each input to a neural mass is converted from an average pulse density to a potential via a PSP transform. Each of these potentials is multiplied by some constant, modeling the average number of synapses to this population. Then the average membrane potential of a population is formed by summing up all potentials from excitatory inputs and subtracting all inhibitory ones. The potential-to-rate function converts the average membrane potential of a neural mass into the average pulse density that this population puts out.

The PSP transformation is a linear transformation and is modeled using a second order differential equation. This second order differential equation is usually characterized in terms of its impulse response. Originally Lopes da Silva *et al.*, (1974) approximated the impulse response of a real PSP by the following impulse responses:

$$h(t) = Q(e^{-q_1 t} - e^{-q_2 t}) \qquad 2.1$$

where $Q(in\ mV)\ and\ q_1 < q_2\ (both\ in\ Hz)$ are parameters. Van Rotterdam *et al.*, (1982) simplified this approximation by a version that has two parameters, $Q\ and\ q$. This impulse response is given by:

$$h(t) = \begin{cases} Qqte^{-qt}, & t \geq 0 \\ 0, & t < 0 \end{cases} \qquad 2.2$$

The impulse response in equation 2.2 corresponds to a linear transformation that is given by the following system of two first order ODE's:

$$\frac{dx}{dt} = y \qquad 2.3$$

$$\frac{dy}{dt} = Qqz - 2qy - q^2x \qquad 2.4$$

Which combine to form a second order ODE:

$$\frac{d^2x}{dt} + 2q\frac{dx}{dt} + q^2x = Qqz(t) \qquad 2.5$$

where$z(t)$ is the input to the PSP transform and $x(t)$ the output of the PSP transform. The potential-to-rate function converts the average membrane potential of a population, v, into an average pulse density. This average pulse density is the output of the neural mass. The potential-to-rate function is a non-linear function. It's usually taken to be a non-decreasing function that converges to zero as $v \to -\infty$and is bound from above. A common choice is a sigmoid function:

$$S(v) = \frac{2e_o}{1 + e^{r(v_o - v)}} \qquad 2.6$$

where parameter e_o is half of the maximal firing rate of the population, v_o the average membrane potential for which half of the population fires and r, a parameter for the steepness of the sigmoid. With the description of the PSP transform and the potential-to-rate function we have discussed the basic principles that describe the behaviour of a single neural mass. In neural mass models multiple neural masses are coupled to model bigger structures in the brain. Now we proceed to discuss some important neural mass models found in literature.

Lopes da Silva *et al.*, (1974) published an article where models for the α-rhythm in the thalamus are investigated. First, they considered a neural network model that consists of two classes of neurons namely thalamo-cortical relay cells (TCR) and interneurons (IN). Their neural network consists of 144 TCR neurons and 36 IN. With computer simulations they showed that this model is able to produce an α-rhythm. In order to understand the influence of parameters they reduced this model to a neural mass model of a single module. This module consists of two interacting neural population, one models the TCR, the other the IN. The TCR population receives external excitatory input and inhibitory input from IN population. The IN receives only excitatory input from the TCR. A schematic overview of this model is given in Figure 2.1.

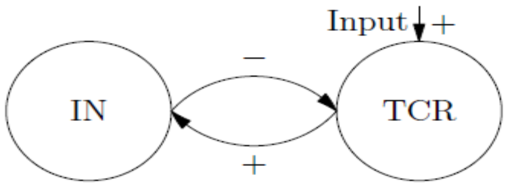

Fig. 2.1: Schematic overview of Lopes da Silva's neural mass model for the thalamus. Arrows marked + represent excitatory connection and those marked - represent inhibitory connection.

In 1993, Jansen, Zouridakis and Brandt developed a model for a cortical column that consists of three neural masses (population): pyramidal neurons, local excitatory and local inhibitory neurons(Jansen, Zouridakis and Brandt, 1993). It was based on the model for the thalamus by Lopes da Silva *et al.*, (1974)and uses the PSP transformation as proposed by van Rotterdam et al. (1982) .

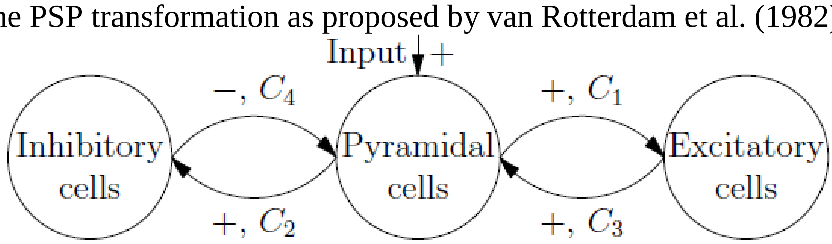

Fig. 2.2: Schematic overview of Jasen&Rit(1995) neural mass model for a cortical column. The constants $C_K, K = 1, 2, 3, 4$ regulate the strength of excitatory and inhibitory connections.

Two years later, Jansen and Rit, (1995) used a slightly different version of this model. In the new model, pyramidal and local excitatory neurons give excitatory input to other populations while local inhibitory neurons give inhibitory input. Local excitatory and inhibitory neurons both receive input from the pyramidal cells with connectivity strength C_1 and C_2 respectively. Pyramidal neurons receive input from both excitatory and inhibitory neurons with connectivity constants C_3 and C_4respectively. Furthermore, pyramidal cells are the only population that receives external excitatory input. This is in contrast with their original model. The external input to a cortical column can consist of output from pyramidal cells of other cortical columns and background activity. The model output that is studied is potential of pyramidal cells, since this is supposed to approximate EEG signals, as pyramidal neurons have by far the biggest influence on EEG signals. See Figure 2.2 for a schematic overview of the model.

Jansen and Rit, (1995) varied some parameters and discovered that their model was able to produce some activity types majorly $\alpha - rhythms$. Wendling *et al.*, (2000) used the Jansen-Rit model with Gaussian white noise input and they observed that at certain parameter value the system oscillates in $\alpha - rhythms$. When the parameter value is increased the model started to create sporadic spikes that become more frequent, till the system was only producing spikes. Grimbert and Faugeras, (2006) investigated the influence of the stationary input I on the Jansen&Rit (1995) model using bifurcation analysis. They used the same parameter values and different range of values of the constant input they observed that the model exhibit stable equilibria, hopf bifurcation occurs at one of these stable equilibria to produce a limit cycle that consequently led to $\alpha - rhythms$ activity and many other interesting dynamics.

Wendling *et al.*, (2000)proposed a modification of the Jansen &Rit (1995) model that is able to produce fast activity that is seen during seizure onset activity in epileptogenic brain regions. Based on experimental findings, they decided to split up the local inhibitory population into a fast and slow population. Therefore this model consists of pyramidal, local excitatory and fast and slow local inhibitory populations, see Figure 2.3. In this model all local population receives excitatory input from the pyramidal cells. The pyramidal cells in their turn receive excitatory input from the local excitatory cells and from outside. Further they receive inhibitory input from the fast and slow local inhibitory cells. In addition the slow inhibitory cells project inhibitory input to the fast inhibitory cells. The parameter q of the PSP transform for the fast inhibitory population is very high ($q = 500Hz$), so the time constant$\frac{1}{q}$ is very small. This is needed to produce the fast activity.

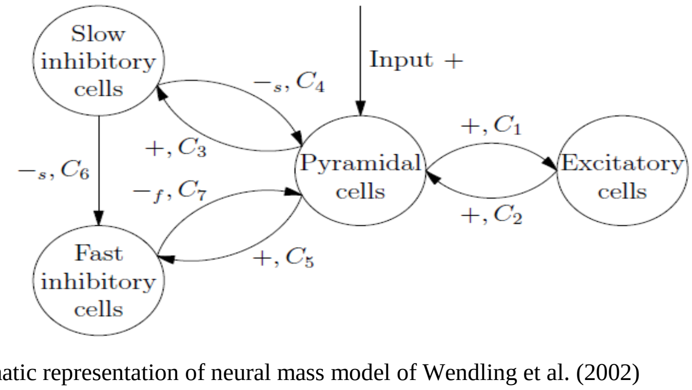

Fig. 2.3: Schematic representation of neural mass model of Wendling et al. (2002)

(Da Silva *et al.*, 2003; Suffczynski *et al.*, 2005)published a research work in which they sought to find the mechanisms responsible for transitions from normal EEG activity to paroxysmal (pathological) Spike wave discharges. They constructed an extended version of the neural mass model of Lopes da Silva (1974) for the study. The new model consist of two modules, namely, cortical and thalamic modules that are mutually interconnected. They also introduced a number of newly discovered physiological facts to enrich the dynamics of the model. They however used data from a genetic animal (rat) model of absence seizure to construct a computational model for their work. This is due to the fact rats' experimental data at cellular and network levels are available in contrast to human data. They concluded that random fluctuations in control parameters and/or dynamical variables can lead to sudden onset of large amplitude paroxysmal activity.

A mix of the Jansen &Rit (1995) and the Wendling*et al.* (2002) models is considered by Goodfellow, Schindler and Baier(2011). A schematic overview of this model is given in Figure 2.4. This model has three populations like the Jansen &Rit (1995) model. However they modeled a fast and slow inhibitory connection from the inhibitory cells to the pyramidal cells instead of only one inhibitory connection. Their target is to model the inhibitory process that, according to them, has a highly variable time course in a better way. The fast inhibitory PSP taken by Goodfellow et al. (2011) uses $q = 200Hz$ which is a lot smaller than in the model of Wendling*et al.* (2002). Goodfellow *et al.* (2011)developed this model to generate SWD activity in a broad region. The model is also capable of producing oscillations with a frequency slightly lower than$15Hz$. These oscillations are comparable with the $\alpha - rhythms$ in the Jansen & Rit model. Furthermore, this model is also able to generate poly SWD (multiple spikes followed by a slow wave) and other complex behaviour.

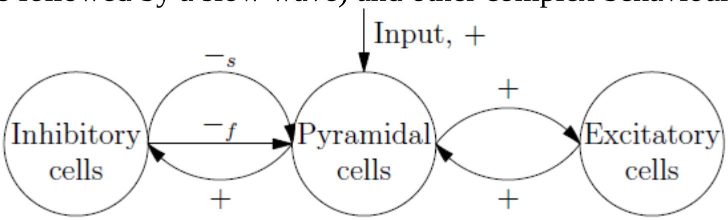

Fig 2.4: Schematic representation of neural mass model of Goodfellow et al. (2011) for the cortical column

It is clear from above reviews that neural mass models developed up to date are based on the classical view of the nervous system which holds that presynaptic and postsynaptic neurons are the two functionally important elements of the synapse while the third cellular components-the glial cell (astrocyte in the central nervous system and shwann cell in the peripheral nervous system) is considered only to provide support to the neurons but not capable of communicating (i.e. exciting or inhibiting) with neurons.Newman, (2003) observed that glial cells can be activated by transmitters from presynaptic cells. The activated glial cell in turn releases gliotransmitters that can directly stimulate the postsynaptic neuron and can feedback to the presynaptic terminal. In 2005, Volterra and Meldolesi studied this glial stimulation and concluded that neuronal excitability and synaptic transmission by astrocytes is mediated by glutamate release while inhibitory effects are mediated by ATP and its derivatives. They also hinted that another form of astrocytic excitation exist that is independent of neuronal input. This is described as spontaneous excitation(Volterra and Meldolesi, 2005).

2.11.2 Model Parameter Estimation

In order to make reasonable hypotheses for clinical studies based on the results of experiments run on computational models, one has to be confident that the structure of the model reflects the neural architecture and that the parameters of the model are within biophysically plausible ranges. This can be relatively easy when a parameter is clearly defined. It is much harder when the parameters are not directly measurable. This is generally the case with the parameters of mass-action models since a parameter such as connection strength between two neural populations" is the aggregated activity of millions of synapses spread across thousands of neurons. One approach is to vary the parameters to fit the model's behavior to clinically obtained data, such as the EEG of epileptic patients. However, this is a nontrivial task due to the nonlinear nature of the system. In all but the simplest cases, the error function is unknown and so traditional methods such as gradient descent are unavailable; Random walks and exhaustive search methods are unusable due to the extremely high dimensionality of the parameter-space. A usual method has been to adopt a two-pronged approach. Firstly, estimate and fix parameters that have a physiological interpretation and second, to use some method to search the system's parameter space to find regions where model behaviour is qualitatively similar to real EEGs. This was the approach taken in the previously cited models of Lopez da Silva (1974), Jansen and Rit (1995), and Wendling*et al.* (2000). Parameters found to give rise to the behaviour of interest were inherited by the future studies since this is an obvious way to reduce dimensionality.

In mathematical modeling what is often required is some measure of our belief in a particular set of parameters given the available data. This makes Bayesian inference an ideal tool for the purpose since this naturally arises from the Bayesian framework. Rather than extracting parameter values directly from data as is the case in frequentist estimation methods, the Bayesian approach yields a subjective belief in different parameter values. Bayesian inference therefore yields distributions of possible parameter values rather than one best parameter set. This is of particular use in neural modeling because the spread of posterior distribution could be regarded as a measure of the robustness of the model to small perturbations in each parameter.

Approximate Bayesian computation methods address many of the identified inefficiencies in the Bayesian framework for parameter estimation either by using conditional density estimation, Markov-chain Monte-Carlo sampling or a sequential Monte-Carlo method. To the best of our knowledge, ABC has not been used to date in neural modeling.

2.11.3 Bifurcation analysis

When the number of parameters which are allowed to vary is as low as three, it is natural to attempt to explore the model's behavior at all parts of the parameter space. Wendling*et al* (2002) did this by qualitatively classifying the model's behavior at every discrete location in the parameter space. Although the approach led to simulated EEG signal similar to those clinically recorded it lacks rigor owing to the fact that the system is unknown and non-linear in nature, interesting dynamics can occur in very small regions. These regions may be missed out by discretizing the parameter space.

A more thorough approach known as bifurcation analysis provides far more thorough exploration of parameter space. If the dimensionality of the parameter space to be explored can be reduced to two or three, bifurcation theory allows for the model behaviour to be completely described within this space without having to run simulations at infinitely small parameter gradations. Beginning from an equilibrium state, a single parameter is smoothly changed until the conditions are detected that indicate a Hopf bifurcation has taken place. The Hopf bifurcation itself can then be tracked through the two dimensional parameter space yielding a line through the space which divides the region of parameter space for which the model gives a steady state solution from the region which gives rise to oscillating solutions.

2.12 Non Deterministic Models

There are yet another category of models for epilepsy that fall under the umbrella of non-deterministic models. These models are based on the assumption that the observed brain dynamics is the result of a non-deterministic, high-dimensional dynamical system. Two broad categories of non-deterministic models have found applications in epilepsy. Statistical models, wherein the focus has been on identifying statistical patterns in brain signals to guide the development of seizure prediction and detection algorithms and stochastic models, wherein the focus has been on the development of probabilistic models that can capture the apparent random transition of brain into and out of an epileptic seizure state.

Statistical models attempt to extract information embedded in brain recordings in order to develop predictors for seizure occurrence. These statistical models employ linear and nonlinear time series measures to identify patterns in the recorded brain signals indicative of an impending epileptic seizure. Furthermore, tools from statistical learning theory such as support vector machines (Shoeb *et al.*, 2009), artificial neural networks (Firpi *et al.*, 2007) have been employed to enhance the efficacy of seizure prediction algorithms. Statistical learning explores the study and construction of algorithms that can learn from and make predictions on data. Such algorithms operate by building a model from example inputs in order to make data-driven predictions or decisions. A core objective of a learner is to generalize from its experience. Generalization in this context is the ability of a learning algorithm to perform accurately on new, unseen examples/tasks after having experienced a learning data set. The training examples come from some generally unknown probability distribution (considered representative of the space of occurrences) and the learner has to build a general model about this space that enables it to produce sufficiently accurate predictions in new cases.

The Support Vector Machine is a binary classification and regression technique. The algorithm aims to find the best hyperplane to discriminate two classes of data. SVMs are robust: they try to maximize the margin between the classes while minimizing error. An artificial neural network is an adaptive mathematical model or a computational structure that is designed to simulate a system of biological neurons to transfer information from its input to output in a desired way. Many variants of ANNs exist with each suited for different types of modeling task. The multilayer perceptron (MLP) has been used extensively in many modeling task due to its versatility and straightforward applications.

A relatively recent modeling approach is fuzzy modeling. In fuzzy modeling the evaluation of the output is performed by a computing framework called the fuzzy inference system. The fuzzy inference system maps fuzzy or crisp inputs to the output which is usually a fuzzy set. The inference system performs a composition of the inputs using fuzzy set theory, fuzzy if-then rules and fuzzy reasoning to arrive at the output. There are two popular fuzzy models: the Mamdani model and the Takagi-Sugeno (TS) model.

2.12.1 Neuro-Fuzzy Modeling

In recent years, the integration of neural networks and fuzzy logic has given birth to new research into neuro-fuzzy systems. Neuro-fuzzy systems have the potential to capture the benefits of both fields in a single framework. Neuro-fuzzy systems eliminate the basic problem in fuzzy system design (obtaining a set of fuzzy if–then rules) by effectively using the learning capability of an ANN for automatic fuzzy if–then rule generation and parameter optimization. As a result, those systems can utilize linguistic information from the human expert as well as measured data during modelling. Such applications have been developed for signal processing, automatic control, information retrieval, database management, computer vision and data classification (Güler and Übeyli, 2004, 2005; Sumer *et al.*, 2011).

2.12.2 EEG Signals: Pre-processing and Analysis

The Recorded brain signals (EEG) not only contain the background signal being sought but also unwanted signals called artefact causing the distortion of the desired information. The removal of the artefact is referred to as pre-processing step. Two commonly used mathematical methods used in removing artefacts are filtering and independent component analysis. In the next step premonitory changes in the recordings are tracked through feature extraction. Feature extraction involves linear or nonlinear analysis of the signals.

2.12.3 Linear Method of EEG Analysis

In linear method of EEG signal analysis it is assumed that underlying individual processes (i.e subsystems) combine linearly to generate the signal with superimposed observation noise. In other words EEG time series is viewed as a realization of a noise-driven linear process. Furthermore, EEG signals are recorded for a specified period of time and so they are a finite-length discrete-time signal of length N(number of samples in the signal). This means the signal is just a collection of N real or complex values and the signal can be seen as a vector that lives in $\mathbb{R}^N$or $\mathbb{C}^N$. This equivalence is of immense importance since all tools of linear algebra become readily available for describing and manipulating EEG signals. *Linear transform*which is also known as *change of basis* is an important tool in linear analysis that can reveal certain hidden information in the EEG signal. Popular linear transforms in use are Fourier, Gabor and wavelets transforms.

2.12.4 Nonlinear Method of EEG Analysis

Here the assumption is that EEG time series is a realization of nonlinear but deterministic processes. An emerging mathematical concept in this area is chaos. We can think of chaos as the dynamical state of a nonlinear deterministic system that looks stochastic (i.e. future states of the system can be determined only probabilistically even though we know the initial conditions and the equations governing the evolution of the system). Chaos theory is being tipped as an explanation for a variety of complex processes in nature because chaotic systems, among other characteristics, can produce what appears to be random output such as seen in the EEG time series. These systems may also exhibit abrupt intermittent transitions between highly ordered and disordered states, a property making it possible to view epilepsy as an example of chaos. Mathematical techniques developed to study properties of non linear dynamical system rely on a phase space portrait of the system. Unfortunately, real-world dynamical systems are generally too complex for us to see directly. There is however, a method ‘phase space reconstruction’ that can be used to indirectly detect attractors in real-world dynamical systems using time series data on a single variable.

3.0 GENERAL METHODOLOGY

3.1 Data and Pre-processing

In other to develop and evaluate the non-deterministic model on EEG data of epileptic patients, filters must be applied to the data to clean some artefacts: a 0.5Hz cut-off high-pass filter to remove dc component of the EEG signal, a 49-51Hz band reject filter to remove power line noise and a low-pass filter whose cut off frequency will depend on the sampling rate of the analogue to digital converter used on the EEG signal.

3.2 Feature Computation

To study the temporal evolution of activities, EEG time series is divided in non-overlapping temporal windows of length L and for each interval i ($i = 1, \dots., N, with\ N = M/L$ and M is the length of the whole time series to be analyzed) a sample of each feature or measure considered is derived and the results normalized by scaling to zero mean and unit variance.

3.3 Feature Selection

A potential feature for seizure prediction must present long-term fluctuations before seizures (Feldwisch-Drentrup *et al.*, 2011). Some features extracted may not possess this characteristic and so need to be discarded. A feature ranking method proposed by Feldswitch et al. (2011) is adopted. The method computes the ratio between the global and local variances. For a given feature f_k, its variance ratio is given by

$$S_k = 2\frac{\sigma^2_{k,global}}{\sigma^2_{k,local}} \quad 3.1$$

where$\sigma^2_{k,global}$ is the global variance of the length N sequence f_k, defined by

$$\sigma^2_{k,global} = \frac{1}{N-1}\sum_{i=1}^{N}\left(f_k^i - \bar{f}_k\right)^2 \quad 3.2$$

$\sigma^2_{k,local}$ is the local variance, i.e., the variance of the first order difference of f_k and is described by:

$$\sigma^2_{k,local} = \frac{1}{N-2}\sum_{i=1}^{N-1}\left(\Delta f_k^i - \overline{\Delta f_k}\right)^2 \quad 3.3$$

withΔf_k^i given by:

$$\Delta f_k^i = f_k^{i+1} - f_k^i$$

3.4

The long-term fluctuations means a high value of S_k. Based on the values of S for all features, one then sort features in descending order to select features at the top.

3.4 Feature Vector Design

The goal here is to find a rule $f(\chi)$ that classifies a feature vector χ derived from EEG time series unto the class $\Upsilon = \begin{cases} 0, & \chi\ is\ non\ seizure\ activity \\ 1, & \chi\ is\ seizure\ activity \end{cases}$. The components of χ are samples of selected features. As an example K univariate time domain feature computed for N non overlapping windows of a pre-processed EEG time series are shown below.

$$\begin{matrix} \chi_1 & \chi_2 & & \chi_N \\ \begin{bmatrix} feature\ 1 \\ feature\ 2 \\ \vdots \\ feature\ K \end{bmatrix} & \begin{bmatrix} feature\ 1 \\ feature\ 2 \\ \vdots \\ feature\ K \end{bmatrix} & \dots\dots\dots\dots\dots\dots.. & \begin{bmatrix} feature\ 1 \\ feature\ 2 \\ \vdots \\ feature\ K \end{bmatrix} \end{matrix}$$

We can think of χ_1, χ_2..........χ_N as points in a K dimensional space. We hypothesize that these vectors should capture the dynamics of the epileptic brain system so that vectors belonging to interictal and preictal states are confined to separate regions in the K dimensional space. We can then draw a decision boundary [i.e. $f(\chi)$] that gives optimum separation between the vectors.

3.5 Training and Testing Datasets

Next,non seizure and seizure feature vectors are divided into two sets, these are the training and testing data sets. The training data set will be used to train the classifier (i.e. make it learn) while the testing data set will be used to test how well the classifier can classify new samples. In addition to the input feature vector, a target output is needed for the training of the classifier. The target output is a time series that discriminates the cerebral state for each input sample.

3.6 Dimensionality Reduction

The separation in space of seizure and non seizure feature vectors might be improved by discarding correlated vector components while retaining the uncorrelated ones. We will further apply principal components analysis which is a mathematical toolused to reduce the dimensionality of data while retaining as much as possible the variation present in the original dataset to our feature vectors.

$$x = \begin{bmatrix} a_1 \\ a_2 \\ \dots \\ a_N \end{bmatrix} \text{- - ->}\ reduce\ dimensionality -> y = \begin{bmatrix} b_1 \\ b_2 \\ \dots \\ b_K \end{bmatrix} (K << N)$$

3.7 Classifier Design

The classifier to be used may be the Adaptive Neuro-Fuzzy Inference System. This classifier combines learning capability from artificial neural network and human-like reasoning ability of fuzzy logic in its Classification. The training dataset is used in designing and testing dataset in the testing our classifier.

3.8 Classifier Evaluation

The performance of the classifier can be assessed by descriptors related to the classification performance on the testing data set, i.e., related with the sample-by-sample classification. The classification descriptors for sample by-sample classification are: sensitivity (SS), specificity (SP) and accuracy (AC), defined as:

$$SS = \frac{TP}{TP + FN} \qquad 3.5$$

$$SP = \frac{TN}{TP+FP} \quad 3.6$$

$$AC = \frac{TN+TP}{TN+FN+TP+FP} \quad 3.7$$

where TP and FP are the numbers of correctly (true positives) and incorrectly (false positives) classified seizure samples, respectively. TN and FN are the numbers of correctly and incorrectly classified non seizure samples, respectively. Sensitivity measures the proportion of the true classified seizure samples, while specificity quantifies the proportion of correctly classified non seizure samples. Accuracy accounts for the proportion of correctly classified samples on all classes.

In addition to the above mentioned predictor performance measures, one may also evaluate the predictors by calculating error measures. The error measures often considered are the following:

1. The root mean square error (RMSE): RMSE is a good measure of prediction accuracy. It is frequently used to measure the differences between values predicted by a model and the values actually observed (i.e. the target in the classification problem). These individual differences are referred to as residuals. RMSE is given by:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{N}\left(y_j - \hat{y}_j\right)^2}{N}} \quad 3.8$$

   wherey_j is the target and $\hat{y}_j$ is the predicted values and N is the number of samples.

2. The Mean Absolute Error (MAE): this is obtained by:

$$MAE = \frac{\left|y_j - \hat{y}_j\right|}{N} \quad 3.9$$

The smaller the MAE the better the model fit.

4.0 Epileptic Seizure Prediction

Regardless of the model used in describing the dynamical changes in complex brain signals leading to epileptic seizure prediction, the following are important issues in the narrative.

4.1 Epileptive seizure can be characterized by three distinct stages

There are three stages in the seizure process: preictal, interictal and postictal.In temporal lobe epilepsy, the dynamical properties of the preictal, ictal, and postictal states are distinctly different and can be defined quantitatively. This result was derived by analyzing EEG recordings from subdural and depth electrodes. As an example, Kreuz *et al.*, (2004) demonstrated that the maximum Lyapunov exponent over time profiles for one seizure in one patient and confirmed in other patients, is that the chaoticity of the signal (reflected by the value of L_{max}) was highest during the postictal state, lowest during the seizure discharge, and intermediate in the preictal state. Also, in all of the cases studied, the characteristic drop in the value of the L_{max} exponent at the time of the seizure's onset occurred first at electrode sites located where the seizure discharge originated. Thus, from a dynamical perspective, the onset of a seizure represents a spatiotemporal transition from a complex to a less complex (more ordered) state. It is likely that the more ordered ictal EEG signal reflects the synchronized rhythmic firing pattern of neurons participating in the seizure discharge(Mormann *et al.*, 2003; Kreuz *et al.*, 2004)

Earlier, Iasemidis and Sackellares, (1996) had identified the practical relevance of the above changes in the dynamical behavior of the ictal states. They observed that the signals from epileptogenic regions have different dynamics from nonepileptogenic regions, even during the interictal state, may be of more immediate practical utility for localization of seizure foci. Currently, clinicians rely primarily on ictal readings for diagnostic evaluation and for presurgical localization of the seizure onset zone. The sampling of a sufficient number of seizures requires recordings over many days. If the seizure focus can be identified through its interictal dynamical properties, however, the diagnostic and presurgical recording time may be reduced dramatically and the epileptogenic focus may be localized more reliably.
In addition, identifying preictal changes would also allow treatment intervention such as administration of a short-acting anticonvulsant drug (Akinbi and Welty, 1999), electrical stimulation (Schiff *et al.*, 1994), or cognitive intervention with neurophysiological or behavioural countermeasures(Kreuz*et al.*, 2004).

4.2 Comparative efficiency of scalp and intercranial EEG in predicting onset of seizure

Firsly, is there a difference between the use of scalp and intercranial EEG in making epileptic seizure predictions? This might be important in some hospital settings where facilities and medical personnel might be limited to scalp EEG. To make seizure anticipation practical in real life conditions, and to study types of epilepsy that do not warrant intracranial implantation, Le Van Quyen *et al.*, (2001)analysed scalp-electroencephalographical (EEG) recordings. Since scalp EEG is well known to be subject to signal attenuation, poor spatial resolution, and noise or artifacts(Quesney, 1993), which may render delicate(Schreiber and Kantz, 1996) and even questionable(Theiler and Rapp, 1996)the detection of changes with current non-linear measures, originally designed to analyse systems with little noise. This non-linear strategy to analyse scalp-EEG recordings from patients with TLE to assess whether changes in brain dynamics can be detected early enough to anticipate the onset of the clinical seizure. In a subgroup of patients, they validated the results on simultaneous surface and intracranial recordings. To improve non-linear analysis they have proposed a strategy well suited to track dynamical changes in complex brain signals(Le Van Quyen *et al.*, 1999, 2000), which measures similarity of EEG dynamics between recordings taken at distant moments in time. This relative measure indicates changes in brain electrical activity with greater accuracy than other non-linear techniques(Manuca and Savit, 1996; Schreiber and Schmitz, 2000). Furthermore, it has the advantage of being very robust against noise and artifacts, and is fast enough to be carried out in real-time. Results indicate that preseizure changes in brain dynamics can be detected from recordings of scalp-EEG activity. These changes were characterised with a reference state taken 1 h before the ictus, and were detected several minutes before the earliest clinical or overt EEG manifestations of the seizure.

The finding that the changes in scalp electrical activity were similar to those detected from intracranial recordings is surprising, given that the scalp EEG is an attenuated and blurred vision of direct intracranial recording because of the distance between the brain and scalp, with the skull as an interposing medium. However, the relations between activity recorded with intracranial and extracranial electrodes is more complex than a simple decrease in the signal-to-noise ratio because of cortical convolutions, anatomical anisotropies, and the orientation, shape, and extension of the underlying generators(Alarcon *et al.*, 1994). Also, potentials produced by neocortical changes and recorded from scalp electrodes might also be driven by events in deeper cerebral structures. For instance, changes in the hippocampal activity could cause secondary activation of several neocortical areas, producing synchronised local field potentials. They concluded that scalp recordings retain sufficient information for use as a preictal marker.

4.3 How sensitive are seizure parameters to the theretical methodology used?

Table 4.1 presents a summary of selected studieson predictive seizure onset using dynamic system modelingon EEG data.In several of the works cited,critical issues of robustness, selectivity, sensitivity and accuracy were addressed. An important seizure parameter is the predictive onset times as the predicted times afford the opportunity for control and therapeutic intervention. These predictive times were found to vary substantially from the order of a few seconds to several hours. The question is:what is responsible for this large variations? Mormann *et al.*, (2007) offered a realistic reason for this variation. In their work, they found that the duration of these times is mosly of the order of 1 h or more just a few minutes which stands in contrast to earlier studies (Adam *et al.*, 1998; Elger and Lehnertz, 1998; Lehnertz and Elger, 1998; Le Van Quyen *et al.*, 1999, 2000; Le Van Quyen, Martinerie, Navarro, Boon, *et al.*, 2001; Navarro *et al.*, 2002) where mean anticipation times from 1 to 2 min were described. The different range of anticipation times implies that changes in dynamics tracked by synchronization measures used by Mormann *et al.*, (2007)are different from those tracked by other nonlinear measures. In two recent studies (Iasemidis *et al.*, 2001; Litt *et al.*, 2001) similar anticipation times have been reported as found in their study. Whether these findings reflect the same dynamical aspects, remains to be investigated. Nevertheless, anticipation times as found by Mormann*et al.* (2007) would provide enough time for possible strategies to prevent the occurrence of a seizure or other intervention strategies.

Table 4.1 Summary of selected studies on predictive seizure onset using dynamical systems modeling

Reference	Method	Model	Result	Remarks
Casdagli *et al.*(1996)	IEEG recordings on 8 patients with TLE	Surrogate data technique, wavelet analysiswith nonlinear prediction algorithm.	Nonlinearities in invasive EEG recordings were exhibiteda few seconds in advance ofcharacteristics.	Clear evidence for precursors to seizure onset was found in only one of the eight patients studied.
Litt et al. (2001)	Continuous 3- to 14-day IEEG recordings were analysed on5 patients with MTLE	Data processed through a combination of MATLAB programs and custom-written C11 code.	Complex epileptiform discharges became more prevalent 7 h before seizures and highly localized subclinical seizure-like activity became more fre-quent 2 h prior to seizure onset.	Epileptic seizures may begin as a cascade of electrophysiological events that evolve over hours.
Quyen*et al*. (2001)	26 scalp-EEG/video recordings, from 60 min before a seizure, in 23 patients with TLE. For 5 patients, simultaneous scalp and intracranial EEG	Non-linear similarity was used, shown to be very robust in spite of large artifacts and runs in real-time.	Long-term changes before seizure onset were observed several minutes before it occurred (mean 7 min).	Scalp EEG recordings retain sufficient dynamical information usable for the analysis of preictal changes leading to seizures.

	recordings were assessed.			
Iasemidis*et al*. (2004)	4 epileptic patients with TLE were subjected to long-term EEG (3.6 to 12 days) continuous recordings	The theory of nonlinear dynamics and global optimization.	Brain areas before seizures disentrain faster and more frequently ($p<$ 0.05) at epileptic seizures than any other periods.	Better understanding of the mechanisms of epileptogenesis, seizure intervention and control.
Kreuz*et al*. (2004)	Quasicontinuous multichannel EEG was recorded from an epilepsy patient over 5 days during which the patient had 10 epileptic seizures recordings.	The seizure prediction algorithm is applied to the original measure profile and their surrogates generated through constrained randomization using simulated annealing.	Existence of a preictal state is detectable from method of measure profile surrogates.	Method of measure surrogates offers serious statistical validation of dynamical systems methodology.
(Saab and Gotman, 2005)	652 h of scalp EEG, including 126 seizures in 28 patients (360 h of scalp EEG, including 69 seizures in 16 patients)	Wavelet decompositionand Bayesian formulation.	High performance established for system parameters: sensitivity of 77.9%, a false detection rate of 0.86/h and a median detection delay of 9.8 s.	A seizure detection system was proposed that can alert medical staff to the onset of a seizure.
Grewal and Gotman.(2005)	407 h of EEG from 19 patients having 152 seizures. The testing data (19 patients, 389 h, 100 seizures, independent of the training data)	Bayesianformulation and spatio-temporal analysis.	The performance: sensitivity of 89.4%, a false detection rate of 0.22/h, and median delay time of 17.1 s when tuning was used, and 86%, 0.47/h and 16.2 s without tuning.	The system offers a performance that is acceptable for clinical use. User tuneability allows for reduction in false detection with minimal loss to sensitivity.
Subasi, (2007)	The EEG data was recorded from both epileptic	An adaptive neuro-fuzzy inference system (ANFIS) model: a	The accuracy of this model was94% for normal and	An adaptive neuro-fuzzy approach is feasible for

	patients and normal subjects. Twenty absence seizures from 5 epileptic patients admitted for video-EEG monitoring.	combination of the neural network adaptive capabilities and the fuzzy logic qualitative approach.AlsoWavelet transform.	epileptic patientssubjects with statistical analysis for specificity and sensitivity parameters.	epileptic seizure detection in EEG.

4.4 Is the reliability of the epileptogenic predictions guaranteed using the nonlinear dynamical models?

Kreuz *et al.*(2004) raised the issue of the statistical validity of the performance of a seizure prediction algorithm. In a study on the predictability of epileptic seizures, a certain characterizing measure is calculated from EEG recordigs. The resulting measure profiles were then scanned for prominent features which can be related to the actual seizure times. The measures' capability to distinguish the preictal from the interictal interval was evaluated with a test statistics quantifying the occurrence of these features relative to the seizure times and resulting in some kind of performance value. If this performance is high, it might on the one hand reflect the existence of a pre-ictal state and the capability of the applied measure to detect it, but it might on the other hand also be due to statistical fluctuations or some (unknown) bias in the algorithm(Kreuz *et al.*, 2004). The authors then issued an indictment on "many (spurious) claims about the existence of a preictal state might just be due to some 'best parameter', 'best measure', 'best channel', and/or 'best patient' selection." They then suggested that the measure profile surrogates is suited to serve the need for statistical validation of seizure prediction results. The result should be verified against some null hypothesis and its level of significance should be estimated. This can be achieved using the concept of surrogates(Theiler *et al.*, 1992; Schreiber and Schmitz, 2000) in which the validity of a given test result is evaluated by applying the test not only to the original data but also to an ensemble of surrogate data generated by means of a Monte Carlo randomization. The null hypothesis $H_0$was stated as follows: The measure under investigation is not suited for seizure prediction. If this null hypothesis is fulfilled, it might be due to two different reasons. Either a pre-ictal state does not exist (and thus there is no measure suited for seizure prediction) or a preictal state does exist, but the measure is not able to detect it. On the other hand, the null hypothesis can only be rejected if both inverse conditions are fulfilled. They then went to suggest that many studies on seizure prediction suffer from a severe lack of statistical validation.

A more serious indictment of previous studies on seizure prediction was presented by Mormann *et al.*(2007) in a review article that considered 43 articleson apeleptic prediction (from 1998 to 2006).Only four were statistically validated even though 13 carried out statiatical analysis of the EEG. In contradiction of popular opinion on seizure prediction, they opined that non-linear measures were not found to exhibit a higher predictive performance than linear measures. In addition, they indicted earlier optimistic findings contained by applying highly optimized algorithms to small, selected data sets could not be reproduced on unselected, more extended EEG recordings that are more closely related to real-life challenge of predicting seizures prospectively from the continuous EEG.

Several of the results indicated in Table 4.1 used statistical analysis different from that suggested above and they clearly detected the preictal state although thepredicted onset times vary widely. The fact that dynamical system modeling of EEG recordings clearly indicated the preictal state would suggest that this state exist and is predictable. The prediction of the onset times may depend on the theoretical metholodogy used as already discussed in section 4.2.

5.0 CONCLUSION

In this review, we have presented a comprehensive appraisal of the dynamical systems modeling of epileptic seizure prediction: the deterministic and nondeterministic methodologies. The popularly held view is that nonlinear dynamics is superior to linear models in detecting the main features of the ictal state. The main characteristics of this discussion are: the three ictal states (preictal, ictal and postictal states); the comparability and efficacy of seizure predictions from scalp and intracranial EEG recordings and the dependence of the predictive onset times on the theoretical model used. A much more serious issue is the sceptism surrounding the validity of the dynamical models for epileptic prediction. It was even pointed out that the performance of the nonlinear models could not said to be better than linear models. Before this sceptism, it was generally held that nonlinear dynamical models are far superior to linear models. It does throw the epileptic seizure prediction debate into a crisis. In spite of thissceptism, there is little doubt that epileptic prediction, using, especially, dynamical systems modeling, has elucidated tremendously the ictal process and so facilitated the path towards epileptic control strategies. The sceptism about the predictability of dynamical systems modeling will only galvanize improvement in epilepsy data gathering (long-term). There is little doubt about the usefulness of the results of these models which has as its ultimate purpose the understanding of epileptogenesis. Since an important parameter in seizure prediction is the preictal state, it is quite worrisome that its anticipation time seem to be dependent on the methodology used, a useful future imperative is to determine the reason for this anomaly.

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AN INTERVENTIONAL STRATEGY FOR ADDRESSING THE SOCIAL DEVELOPMENT AND REPRODUCTIVE HEALTH NEEDS OF THE YOUTH IN NIGERIA; LESSONS LEARNT

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ABSTRACT

The youth constitute a critical age group especially in a populous nation like Nigeria. Therefore, a lot more needs to be done to address the needs (social development and reproductive health) of the youth. The Nigerian Academy of Science set up a project to address the needs of youth by working with the youth and various stakeholders, including two state governments, to identify and develop evidence-based policy to respond to the needs. The needs assessment involved data collection from the youth and other stakeholders and the collective review of the findings. Consequently, strategic plans were developed for each state. Diverse strategies were employed which promoted partnership among the stakeholders and led to ownership of the policy documents (strategic plans) developed.

Keywords: Youth, policy, evidence-based policymaking, intervention, strategy, Nigeria.

INTRODUCTION

The youth are a much talked about group though the definition of youth is often varied depending on diverse factors including social, economic, and cultural factors, among others. According to the United Nations Department of Economic and Social Affairs, youth being a period of transition from the dependence of childhood to the independence of adulthood, explains the fluidity of that category compared to other age-groups (UNDESA, 2014). United Nations entities and regional organizations have somewhat different definitions but all put youth as those somewhere between the ages of 15 and 35 years. The World Health Organization defines youth as being between 10 and 24 years (UNDESA, 2014).

Globally, young people (aged 10 to 24 years) are about 1.8 billion, and more than 90% of them live in less developed countries (UNFPA, 2014). Africa is the most youthful continent with more than a third of the population being between 10 and 24 years while Nigeria is the most populous nation in Africa (UNFPA and PRB, 2012; NPC and ICF, 2013). In Nigeria, the youth are estimated to be 80 million, representing 60% of the population. (Okafor EE, 2014).

Youth comprises a critical period of vulnerability due to the physiological and sociological changes taking place. Not only so, but the youth form a critical mass in the population structure of the society. They form a significant part of the workforce required for national development apart from constituting a significant fraction of the general population itself. It is now thought that sustainable national socio-economic development is only achievable with youth development (UNFPA, 2014).

However, the youth today are in a world that is far more complex than what it used to be and, consequently, are challenged in ways only imagined decades ago (Fatusi and Hindin, 2010). Globalization, technological advancements, political changes, migration, and economic challenges all pose serious challenges to the development of the youth, especially in developing countries. To measure up and be able to meet the productivity demands of the current age will take deliberate and concerted effort by the youth themselves and their governments.

The issues affecting the youth in Nigeria, and indeed globally, are many and relate to all aspects of life, be it developmental, economic, sociological, etc. They also include reproductive health challenges such as early sexual initiation, early marriage and unsafe sexual practices, among others, with the consequences of increasing rate of unwanted pregnancies, unsafe abortions, and sexually transmitted infections (STIs), including HIV and AIDS (Denno, Hoopes, and Chandra-Mouli, 2015; Bernat and Resnick, 2006). When the social development needs of the youth are not met, it is revealed in unemployment, restiveness, high crime rate, low literacy, lack of access to health care and non-involvement in decision making on national issues.

To respond to the challenges of young people’s health and development, the governments in Nigeria (at federal and state levels) have drafted various policies and also set up ministries of youth to serve as focal ministries to adequately address the challenges facing the youth. The Child Rights Act has also been passed in at least 23 states of the federation. Despite these laudable acts, there seems to be a lack of a systematic and collaborative approach to dealing with the issues of the youth.

It has been suggested that, in order to effectively address the problems of the youth, strategies that promote collaboration among various partners should be utilized (Barton, Watkins, and Jarjoura, 1997). All stakeholders have to partner to develop the necessary policies as well implement them.

However, making effective policies in Nigeria is problematic for many reasons. There is a critical gap of translating research evidence into appropriate policies. Oftentimes, policies have been enacted without an adequate evidence-base leading to ineffective policies that fail to be implemented and, indeed, cannot be implemented. Policymakers have to develop a culture of evidence-based policymaking. Also, policies are developed without input from critical stakeholders. Many previous efforts at effective policymaking in Nigeria have focused more on developing the capacity of the policymakers to appreciate evidence and the use of same for policymaking and not particularly on strategies that promote collaboration among key stakeholders towards the development of policies (Uneke, Ezeoka, and Ndukwe, 2011; Uneke, Aulakh, Ndukwe, and Onwe, 2012).

The Nigerian Academy of Science (NAS) had also explored ways of influencing evidence-based health policies by enhancing the capacity of policymakers to use evidence (Hawkes et al. 2015). For the current effort at addressing youth development, the evidence to policy gap is bridged by working with the youth and key stakeholders in two states in Nigeria to develop strategic plans of action. The aim of the project was to help two state governments come to a realization of the challenges facing the youth in their localities, think through what needs to be done, and work with the stakeholders in their states to address the social wellbeing and reproductive health of the youth.

This paper summarises the strategy used for the development of appropriate policies (strategic plans) to address the social reproductive health of the youth in two Nigerian states with a focus to highlight lessons learnt.

Goal and Objectives of Project

The goal of the intervention project was to mainstream the promotion of life skills, livelihood, and social development of youth into the broader development agenda at all levels in Nigeria.

The specific objectives of the project were as follows:

1) To build partnerships and collaboration for understanding the social development and reproductive health needs of youth aged 10-24 years in Nassarawa and Ekiti States of Nigeria;
2) To develop a strategic plan of action for improving the social development and reproductive health of the youth in partnership with policymakers and official gatekeepers in the two states using the results of the needs assessment; and
3) To mobilize top level political leadership and relevant multi-stakeholders in both states to accept the plan and to commit resources to implementing it and sustaining it over time.

Strategies for implementing the project

Intervention Sites

The states were purposively selected based on their reputation for purpose-driven governance as well as the relative ease of access to their governments at the highest level, given the clout of the members of the Nigerian Academy of Science within the states.

Ekiti State is located in the south-western geo-political zone of Nigeria. The 2006 national census (the last one conducted till date) put the population of the state at 2,384,212. On the other hand, Nasarawa State is located in the north-central geo-political zone of Nigeria. The state is bordered on the west by the Federal Capital Territory (FCT), Abuja. According to the 2006 population figures, the population of the state is 1,863,275.

The project was carried out in two main phases in both states. The first phase was a needs assessment study with the objective of determining the needs of the youth in the states, present the report to the relevant stakeholders, and obtain their commitment to address the needs by committing to a process of drafting appropriate strategic plans.

The second phase was the inclusive development of state-specific strategic plans that address the needs identified (in phase one above) and adoption of the same by the states. It was important that the strategy used to develop the strategic plans encouraged collaborative partnership among the stakeholders to achieve ownership of the plans developed.

Conducting a Needs Assessment Study

There were advocacy visits to the executive council and legislature of each state at the start of the project. The visits were led by the President of the Nigerian Academy of Science to secure the consent of the highest political leaders in the states. Then, field study teams were competitively selected to conduct needs assessment studies using various data collection tools including questionnaires, observational checklists, as well as focus group discussion and interview guidelines. The studies were conducted between October and December 2013.

Subsequently, a meeting of key stakeholders (including the youth) was held where the findings of the needs assessment study were presented and discussed before the report of the study was finalised for publishing.

Ethical approval for the needs assessment study was received from the Nasarawa State Ministry of Health. With the approval of the Ekiti State government, ethical clearance for the study was received from the Oyo State Ministry of Health Ethics Review Committee (as Ekiti State had no approved Ethics Review Committee at the time).

Development of Strategic Plans

At the meetings to discuss the findings of the needs assessment studies, the stakeholders constituted two multi-stakeholder committees towards the drafting of strategic plans for their states. The Political Committee, consisting of high level political office holders, was for advocacy and helped to facilitate interactions with stakeholders (especially government) within the state. The second was the Technical Committee with the responsibility of drafting the strategic plan.

Specifically, in Nasarawa State, the Political Committee consisted of the Commissioners of Finance, Health, Youth and Sports, Women Affairs and Social Development, and Education, Science and Technology, as well as the Chairman of the Committee on Youth and Sports at the Legislature. The Technical Committee had 20 members drawn from the government ministries, schools, and youth related non-governmental organisations.

The Political Committee in Ekiti State had 14 members including Commissioners and Permanent Secretaries of related ministries as well as a Special Adviser to the Governor and two senior legislators (the Majority Leader and the Chair of the Health Committee). The Technical Committee had 25 members with a similar composition as in Nasarawa, but with representatives from the job creation agency and skills acquisition centres in the state.

In all, there were two strategic planning sessions held in each state in June and July 2014. The sessions in Ekiti were hosted by the Ministry of Health while the Ministry of Finance hosted the meetings in Nasarawa.

Ownership and Adoption of Strategic Plans

The process of building ownership and adoption of the strategic plans in the states started with the advocacy visits by the Academy at the commencement of the project. Further advocacy visits were made by the field study teams and the staff of the Academy at intermittent periods throughout the project.

The youth and other stakeholders were involved in the project from its beginning, having completed questionnaires and participated in interviews and focus group discussions. Additionally, meetings were held with the stakeholders within each state following the collection and analysis of needs assessment data in the state. The drafting of the strategic plans involved representatives of the various stakeholders.

Outcome of intervention project

The project set out to build partnerships and collaboration for understanding the social development and health needs of the youth, and develop a strategic plan that would be owned and accepted by the stakeholders in the state. The strategy employed to achieve this is described below.

Partnership for Understanding the Needs of the Youth

The needs assessment reports of the studies conducted were well received and adopted by the states. Following the advocacy visit by the Academy leadership to the executive councils and legislature of each state, the field study teams paid additional advocacy visits to stakeholders (having received official letters of introduction from the Academy) before commencing the needs assessment studies. Intermittently, during the program, staff of the Academy liaised with government officials and other stakeholders (through site visits, telephone, and email communication) to ensure their continued support and involvement in the process.

The selection of study teams had to be carefully done. It was important to select teams with the capacity as well as local knowledge (especially given that the needs assessment study would request sensitive information on reproductive health) to conduct the studies. It was important that the teams inspired collaboration among the different stakeholders. Teams were recruited only following interviews by the Academy's project team.

Data collection tools were developed collectively among the study teams to enable comparison of the findings in the two states as may be necessary. Two joint meetings were held to develop and harmonise the tools. The tools were then tested on the field and adapted, to ensure appropriateness for the stakeholders, before being deployed for the needs assessment studies.

In order to ensure the participation of the youth, needs assessment studies were planned with consideration for the school calendar. Given the challenge of program timeline (as agreed with the funder), data collection was timed to coincide with the end of examinations but before school closure for holidays. In all, 633 in-school and out-of-school youth participated.

To promote partnership, among the various stakeholders, for understanding the social development and reproductive health needs of the youth in each state, the stakeholders participated in the needs assessment study. Also, closed door meetings were held with the youth and other stakeholders present to discuss the findings of the studies and to agree on plans of action for developing strategic plans that address the needs identified.

The project held at a time of political instability and violence in both states. There were governorship elections held in both states during the period of the program in the states, and such is often marked by instability and even violence in the country. Teams travelling in and out of the states had to be aware of the security implications at each period and conducted their visits accordingly. In addition, the needs assessment findings had to be presented during closed-door meetings (with the exclusion of media representatives) to avoid the studies being used as instruments during the political campaigns.

Having presented the needs assessment reports to the stakeholders, it was necessary to ensure that the strategic plans to be developed would be accepted by the top level political leadership and other stakeholders. This was achieved by ensuring that the stakeholders present during the presentation of the findings of the needs assessment study immediately constituted two committees (in each state) towards the development of the strategic plans. Both committees were chaired by senior government officials.

The first committee (the Political Committee) constituted towards the development of the strategic plans was for advocacy and, consequently, had senior policymakers as members. The committee facilitated interactions with government at any level required and ensured the hosting of the strategic planning meetings at venues provided by government ministries.

The second committee (the Technical Committee) consisted of the youth, senior and middle level government officials, and other stakeholders. The committee held two strategic planning sessions (in each state) to analyse, discuss, and agree on the contents of the plan. The meetings were facilitated by the academy's study teams, which also wrote the draft plans. The draft strategic plans were subsequently shared with various stakeholders and senior government officials for their input before being finalised for publishing.

Political Acceptance and Ownership of Strategic Plans

The strategic plans, having been developed inclusively by relevant stakeholders in the state, were launched by the governors of the states at events that were well publicised. Attendance at these events were by all relevant stakeholders including the youth, civil society groups, government officials, and the media. Policy statements indicating their adoption of the reports and support for implementation were made by the governors and other policymakers at the events. Other stakeholders also expressed their support for the implementation of the plans.

Forewords to the strategic plan reports were written by the most senior government officials of some of the ministries (ministries of youth, education, women affairs, science and technology, and health) involved in both states. Having obtained the necessary permission, the plans were also branded with the insignias of the respective state governments. These were important to demonstrate ownership and adoption of the plans by the governments.

The change in political leadership in Ekiti State, following governorship elections held, and just before the state's strategic plan was to be publicly presented necessitated a delay in the event. An advocacy visits by the Academy leadership had to be made to the Governor (and the team was received by the Deputy Governor) to intimate him about the project and the need to ensure continuity. The strategic plan developed was presented and the governor's review requested. With the consent of the new government in Ekiti, a date was agreed when the public presentation of the plan was done.

Facilitating the commitment of state resources to the implementation of the strategic plans was the reason for the inclusion of representatives of the ministries of finance and the legislature in the program from the beginning. In fact, the chairman of the Political Committee in Nasarawa was the Commissioner of Finance and the strategic planning sessions in the state were held in the conference room of that ministry.

Media Presentation of Strategic Plans

The academy organised a presentation of the strategic plans to representatives of various media agencies (covering television, radio, and newspaper organizations) to ensure wide publicity and indirectly stimulate political will and commitment. Various media representatives were invited to the event where a brief presentation of the process of development and the key contents of the plans were made. This was followed by a robust discussion session which allowed the media representatives to clarify issues.

Copies of the plans were then given to them. The involvement of the media was also to ensure that the strategic plans were well publicised and many more stakeholders would be aware of their existence. Ultimately, this would help to ensure that the governments kept youth development and the implementation of the plans on their agenda for development in their states.

Lessons Learnt

Several lessons were learnt in the course of implementing the intervention studies in the two states. Some of the key lessons are with respect to the development of program timelines, the importance of advocacy in influencing evidence-based policymaking, the need to ensure a process that engenders ownership of projects by stakeholders, and the need to work with all categories of government officials (employee's/decision makers) and not elected officials (political office holders) alone in implementing such programs. Various

Flexibility in Program Design

Given the unpredictable nature of the socio-political environment, there is a need to design programs with some flexibility in-built. There were some occurrences of violence in both states during the period of the program that necessitated variations in timing of activities and visits. There was also sudden cancellation of appointments given by the state officials due to the prevailing circumstances and, sometimes, unexplained reasons. Without a degree of flexibility being built into the programmatic timeline to accommodate some of these changes, the project would have failed.

Importance of Advocacy

The project would not have been a success without the use of advocacy. It was particularly important to have paid advocacy visits to the top level government officials. Visits made to the governors and their respective executive councils at the inception of the project facilitated access to the government ministries and schools in implementing the project. Necessary access to records was made easy by the prior advocacy visits. The project was at risk of being abandoned in Ekiti following the change of governors in the state. Delaying the publishing of the report till after an advocacy visit was made to the new government helped to keep the project on track by securing the buy-in of the new government.

Involvement of Career Civil Servants and not just Political Office Holders

The involvement of the career civil servants and not just elected policymakers aided continuity of the project in Ekiti. Oftentimes, emphasis is put on the need to engage the highest level of policymakers in influencing policymaking for the youth, especially as they are often much older and belong to another generation. These high level policymakers are usually elected into office and so may leave before the desired policies can be enacted or implemented. As it occurred in Ekiti State, the senior career government officials at the ministries, helped to ensure continuity of the program having been involved from the beginning. These officials were able to brief the new government of the existing program and advise on the need for continuity.

Importance of Ownership

Policies are written up many times that are never accepted by the relevant stakeholders. Uzo. To ensure that these strategic plans to address the social development and reproductive health needs of the youth were well accepted by all stakeholders in both states steps to engender ownership had to be implemented at various stages of the development of the plans.

Various stakeholders participated in the data collection, completing questionnaires, or being interviewed or participated in focus group discussions. Also, all the stakeholders attended the meeting to discuss the findings of the needs assessment study. All were also represented in the committees that developed the strategic plans. Obasanjo and Oduwole (ND), in analysing how HIV/AIDS programs and policies is influenced in Nigeria pointed out the important role of a participatory approach and even involving the stakeholders in research.

The advocacy visits to the top level political leadership, involvement of government and other stakeholders in the development of the plans, and the public presentation of the plans by these political leaders eased acceptance by all stakeholders.

Conclusion

The project set out to promote collaboration among stakeholders to address the social and development needs of the youth. The participatory approach employed in the conduct of a needs assessment and strategic plan development in Nasarawa and Ekiti States resulted in the launching of policy documents that were acceptable to the youth and the other stakeholders in the states.

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Conflict of interest

None declared.

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