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Nathaniel Howard
Department of Statistics, School of Physical Sciences, College of Agriculture and Natural Sciences, University of Cape Coast, Cape Coast, Ghana

Mustapha Adams
SD Dombo University of Business and Integrated Development Studies, Department of Applied Statistics, Box WA 64, Wa, Ghana

Corresponding Author:
Nathaniel Howard
Department of Statistics, School of Physical Sciences, College of Agriculture and Natural Sciences, University of

Multi-State analysis of secondary prevention of stroke in Northern Ghana

Nathaniel Howard and Mustapha Adams

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Abstract
We obtained secondary data from the medical unit of the Tamale Teaching Hospital in which stroke patients were on rehabilitation. The purpose of the study is to develop an illness-to-death model that will enable us to observe the transition rates of patients during rehabilitation at some discrete points in time. A review of literature on stroke in many research works revealed that none of the articles estimated the probabilities of transition at different level of the disease. We employed Continuous Time Markov Model (CTMC) in Multi-state Models (MSM) to observe the transition rates of the patients at two equal monthly intervals for two years. Results from the transition analysis indicated that patients with mild stroke will remain in this state for about 10 months before recovery and will never become severe if the patient adheres to treatment. While old and older age groups have some chance of transiting to a less severe state and similar probabilities of transiting from mild to a more severe state, the study also suggests that the recovery rate is fast in higher states than in lower states. It must be noticed that patients spent more time at state 2, followed by state three (3), and less time at state 4. This suggests that patients with mild stroke longer at mild state than other states and hence they need to continue to adhere to treatment to gain total recovery. We therefore recommend that; patients who transit to mild state should be advised by medical officers to continue to adhere to treatment to speed up total recovery

Keywords: Stroke, secondary prevention, Ghana, rehabilitation, state, and multi-state

1. Introduction

Globally, stroke is a healthcare problem that is common, serious, and devastating [1, 2] It is a serious health concern for both young people and the elderly. This is due to the fact that it impacts not only physical impairment but also causes depression, incapacity, and stigmatization [3].

Stroke is one of the top five causes of death in Ghana and one of the most common medical conditions to be treated in hospitals [4]. Stroke rose from being the eleventh cause of early death in 1990 to being the seventh cause in 2010 [1]. Furthermore, between 1990 and 2010, stroke was the most common non-communicable condition to result in premature mortality. Additionally, the country has a high prevalence of stroke case fatalities [5]. Study has further revealed that the main risk factors of stroke in Ghana are hypertension, diabetes, obesity, aging, and plasma level of homocysteine. Stroke is said to have been among the top three causes of death in Ghana [6]. With the growing incidence of uncontrolled hypertension, there has been a sharp rise in the number of stroke patients in Ghana [7].

[8] Asserts that secondary prevention is an essential part of stroke treatment, for example (walking, functional skills, or swallowing disorders). In [8], the importance of secondary stroke prevention in patients with antithrombotic brain infarction and the problem of reducing the risk of other major vascular events like myocardial infarction were acknowledged. Lowering the risk of recurrence in patients who have already had a stroke is a component of secondary stroke prevention [9]. In rehabilitation of stroke, the state of the disease is usually composed of a series of mutually exclusive states. The transition between any two states can provide important statistics about the disease's severity [10].

Such data can be analyzed through longitudinal studies, where patient's disease states are measured over time during follow-up visits. Patients are normally scheduled by their medical officers for successive visit. However, patients do not always follow scheduled appointments due to practical reasons associated in unevenly spaced follow-up time points that vary individually [11].

Upon the high public burden of stroke in Ghana, there are scarcely a few detailed research on rehabilitation and severity of stroke among survivors. Very few stroke studies seem to have concentrated on risk factors, mortality, morbidity, case fatality rate, and burden of stroke. There is a single study on the quality of life of stroke survivors in southern Ghana, ignoring the severity of stroke among survivors. The few researchers that studied stroke severity among survivors; [12, 13, 14, 15] did prospective studies on predictors of initial stroke severity without considering the exact transition times between disease states. This study seeks to investigate the efficacy of secondary prevention therapies on the severity of stroke at different states of the disease among survivors in Ghana over time, using Continuous Time Markov Chain (CTMC) in multi-state modeling.

2. Methodology

2.1 Study Design

CTMC models are generated to fit the progression of individuals through various illness states or stages. Subjects are monitored infrequently; typically, information is in the form of a health indicator or disease status at several distinct times in time [16]. For many subjects, it is typically difficult to determine the precise times when one illness state changes to another. Individual disease histories are often observed for a relatively small fraction [17]. Because of the difficulty in handling many intricate models, such as non-homogeneous Markov or semi-Markov models, one typically turns to time-homogeneous Markov models with straightforward transition structures [18].

A stroke patient on rehabilitation has undergone a series of stages; mild, moderate, severe, and absorbing state (death). The transition between the states depends on how the patient adhered to treatment. Multi-state models would be used to describing how the individual patients move between a series of states in continuous time. An individual in the state i at the time t will transit to a less or more severe state at the time $t+1$ depends on whether the patient adheres to treatment. We would focus on fitting a multi-state model to continuously observe the recovery process, where the state of each individual is known at all-time in the study period.

2.2 Data Set

A longitudinal study was adopted retrospectively for a cohort from January 2014 to December 2019. The study participants comprised of stroke patients (patients who had recovered from a past cerebrovascular accident and are receiving treatment) from the Medical Unit of the Tamale Teaching hospital. The Hospital serves all the five Northern regions in Ghana. Selection criteria included those individuals who had an initial or were referred for hospitalization for stroke from January 2014 to December 2019. Patients who could not survive for more than 60 days of admission were excluded from the selection criterion. The main outcome measures were survival and discharge at home. Patients who survived the stroke were given rehabilitation therapy under the Medical Unit in the hospital. Monitoring of patients was done by the stroke unit. Disease progression was recorded at different two months-time intervals using the Modified Barthel Index (MBI). Patients who were lost to follow-up were also excluded from the data.

2.3 Model Description

Consider a longitudinal research with M individuals where each participant can move independently between S states and K_m states in the state space of$1,\ 2,\ 3, \dots,\ S$.

Let $y(t_m, k)$

We represent the outcome of the stage observed at time t_m, k for $m\ =\ 1,\ 2, \dots\ M$ and$k\ =\ 1,\ 2,\ \dots\ K_m$, where the number of observations made on subject M is represented. Assume that each subject's underlying process is a first-order homogeneous continuous-time Markov chain that can be completely explained by the infinitesimal rate matrix.

$Q\ =\ \{q_{ij}\}$ where $q_{ij} \geq 0$ for $j\ \neq\ i$ and

$-q_{ii} = \sum_{i \neq j} \quad q_{ij}$ for$i,\ j\ =\ 1,\ 2,\ 3, \dots,\ S$.

Assuming that the transition rate $q_{ij}$is constant across time, the future and past states are independent given the current state. The duration of a subject's time in state i is exponentially distributed in this model, with a mean of$1/q_{ii}$. Additionally, the transition rate q_{ij} can be understood as the hazard rate of transition from state i to state$j$, which can be determined using competing risk models [10]. The likelihood of a participant m changing from state i to state at time $t_m, k-1$ to state j at time t_m, k is defined as

$p_{ij}(t)] = \Pr\{y(t_m, k) = j/y(t_m, k-1)\} = i$

Where

$t = [(t_m, k) - (t_m, k-1)] \geq 0$

For$i,\ j\ =\ 1,\ 2,\ 3, \dots,\ S$ and$k\ =\ 1,\ 2,\ 3, \dots\ K_m$.

$P(0) = I$

The $S \times S$ transition probability matrix

$P(t) = \{p_{ij}(t)\}$

is determined by the infinitesimal rate matrices Q, which have the following expressions:

$$p(t) = e^{Qt} = I + \sum_{k=1}^{\infty} \frac{Q^k t^k}{k!}$$

where I is the identity matrix.
A continuous time Markov model is fully defined by the computed matrix of probabilities of each state being the next (sometimes referred to as the jump chain) and the mean sojourn periods in each state. In comparison to the transition intensity matrix, this provides a more meaningful and intuitive description of a model. The matrix for the chances that the state after state $i$is j state is roughly represented as $p_{ij} = \frac{1}{4}\alpha_{ij}\lambda_{ij}$
for each i and j such that $i \neq j$."
α_{ij} is the force needed to move from state i to state j , and α_{ii} is the overall force needed to leave state i.

2.4 Time Homogeneous Markov Chain
If the

$P[X(t+s) = j|X(s) = i]$

is independent of$s$, then the process

$X(t),\ t \geq 0$

is said to be time homogeneous Markov Chain and have stationary (or homogeneous) transition probabilities.

If we let

$$p_{ij}(t) = P[X(t+s) = j|X(s) = i] \tag{1}$$

then, $p_{ij}(t) = P[X(t) = j]$ (2)

That is $p_{ij}(t)$ is the probability that a Markov chain that is presently in state i will be state j after another time t, and $p_{ij}(t)$ are the transitional probability functions that satisfy the condition

$0 \leq p_{ij}(t) \leq 1.$

Also,

$$\sum_j p_{ij}(t) = 1 \tag{3}$$

$$\sum_j p_j(t) = 1 \tag{4}$$

Equation (4) results from the fact that the process must always be in some state. Moreover,

$$p_{ij}(t+s) = \sum_k P\big[X(t+s) = j,\ X(t) = k|X(0) = i\big]$$

$$= \sum_k \left\{\frac{P\big[X(0)=i, X(t)=k, X(t+s)=j\big]}{P[X(0)=i]}\right\} = \sum_k \left\{\frac{P\big[X(0)=i, X(t)=k\big]}{P[X(0)=i]}\right\}\left\{\frac{P\big[X(0)=i, X(t)=k, X(t+s)=j\big]}{P[X(0)=i, X(t)=k]}\right\}$$

$$= \sum_k P\big[X(t) = k\big|, X(0) = i\big]P\big[X(t+s) = j\big|, X(0) = i,\ X(t) = k\big]$$

$$= \sum_k P\big[X(t) = k\big|, X(0) = i\big]P\big[X(t+s) = j\big|\ X(t) = k\big] \tag{5}$$

This equation is denote the Markov proper

$$= \sum_k p_{ik}(t)p_{kj}(s) \tag{6}$$

Then Equation (6) is refer to as the Chapman-Kolmogorov for CTMC.

Suppose that we define the matrix of $p_{ij}(t)$ as

$$P(t)=\begin{bmatrix} q_{11}(t) & q_{12}(t) & q_{13}(t) & q_{14}(t) & q_{15}(t) \\ q_{21}(t) & q_{22}(t) & q_{23}(t) & q_{24}(t) & q_{25}(t) \\ q_{31}(t) & q_{32}(t) & q_{33}(t) & q_{34}(t) & q_{35}(t) \\ q_{41}(t) & q_{42}(t) & q_{43}(t) & q_{44}(t) & q_{45}(t) \end{bmatrix}$$

Then the Chapman-Kolmogorov equation becomes

$$P(t+s) = P(t)P(s) \tag{7}$$

Whenever a CTMC enters a state i, it spends an amount of time called $\frac{1}{vi}$ the dwell time (or holding time) in that state. The holding time in state is exponentially distributed with mean $(1/-q)$."
"At the expiration of the holding time, the process makes a transition to another state j with probabilityp_{ij}, where

$$\sum_k \quad p_{ij} = 1 \tag{8}$$

Because the mean holding time in state i is $\frac{1}{v_i}$, v_i represent the rate at which the process leaves state$i$, and $v_i p_{ij}$represents the rate when in state i that the process makes a transition to state$j$. Also, because the holding times are exponentially distributed, the probability that when the process is in state i a transition to state $j \neq i$ will take place in the next small time

$\Delta t \; is \; v_i p_{ij} \Delta t.$

The probability that no transition out of state i will take place in Δt given that the process is presently in state is

$1 - \sum_{j \neq i} \quad p_{ij} v_i \Delta t \; i$ and

$\sum_{j \neq i} \quad p_{ij} v_i \Delta t$ is the probability that it leaves state i in Δt.

2.5 The Expected Holding Time

The patient stays in one state before moving on to another state, which is known as the predicted holding time in each state or the mean sojourn time a patient spent in each state. The average length of stay in each state i, for $i = 1, \; 2, \; 3, \; 4$ is estimated as

$\frac{1}{\lambda}$,

where $\lambda_i = \sum_{i \neq j} \quad a_{ij}$ is the entire force of state transition. i (Rubino and Sericola,1989).

2.6 Model Formation

The state of each patient is determined based on whether they have had a stroke, a mild stroke, a moderate stroke, or are dead at any given time Δt as follows; The state diagram below depicts how patients receiving therapy for a stroke might proceed through these five states. The diagram's arrows depict possible transitions between the five stages.

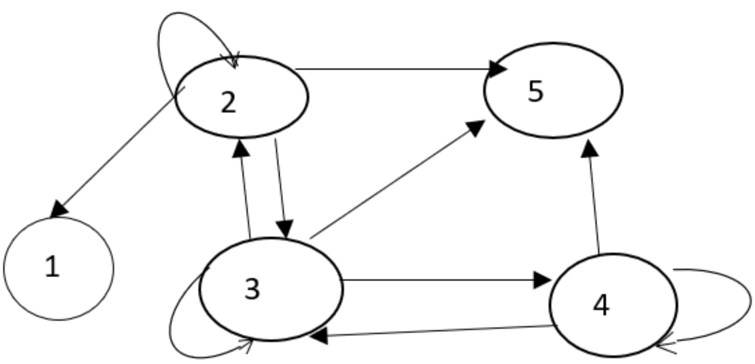

Fig 1: General Transition Diagram

Since state number five is an absorbing state (death), there are no transitions from it. There is a chance that a person will experience a stroke and remain in the same state for two visits in a row. The possible transition counts that took place for the whole period of study 2014 to 2019 can be explained as; the transition count from state i to $i \pm j$ be higher for all the values in which $j = i + 1$ than for $j = i - 1$ where $i, j \in i\ (2,3,4)$ are transient states. A model would be formulated based on the assumption that between times$(t,\ t + \Delta t)$, where t is a very small value, there is a transition from anyone of the states $i = 2,\ 3,\ 4$ (transient states) to state $j = 1, 2, 3, 4, 5$ defined as follows:"

1. "A patient can continue in the same state at a rate of $a_{ij} = -\lambda_i = -(a_{i,i-1} + a_{i,\ i+1} + a_{i5})$.
2. Some people might not follow their prescribed treatment plan. These patients can transition to a more severe state at a rate ofq_{ij} where $j = i + 1$
3. Some people might follow their treatment plan. These people can leave their severe state and enter a mild one at a rate ofq_{ij} where $j = i - 1$
4. An individual in state $i = 1,\ 2, ..4$, can die (state 5, absorbent state) at a rate of q_{i5}.

The premise behind this is that all transition rates from any state add up to zero. The following transition rate matrix $Q(t)$ can be used to describe these assumptions [19, 20].

.

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ q_{21} & -(q_{21} + q_{25}) & 0 & 0 & q_{25} \\ 0 & q_{32} & -(q_{32} + q_{32} + q_{35}) & 0 & q_{35} \\ 0 & 0 & q_{43} & -(q_{43} + q_{45}) & q_{45} \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

2.7 Goodness-of-fit Tests
We use prevalence counts to perform a goodness-of-fit test for the suggested model in this study [21]. The prevalence counts serve as an ad hoc empirical indicator of state population density. The expected state occupancies by the fitted model should be close to the observed state occupancies if the model fit the data well. We may assess the fitted model's general goodness-of-fit by comparing observed and expected prevalence counts [21].

2.8 Data Visualization and Analysis
In preparing the data for analysis, we installed the MSM package from the CRAN archive in the *R* console (version of 4.1.0) on a computer through the internet. Data in an excel sheet was put in long format (data frame) to enable the package to run it. The time of observations and the observed states for the process were: state 1 (disease free), state 2 (patients with mild stroke), state 3 (patients with moderate stroke), state 4 (patients with severe stroke), and state 5 (patients who die during the study period). The excel file was saved in **CSV** format to enable reading of the data by *R* console. The first output was to display a sample of the data in the long format. Our second result displayed the summaries of the multi-state, indicating the number of individuals in the various states. This output defines our matrix
(Q).
To tell MSM what the allowed transitions of the model are, we define a matrix of the same size as containing zeros in the positions where the entries are zeros. All other positions contain an initial value for the corresponding transition intensity. The diagonal matrix would also be assigned zeros. In the model, this diagonal matrix entry is defined as the minus the sum of all entries in the row (a unique property of the infinitesimal generator matrix).
Our next analysis was estimates of the main model (model 1 = illness-to-death). This result shows the baseline transition intensities among the various states. We estimated the expected frequencies and percentages and compared these estimates with the observed frequencies and percentages. These expected and observed Frequencies were used to fit the survival plots of all the states over time.

3. Results

Table 1: Frequency Distribution of Patients on Rehabilitation

Factor	Code	Frequency	Percentage	Factor	Code	Frequency	Percentage
Age	Youth (≤45) = 0	9	21.6	Location	Upper East (0)	5	13.5
	Old (≤60) = 1	13	37.1		Northern Region (1)	22	59.5
	Older (60) = 2	15	41.3		North East (2)	5	13.5
Sex	Male (0)	14	37.8		Savanna Region (3)	4	10.8
	Female (1)	23	62.2		Upper West (4)	1	2.7
Religion	Islamic (0)	24	35.1	Comorbidity	Hypertension (0)	14	37.8
	Christianity (1)	13	64.9		Hypertension/ diabetes (1)	8	18.9
Marital status	Single (0)	1	2.7		No comorbidity (2)	15	40.5
	Married (1)	33	89.2	Alcohol	Yes (0)	2	5.4
	Widowed (2)	3	8.1		No (1)	35	94.6
Occupation	Civil servant (0)	6	16.2	Smoking	Yes (1)	3	8.1
	Self Employed (1)	16	42.2		No (0)	34	91.9
	House wife (2)	4	10.8	Stroke status	Mild	4	10.8
	AGRA Ghana (3)	1	2.7		Moderate	14	37.8
	Other (4)	10	27		Severe	19	51.4
Local Treatment	Yes (1)	15	40.5				
	No (0)	22	59.5				

Table 1 shows the frequency distribution of stroke patients who were on rehabilitation at TTH. Thirty-seven (37) were followed up during the study. Table 1 above indicated that, among the age groups, patients within the youth group (9) were the least in the study. The majority of the patients belong to the older age group (15). Female patients (23) also outweigh male patients (14). A patient was either a Christian (13) or Islamic religion (24). Only one (1) patient was single, three (3) were widowed, and the majority (33) were married. Four (4) patients were housewives and the rest have at least one type of job for survival; teacher (4), civil servant (1), trader (9), farmer (4) driver (2), nurse (1), plumber (1) and ARIED Ghana (1), stroke keeper (1) and nine (9) have no history of occupation. Fifth-teen (15) patients combine treatment with rehabilitation while 22 patients stuck to rehabilitation measures. Most of the patients were very alert of some risk factors of stroke as such few patients (3) went into smoking and the rest (34) were mindful of smoking. Thirty-five (35) patients reported not taking alcohol while two (2) patients could not fail to take it. All the patients report to come from one of the five regions; Northern (22), Upper East (5), Upper West (1), North East (5), and Savanna region (4). While 14 patients were living with hypertension, eight (8) patients were living with diabetes and hypertension and fifteen (15) were free from any other diseases. Patients on admission had different severity levels. Four (4) patients were diagnosed with mild stroke; fourteen (14) patients had a moderate while the majority (19) was diagnosed with severe stroke.

Table 2: Transition Distributions

State	State (1)	State (2)	State (3)	State(4)	State (5)
(2)	13	128	9	1	4
(3)	0	35	54	12	4
(4)	0	2	27	18	3
(5)	0	0	0	0	0

Table 2 shows the transition distributions of the disease among the five states: no stroke, mild, moderate, severe and death. The table revealed there were 13 patients transited from mild to a disease-free state at the end of the two years. Nine (9) patients transited from mild to moderate stroke 128 patients transited or retained to the mild state whiles a patient transited to a more severe state four (4). Thirty-five (35) patients from moderate state recovered to mild state, twelve (12) patients had developed severe stroke and 54 patients maintained or transited to moderate state. Of patients who had severe stroke, two recovered to mild, 18 probably had not adhered to treatment (severe). Thus, there were four (4) deaths with mild stroke, two (2) deaths with moderate stroke and 3 deaths with severe stroke. Patients who were on admission with more severe stroke never recovered during the two years studies.

Table 3: Transition Intensity Matrix

	State 1	State 2	State 3	State 4	State 5
State 2	0.079 (0.05, 0.13)	-0.196 (-0.29, - 0.13)	0.085 (0.05, 0.16)	0	0.031 (0.01, 0.08)
State 3	0.0004 (0.001,Inf)	0.435 (0.31, 0.62)	-0.716 (-0.98, -0.52)	0.28 (0.15, 0.52)	0.00004 (0.00, 1.72)
State 4	0	0.0001 (-0.01, Inf)	1.011 (0.65 1.56)	-1.105 (-1.7, -0.73)	0.094 (0.02, 0.35)
State 5	0	0	0	0	0

-2*log-likelihood 527.2319

Table 3 displays the estimated transition ratios (together with 95% confidence intervals, in parenthesis) for two years periods. The result indicated that a patient with a mild stroke (state 2) has a 0.07965 probability of recovery from stroke, 0.0855 probability of transiting to a moderate (state 3), and about 0.03108 probability of being dead. Similarly, a patient with a moderate stroke (state 3) has very little probability (0.0000004) of total recovery from state 3. But a patient with moderate stroke who adhered to treatment has a higher probability (0.4357) of transiting to a less severe state compared to a 0.2804 probability of developing a severe stroke after the 2 years of follow-up. Finally, a patient with a severe stroke (state 4) never transited to disease free state, has little probability of (0.0000001) of transiting to mild state, has no information of being moderate (state 3), and could die with probability of 0.0822.

3.1 The Mean Sojourn Time

The length of time invested at a transient state before transiting to a less severe state or recovery can be estimated using the mean sojourn time. This is calculated as$\frac{1}{-\hat{q}_{rr}}$, where r^{th} represents the diagonal entry of the calculated transition intensity matrix $\hat{q}_{rr}$

Table 4: Mean Sojourn Time Estimates

	Estimates	SE	L	U
State 2	5.0946	1.001	3.4663	7.4879
State 3	1.3961	0.2267	1.0156	1.9192
State 4	0.9049	0.1898	0.5998	1.3652

Table 4 above shows the estimated average time spent in the state; 2, 3, and 4 before transiting to other states. The results indicated that patients spent on average about 10 months (5.0946; CI = 3.4663, 7.4879) at mild state before total recovery. Patients with moderate stroke stay for about three (3) months at moderate state before transiting to mild state (1.3961; CI =1.0156, 1.9192). Thus, patients admitted with severe stroke or transited to severe state do not stay long at this state (about 2 months: 0.9049; CI =0.5998, 1.3652).

3.2 Model Assessment

3.2.1 Expected Frequency

Through the use of prevalence counts, we provide a goodness-of-fit test for the suggested model. The prevalence counts offer a free-form empirical measurement of state occupancy. If the model correctly described the data, the predicted state occupancy values should closely match the actual state occupancy values. We would be able to evaluate the fitted model's general goodness-of-fit by contrasting the observed and forecasted prevalence counts.

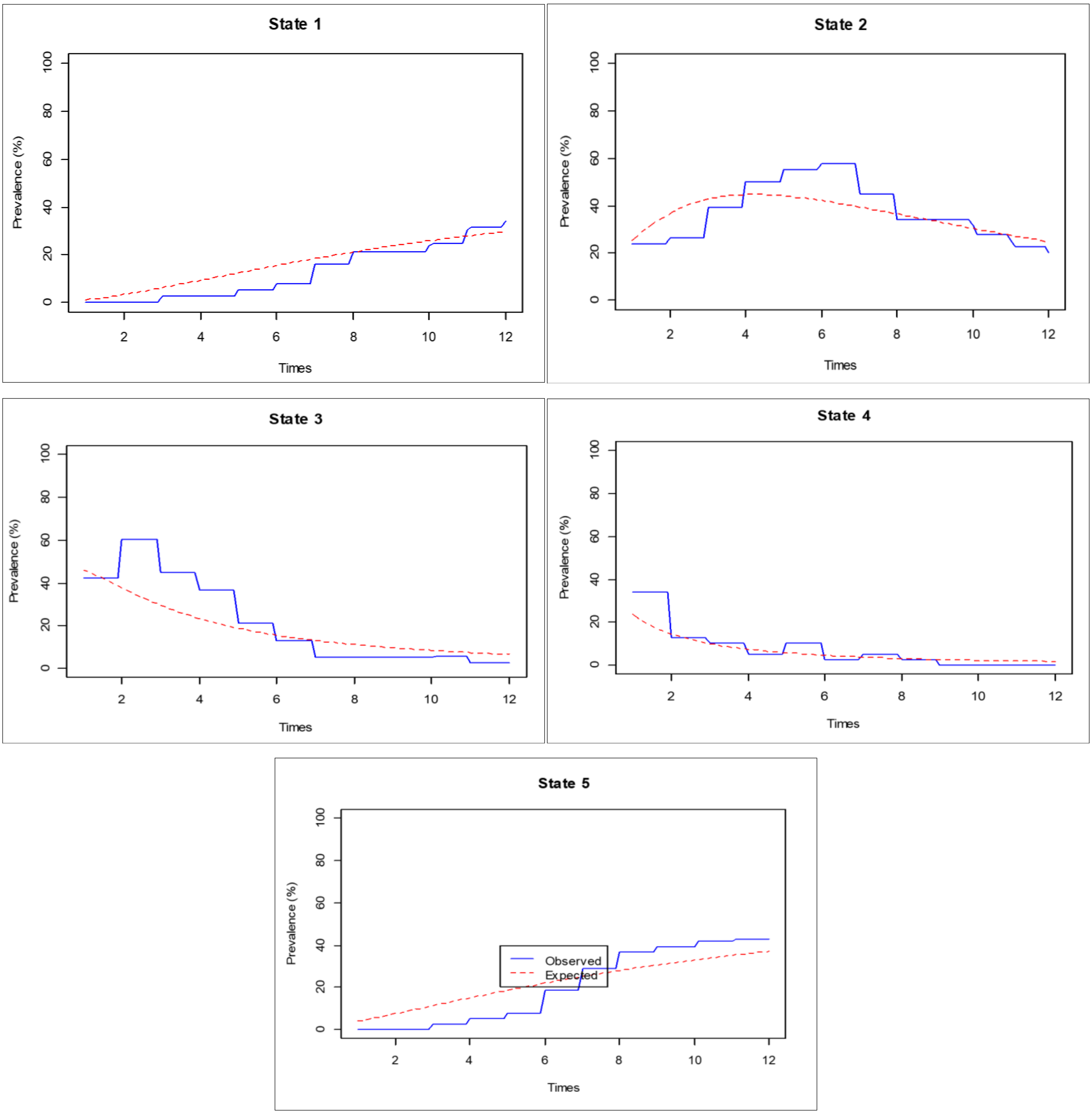

Figure 2: Prevalence Plot

Figure 2 above Compares the observed and expected percentages in each state; we noticed that in state one, our model underpredicted the probability of recovery after the time ($t = 0$) to time $t = 8$. At state 4, the severity of stroke was overestimated before $t = 2$. On average, the model predicted well for patients with severe stroke. The probability of death was under-predicted at $t = 7$ and over predicted thereof. For a period of four visits, our model under-estimates the hazard rate at (state 2) and over predicted the hazard rate in the next four visits. The model could predict well at state two after $t = 8$.

3.3 Discussion of Results

The Continuous-time Markov chain model in multi-state modeling was used to model the transitions rates between the various stroke states. Studies have shown that when data are equally spaced, both the discrete-time Markov chain model and continuous-time Markov model can perform well. However, CTMC models can perform better when the data set is not equally-spaced

Monitoring of patients was taken periodically at two-month discrete time points; a transition from one state to another is interval-censored. Thirty-seven (37) patients were monitored at two months intervals for two years.

The purpose of this study is to model an illness-to-death model that will enable us to observe the transition intensities of stroke patients on rehabilitation at some discrete points of time. The model will enable us to determine some risk factors that negatively influence recovery and the effect of comorbidity. This model could inform us about the average length of stay at the various transient states. The model may also serve as a guideline for medical officers on the cost treatment of stroke since the model provided some fair knowledge during treatment.

The results in Table 1 shows that the prevalence of stroke among female patients (23, 62.2%) is almost double the number of male patients (14, 37.8%). This may suggest that more females are at risk as compared to males. This is consistent with [22]. Older patients (15, 37.8%) numbered more than old age (13, 37.1%). The youth group was the least admitted in the facility (9, 21.6%). About 40.5% of the patients went for local treatment whiles 40.5% may not have any treatment outside the health facility. The number of patients living with one or comorbidity (14 or 8, 18.9% or 40.5%) was more than patients with no comorbidity (15, 37.8%).

The majority of the patients (22, 59.5%) came from the Northern region. Upper East and North East were equally admitted (5, 13.5%), four (4) people (10.8%) from the Savanna region, and only one patient (2.7%) came from the Upper West region. Only two (2, 5.4%) never quit alcohol whiles on rehabilitation but majority of the patients (35, 94.6%) deserted from alcohol intake.

Similarly more patients (34, 91.9%) quitted smoking and very few patients addicted to smoking (3, 8.1%). Self-employed persons were more at risk (16, 42.2%), no history of employment (10, 27%), Civil servants (6, 16.2), house wife (1, %2.7) and AGRA Ghana (1, 2.7%).

The transition intensities in (Table 3) indicated that a patient with mild stroke will remain in this state for about 10 months (1/0.1963) before transiting disease free-state with probability (0.07965) and will never become severe (0) before death (0.03108) if the patient adheres to treatment. This finding is similar to [23]. While patients with moderate state are more likely (0.4357) to transit to less severe state, they also have higher probability (0.2804) of transiting to more severe state than the other states. Also, patients with severe stroke are more likely (0.0942) to die than patients with moderate (0.0000004) or mild stroke (0.03108). This result do not contradict literature [24].

Estimates from (Table 4) shows that a patient spent an average of (5 visits points) 10 months (5.0946, SE=1.001) at state 2 before transiting to state 1, average of 1.396 visits (about 3 months) at state 3 before transiting to state 2 (1.396, SE = 0.8189) and an average of 2 months (0.9049, $SE = 0.19051$) at state 4 and then transiting to state 3. This may suggest that patients with mild stroke spent a maximum of 15 months (7.489) and minimum of 6 months (3.16) at mild state before recovery. This finding may suggest rate of recovery is faster at state 4 than at state 3. Once a patient transit to state 2, it will take him or her more time to attain to state 1. This outcome is similar to a study in multi-state model for kidney disease progression [24].

3.4 Conclusion

In using CTMC in MSM approach in modeling the state of stroke patients at TTH, we realized that, patients who adhere to treatment measures, as well as successful risk management strategies, in-hospital initiation and ongoing advice and support from family members and medical officers may have early recovery of stroke.

The research also revealed that CTMC models best estimated the transition rates of stroke patients who were on rehabilitation at the TTH. The model can estimate the transition intensities for all states (1, 2, 3, 4, and 5). The transition rate from state 2 to state four (4) is zero (0). Also transition from state 2 to state 5 is higher (0.0581) than transition from state 3 to state 5 (0.0003).

The study suggests that the recovery rate is fast in higher states than in less severe states. It must be noticed that patients spent more time at state 2, followed by state three (3), and less time at state 4. This suggests that patients with mild stroke than other states and hence need to continue to adhere to treatment to gain total recovery. We therefore recommend that; patients who transit to mild state should be advised by medical officers to continue to adhere to treatment to speed up total recovery. Awareness and educational intervention should be focused on the long-term rehabilitation so that patients may not withdraw from treatment.

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