Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 *https://dx.doi.org/10.4314/sa.v21i1.18*
 ISSN 1118 – 1931

STOCHASTIC MODEL FOR THE PREDICTION OF SHORT TIME NUMBER OF FIRE ACCIDENT OCCURRENCE IN NIGER STATE USING VITERBI ALGORITHM

Lateef, I.[1*], Adamu[1], L., Didigwu, N. E.[2], Abubaka, A.[3], and Yakubu, D. S.[4]
[1] Department of Mathematics, Federal University of Technology, Minna, Nigeria
[2]Department of Industrial Mathematics/Applied Statistics, Enugu State University of Science and Technology, Agbani, Enugu, Nigeria
[3]Department of Mathematics, Faculty of Science, Air Force Institute of Technology, Kaduna, Nigeria
[4]Department of Mathematical Science, Ibrahim Badamasi Babagida University, Lapai, Nigeria
lawal.adamu@futminna.edu.ng

Received: 19-02-2022
Accepted: 20-03-2022

ABSTRACT

In this paper, we look into ways by which fire outbreak (accident) can be suppressed. A stochastic model that predicts the number of fire accident occurrence in Niger State using Viterbi Algorithm is presented. A three-State stochastic model was formulated using the principle of Markov and each state of the model has four possible observations. The parameters of the model were estimated using the fire accident data collected from the archive of Niger State Fire Service, after which the model was trained using Baum-welch Algorithm to attend maximum likelihood. The Validity test for the model recorded 75% accuracy for short time prediction and shows 50% accuracy for long time prediction. This indicates that the model is more reliable and dependable for short time prediction.Information for this study could serve as a guide to the government in policy formulation that might assist in curbing the number of fire accident occurrences in Niger State.

Keyword: Hidden Markov Model, Transition Probability, Observation Probability, Fire accident Occurrence, Viterbi Algorithm

INTRODUCTION

Fire is the rapid oxidation of a material in the exothermic chemical process of combustion, releasing heat, light, and various reaction products (Charles, 2000). Fires start when a flammable and/or a combustible material, in combination with a sufficient quantity of an oxidizer such as oxygen gas or another oxygen-rich compound is exposed to a source of heat or ambient temperature above the flash point for the fuel and is able to sustain a rate of rapid oxidation that produces a chain reaction (Yusuf, 2012). Fires are both natural and social phenomena that cause extensive harm to societies in terms of human lives, economic losses, and operational costs (Corcoran *et al*., 2011; Corcoran and Higgs, 2013; Jennings, 2013; spatenkova and Virrantaus, 2013). Fires also affect communities, their livelihoods and productivity, and can create serious damage and havoc to urban infrastructure, reserved or unreserved (Jennings, 2013 and Corcoran, 2007). All types of fire that is residential fires pose the greatest risk to human lives and the surrounding environment because of their higher likelihood to lead to fatal consequences

(Ceyhan *et al*., 2013).The complexity of people's behaviour at an individual and collective level in cities has made fire risk extremely complicated to model and theorize (Corcoran *et al.,* 2011; Jennings, 2013; Spatenkova and Virrantaus, 2013). While the number of studies have been increasing in recent years, the current knowledge about the spatial aspects of fire risk is still limited to a few studies mostly from developed countries, such as the United Kingdom (UK), Australia, Canada, Sweden and Finland (Corcoran *et al.* 2007; Chhetri*et al.,* 2010; Asgary*et al.,* 2010; Corcoran *et al.,* 2011; Spatenkova and Virrantaus 2013; Wuschke*et al.* 2013; Guldaker*et al.* 2018; Ardianto and Chhetri 2019).

Dry weather has been identified as the major cause of the recent spate of incidents while storing of petrol in living houses and markets, careless disposal of cigarette stubs, adulterated fuel, power surge, electric sparks and illegal connection of electricity are all sources of fire outbreaks. Many people have faulted the responsiveness of fire services and emergency first responders in the country, who have been reputed to always arrive late and without sufficient equipment to the scene of fire incidents. There have also been renewed calls for the federal and state governments to adequately fund the fire department and emergency agencies, and the culture of insuring properties is not imbibed by Lagos residents to mitigate the damage and misery of the misfortune (Yusuf, 2012). Many countries have introduced, or are planning to introduce in the near future, performance-based codes by the use of engineering analysis of fire development and occupant evacuation. The performance-based codes were considered and the level of safety provided to the occupants in a building by a particular fire safety design were assessed Central to this performance, based on the approach that was used for a suitable design fires that can characterize typical fire growth in a fire compartment. Pantousa*et al*. (2017), developed a Fire-Structure Interface (FSI) simplified dual-layer model. The model calculates the temporal evolution of the gas-temperature in the fire compartment in every virtual zone which is divided in two layers (hot and cold layer). Sakurahara *et al.* (2018), developed an integrated probabilistic risk assessment methodological framework for Fire PRA. The Fire Simulation Module (FSM), includes state-of-the-art models of fire initiation, fire progression, post-fire failure damage propagation, fire brigade response, and scenario-based damage is used in simulation using a computational fluid dynamics (CFD) code, fire dynamics simulator.

The outbreak of fire in Niger State and some other parts of the country is one of the challenging situation faced by inhabitants of this geographical location as in most cases lives and properties worth millions of naira are lost. Fire accident could be very difficult to combat/fight as it can emanate from diverse sources. Prediction of fire accident has been a task to researchers for several decades, because its occurrence is stochastic in nature.

Hence the need to use a stochastic model with pattern recognition capability based on the empirical data to conceivably capture the behavior of the system become paramount. It is on this note, that Hidden Markov Model is selected for this purpose.

Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 https://dx.doi.org/10.4314/sa.v21i1.18
 ISSN 1118 – 1931

Hidden Markov models are extensions of Markov models where each observation is the result of a stochastic process in one of several unobserved states. Hidden Markov model is very influential in stochastic because of its track record of unraveling hidden parts of a complex system and make prediction with high level of accuracy. Hidden Markov Models have been successfully applied in the following areas; automatic speech recognition and speech synthesis (Rabiner, 1989), identification and inverse filtering (Robert Mattila, 2020), molecular biology for DNA and protein sequencing (Durbin *et al.*, 1998), pattern recognition (Fink, 1989) and in rainfall pattern prediction (Lawal, 2018), Rice yield forecast (Yahaya and Lawal, 2020).

METHODOLOGY

a. Hidden Markov Model

A Hidden Markov Model (HMM) is a double stochastic process in which one of the stochastic processes is an underlying Markov chain which is called the hidden part of the model, the other stochastic process is an observable one. Also a HMM can be considered as a stochastic process whose evolution is governed by an underlying discrete (Markov chain) with a finite number of states which are hidden, i.e. not directly observable (Enza and Daniele, 2007)

b. Characteristics of Hidden Markov Model

Hidden Markov Model is characterized by the following

N = number of states in the model
M = number of distinct observation symbols per state
Q = state sequence

$$Q = q_{1,} q_2, q_3, \ldots\ldots\ldots\ldots q_T$$

O = observation sequence

$$O = o_{1,} o_{2,} o_3 \ldots\ldots\ldots\ldots o_T$$

Transition probability matrix $A = \{a_{ij}\}$

Observation probability matrix $B = \{b_j(o_t)\}$

where $b_j(o_t) = p(o_t \mid q_t = s_j)$

If the observation is continuous a probability density function is used as follows:

$$\int_{-\infty}^{+\infty} b_j(x)dx = 1$$

$\pi = \{\pi_j\}$ Initial state probabilities

$\lambda = (A, B, \pi)$ The overall HMM

c. Model Formulation

Fire accidents are influence by many complex factors such as environment, climate, Fire investment, public fire safety consciousness and so on, the statistical data of fire accidents always take on the characteristic of both randomicity and fluctuations (Sun and Mao 2011). Since the fire accident occurrence depends on these factors and these factors are not static both varies along the quarters of the year this means that, the number of occurrence of fire accident also varies along the quarters of the year. This situation is stochastic in nature and of the double type. This means that the number of occurrence of fire accident in each quarter of the years varies and the factor influencing the occurrence of the fire accident also varies along the quarters of the year. In general, fire accident occurrence among quarters of the year is a double stochastic process. It is based on this that HMM is being adapted to model number of fire accident occurrence in Niger State.

Now, Let the number of fire accident occurrence within the quarters of the year be taken as the state of the model and the factors influencing fire accident occurrence within the quarters be taken as emission of the Hidden Markov Model, hence we have the following model assumptions

(i) The transition between the states is governed by first order Markov dependency as represented in equation (1)

$$P\{X_{n+1} = j \mid X_0 = i_0, \ldots, X_{n-2} = i_{n-2}, X_{n-1} = i_{n-1}, X_n = i\} = P_{ij} \quad (1)$$

(ii) The probability of generating current observation symbol depends on current state, as represented by equation (2)

$$P(O \mid Q, \lambda) = \prod_{t=1}^{T} P(o_t \mid q_t, \lambda) \quad (2)$$

(iii) The number of fire accident occurrence in a year is considered be low, if it is less than 83

(iv) The number of fire accident occurrence in a year is considered to be moderate, if it is within the range (83 - 159)

(v) The number of fire accident occurrence in a year is considered to be high, if it is above 159

Hence, we have the following states and observations for the Hidden Markov Model of fire accident occurrence prediction in Niger state

State 1: Low Fire accident occurrence
State 2: Moderate Fire accident occurrence
State 3: High Fire accident occurrence

Observations:

$Q_1 = O_1$ = Quarterly (January to March)
$Q_2 = O_2$ = Quarterly (April to June)
$Q_3 = O_3$ = Quarterly (July to September)

Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 *https://dx.doi.org/10.4314/sa.v21i1.18*
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

$Q_4 = O_4$ = Quarterly (October to December)

The classification of states and the observations, and the assumption made in this work are based on the study area and the data obtained

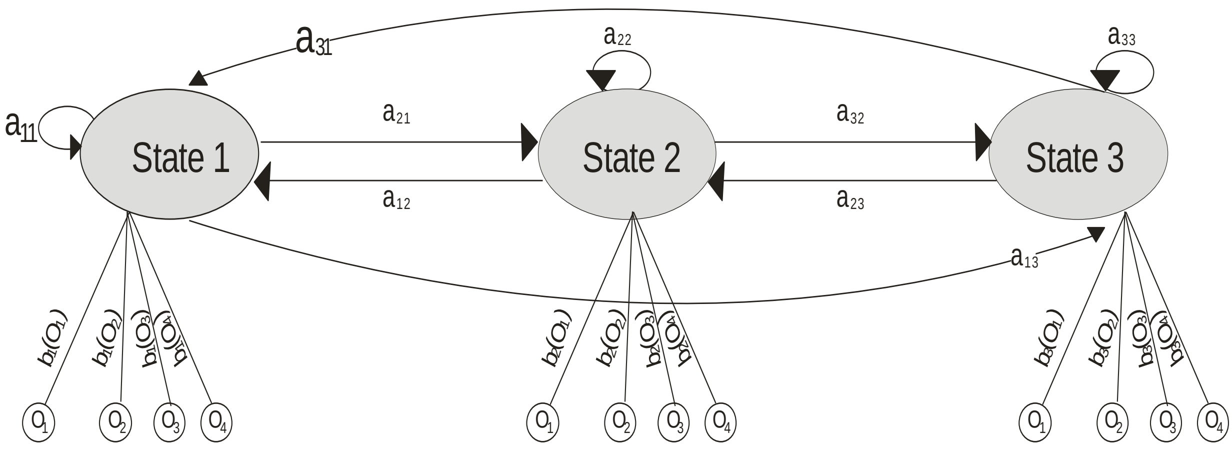

Figure 1: Transition Diagram of the Fire Accident Occurrence Model

Transition Probability Matrix

The transition between the states are represented by equation (3)

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad (3)$$

Observation probability matrix

The matrix below represents observation emitted from the model

$$B = \begin{bmatrix} b_1(O_1) & b_1(O_2) & b_1(O_3) & b_1(O_4) \\ b_2(O_1) & b_2(O_2) & b_2(O_3) & b_2(O_4) \\ b_3(O_1) & b_3(O_2) & b_3(O_3) & b_3(O_4) \end{bmatrix} \quad (4)$$

Initial probability distribution

The initial probability distribution for the model is given below

$$\pi = [\pi_1, \pi_2, \pi_3] \quad (5)$$

The Hidden Markov Model for Fire Accident Occurrence

The general Hidden Markov Model for the number of fire accident occurrence prediction is given by the compact notation in equation (6)

$$\lambda = (\mathrm{A}, \mathrm{B}, \pi) \quad (6)$$

RESULTS

Application of the Hidden Markov Model for Prediction of Fire accident Occurrence

The data used in this research work were collected from the Niger State Fire service for the period of 8 years (20013 – 2020). Niger state with a population of 5,556,247 million people (National population commission, 2020) is located in the North central zone along the Middle Belt region of Nigeria. It is classified as one of the largest states in the country (in terms of landmarks), spanning over 86,000 km^2 in land area. The summary is presented in Table1below

Table 1: Summary of State and Observation of Fire Occurrence for a Period of Eight Years

Years	States	Observations
2013	1 (L)	(Q_1)
	1(L)	(Q_2)
	1(L)	(Q_3)
	1(L)	(Q_4)
2014	1(L)	(Q_1)
	1(L)	(Q_2)
	1(L)	(Q_3)
	1(L)	(Q_4)
2015	1(L)	(Q_1)
	1(L)	(Q_2)
	1(L)	(Q_3)
	1(L)	(Q_4)
20016	1(L)	(Q_1)
	1(L)	(Q_2)
	1(L)	(Q_3)
	1(L)	(O_4)
2017	2(M)	(Q_1)
	1 (L)	(Q_2)
	1(L)	(Q_3)
	1(L)	(Q_4)
2018	2(M)	(Q_1)
	1(L)	(Q_2)
	1(L)	(Q_3)
	1(L)	(Q_4)
2019	2(M)	(O_1)
	2(M)	(Q_2)
	1(L)	(Q_3)
	2(M)	(Q_4)

Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 *https://dx.doi.org/10.4314/sa.v21i1.18*
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

2020	3(H)	(Q_1)
	2(M)	(Q_2)
	1(L)	(Q_3)
	2(M)	(Q_4)

Validity Test for the Model

To test for the validity of the model, the parameters of the HMM were estimated using the fireaccident occurrence data from 2013 to 2017, then make forecast for 2018, 2019 and 2020.

The Transition Count Matrix (C), Pseudo count Transition Matrix (S) and Transition Probability Matrix (A) are given in Equations (7), (8) and (9) respectively.

$$C = \begin{bmatrix} 17 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{7}$$

$$S = \begin{bmatrix} 18 & 2 & 1 \\ 2 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \tag{8}$$

$$A = \begin{bmatrix} 0.8571 & 0.0952 & 0.0476 \\ 0.5000 & 0.2500 & 0.2500 \\ 0.3333 & 0.3333 & 0.3333 \end{bmatrix} \tag{9}$$

While Observation count matrix (E), Pseudo count Observation matrix (D) and Observation probability matrix (B) are given in equations (10), (11) and (12), respectively.

$$E = \begin{bmatrix} 4 & 5 & 5 & 5 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{10}$$

$$D = \begin{bmatrix} 5 & 6 & 6 & 6 \\ 2 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \tag{11}$$

$$B = \begin{bmatrix} 0.625 & 0.750 & 0.750 & 0.750 \\ 0.250 & 0.125 & 0.125 & 0.125 \\ 0.125 & 0.125 & 0.125 & 0.125 \end{bmatrix} \tag{12}$$

The initial state probability is given below

$$\pi = [0.95, 0.05, 0] \tag{13}$$

The general HMM1 is represented by equation (14)

$$\lambda_1 = (A, B, \pi) \tag{14}$$

After 1000 iteration of the Baum Welch Algorithm, Theequation stabilised to equation(15) we trained equation *(*14) using a built-in Baum algorithm function in the Matlab 2015.

$$\lambda_1^{*} = \left(\hat{\mathrm{A}}, \hat{\mathrm{B}}, \hat{\pi} \right) \tag{15}$$

where

$$\hat{A} = \begin{bmatrix} 0.5556 & 0.4444 & 0.0000 \\ 0.0000 & 0.0000 & 1.0000 \\ 1.0000 & 0.0000 & 0.0000 \end{bmatrix} \tag{16}$$

$$\hat{B} = \begin{bmatrix} 0.000 & 0.000 & 0.500 & 0.500 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 \end{bmatrix} \tag{17}$$

And $\pi =$ [0.95, 0.05, 0] (18)

Making Prediction with the Model

From the summary of the fire accident data presented in table 1, the process is in State 1at the last Quarter of 2017 (that is with Observation Q_4). Now, to obtain the likely state sequence of the process in 2018 given the observation sequence of the year 2018 that is Q_1, Q_2, Q_3 and Q_4, we use Viterbi algorithm as shown in figure 1

To avoid underflow of the Viterbi algorithm, we normalised each of the obtained node in the computation process using the following equations:

$$c_t = \frac{1}{\sum_{t=1}^{N} \alpha_t(i)} \tag{19}$$

$$\hat{\alpha}_t(i) = c_t \times \alpha_t(i) = \frac{\alpha_t(i)}{\sum_{t=1}^{N} \alpha_t(i)} \tag{20}$$

Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 https://dx.doi.org/10.4314/sa.v21i1.18
© Faculty of Science, University of Port Harcourt, Printed in Nigeria ISSN 1118 – 1931

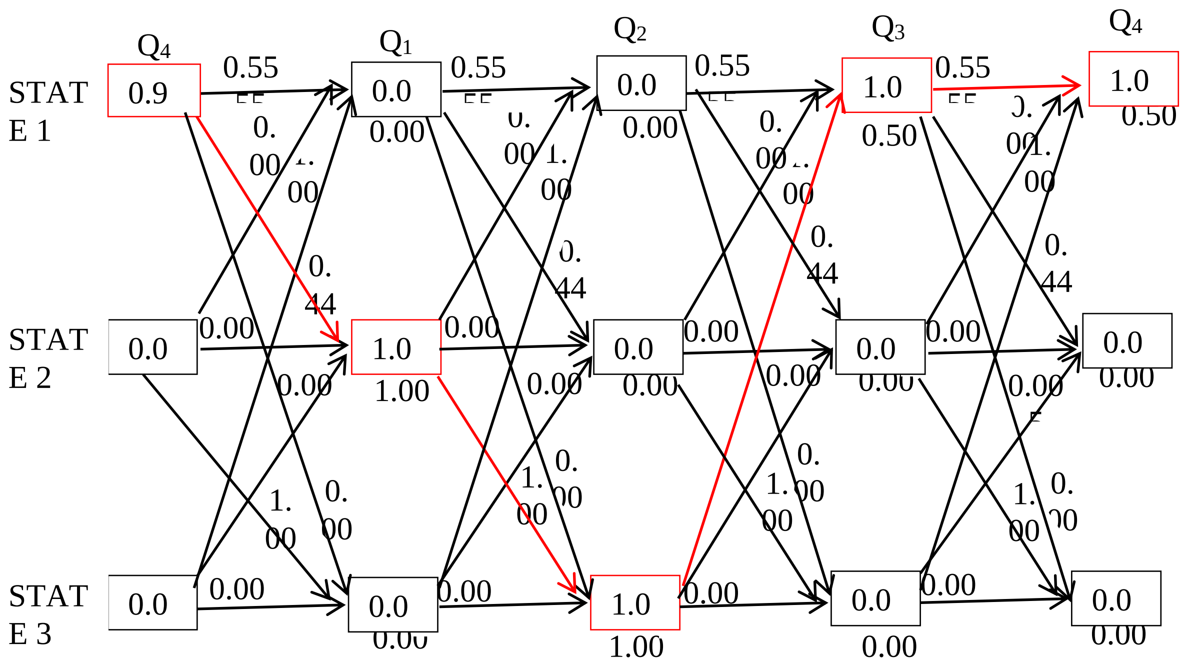

Figure 2: Viterbi algorithm for Observation Sequence Q₄,Q₁,Q₂,Q₃Q₄of 2018

State 1 to state 2, has the highest probability value under Q_1 that is, (0.95 x 0.44)1.00=0.4222, normalising this value using equation (19) and (20) we obtain the value 1, then we move to the next path of computation.

State 2 to state 3, has the highest probability value under Q_2 that is (0.05 x 1.00)1.00=0.0500, normalising this value using equation (19) and (20) we obtain the value 1, then we move to the next path of the computation.

State 3 to state 1, has the highest probability value under Q_3 that is (0.95 x 0.55)0.50=0.2639, normalising this value using equation (19) and (20) we obtain the value 1, then we move to the next path of the computation.

State 1 to state 1, has the highest probability value under Q_4 that is, (0.95 x 0.55)0.50=0.2636, normalising this value using equation (19) and (20)we obtain the value 1, The results of the computation of figure 2 are represented in Table 2 below.

Table 2: The Result for 2018 Number of FireAccident Occurrence Based on Viterbi Algorithm Prediction

Year/Months	2017		2018		
States:	1	2	3	1	1
Observation:	Q_4	Q_1	Q_2	Q_3	Q_4

Similarly, from the calculation of Table 2, the process is in State 1 at the last Quarter of 2018 (that is with Observation Q_4). Now, to obtain the likely state sequence of the process in 2019 given the observation sequence of the year 2019 that is Q_1, Q_2, Q_3 and Q_4, we use Viterbi algorithm as shown in figure 3.To avoid underflow of the Viterbi algorithm we normalised each of the obtained node in the computation process using the following equations (19) and (20)

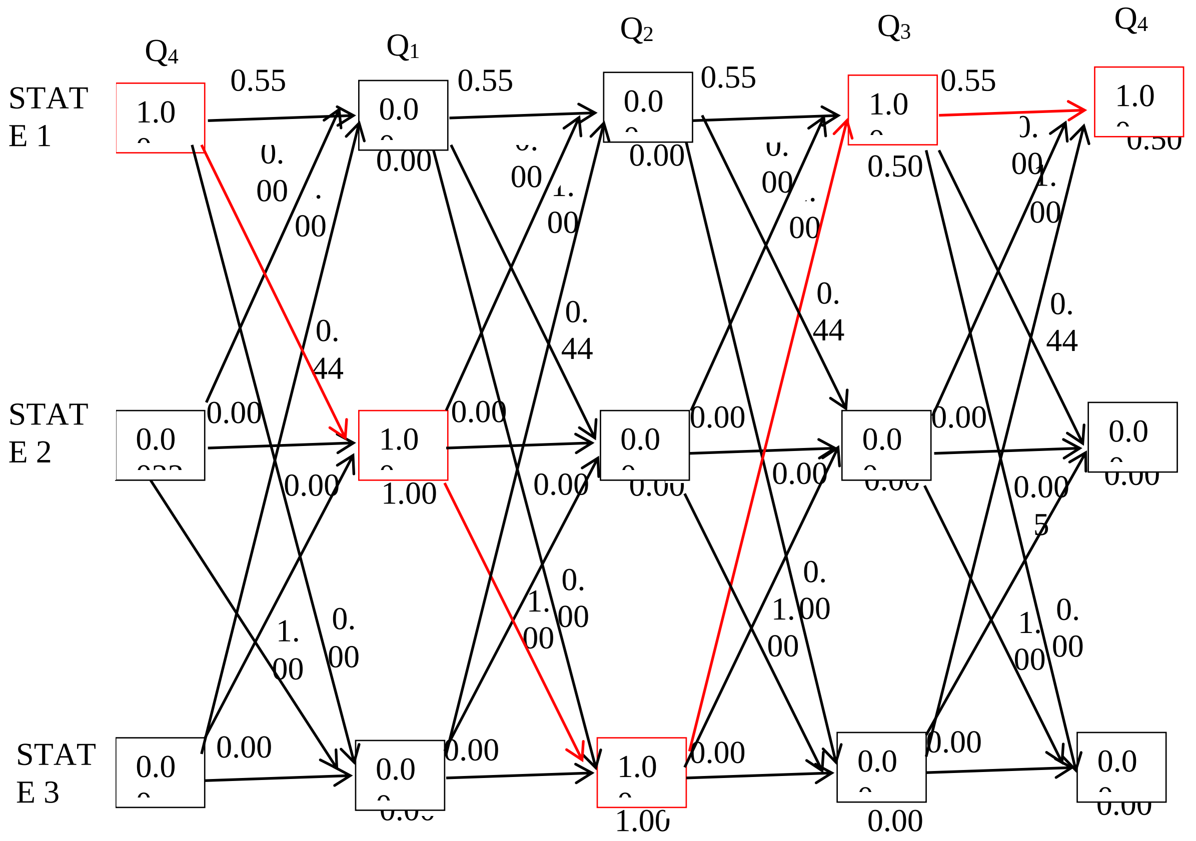

Figure 3: Viterbi algorithm for Observation Sequence Q_4,Q_1,Q_2,$Q_3$$Q_4$of 2019

State 1 to State 2, has the highest probability value under Q_1 that is (0.444 x 1.00)1.00=0.444, normalising this value using equation (19) and (20)we obtain the value 1,

State 2 to State 3, has the highest probability value under Q_2 that is, (1.000x1.000)1.00=1.000, normalising this value using equation (19) and (20) we obtain the value 1.

State 3 to state 1, has the highest probability value under Q_3 that is, (1.000x1.000)0.50= 0.50, normalising this value using equation (19) and (20) we obtain the value 1.

State 1 to state 1, has the highest probability value under Q_4 that is, (1.000x0.55)0.50 = 0.2775, normalising this value using equation (19) and (20) we obtain the value 1.

The results of the computation of figure 3 are represented in Table 3.

Table 3: The Result for 2019 Number of FireAccident Occurrence Based On Viterbi Algorithm Prediction

Years		2019		
States	2	3	1	1
Observation	Q_1	Q_2	Q_3	Q_4

Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 https://dx.doi.org/10.4314/sa.v21i1.18
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

Similarly, the process is in State 1at second Quarter of 2019 (that is with Observation Q_4). Now, to obtain the next likely state sequence of the process in 2020 given the observation sequence of the year 2020 that is Q_1, Q_2, Q_3 and Q_4, we use Viterbi algorithm as shown in figure 4.

To avoid underflow of the Viterbi algorithm we normalised each of the obtained node in the computation process using the following equations (19) and (20).

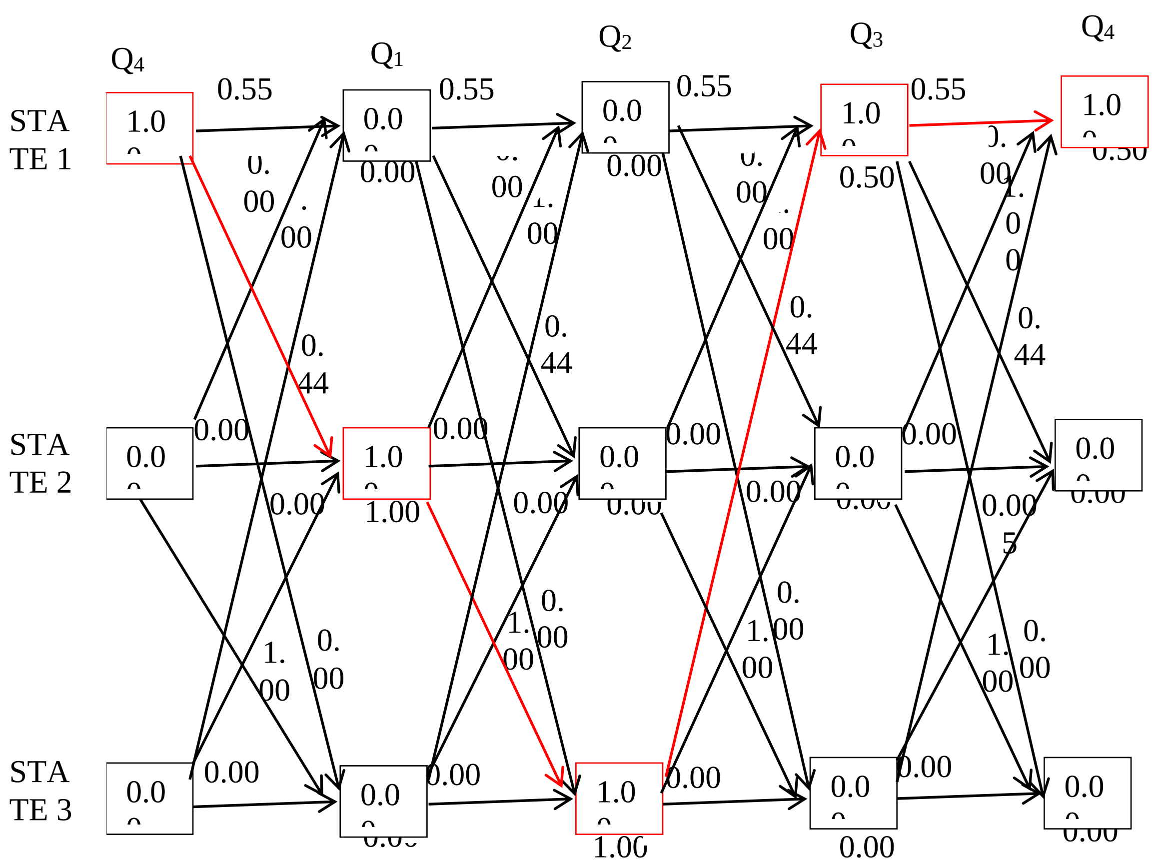

Figure 4: Viterbi algorithmfor Observation Sequence Q_4,Q_1,Q_2,$Q_3$$Q_4$of 2020

state 1 to state 2, has the highest probability value under Q_1 that is(0.444 x 1.00)1.00=0.444, normalising this value using equation (19) and (20) we obtain the value 1,

State 2 to state 3, has the highest probability value under Q_2 that is, (1.000x1.000)1.00=1.000, normalising this value using equation (19) and (20) we obtain the value 1,

State 3 to state 1, has the highest probability value under Q_3 that is, (1.000x1.000)0.50= 0.50, normalising this value using equation (19) and (20) we obtain the value 1,

State 1 to state 1, has the highest probability value under Q_4 that is, (1.000x0.55)0.50 = 0.2775, normalising this value using equation (19) and (20)we obtain the value 1,

The results of the computation of figure 4 are represented in Table 4 below.

Table 4: The Result for 2020 Number of FireAccident Occurrence Based On Viterbi Algorithm Prediction

Year	2020			
States	2	3	1	1
Observation	Q_1	Q_2	Q_3	Q_4

In general, the summary of the fire accident occurrence which shown below in table 5

Table 5: Summary of the Fire Accident Occurrence

Year	2018				2019				2020			
States	2	3	1	1	2	3	1	1	2	3	1	1
Observation	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4

Table 6: Comparison of the Predicted States and Observations, and the Actual States and Observations from Table 1.

Year	2018				2019				2020			
Actual States	2	1	1	1	2	2	1	2	3	2	1	2
Predicted States	2	3	1	1	2	3	1	1	2	3	1	1
Observation	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4

From the table 6, it can be observed that the prediction for 2018 Quarters has 75% accuracy, then 2018 to 2019 Quarters has 62.5% accuracy and lastly for 2018 to 2020 has 50% accuracy. The result of the model clearly shows that, the model perform better for only short time prediction and perform fairly for long time prediction.

Hidden Markov Model for future prediction

Hidden Markov model for future prediction is developed to predict number of Fire Accident Occurrence for future years, the parameters of the model were determined using Fire Accident Occurrence data from 2013 to 2020 (the whole data set) after which, we predict for 2021 and 2022.

Transition Count Matrix

$$C = \begin{bmatrix} 19 & 5 & 0 \\ 4 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{21}$$

Pseudo count Transition Matrix

Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 https://dx.doi.org/10.4314/sa.v21i1.18
© Faculty of Science, University of Port Harcourt, Printed in Nigeria ISSN 1118 – 1931

$$S = \begin{bmatrix} 20 & 6 & 1 \\ 5 & 2 & 2 \\ 1 & 2 & 1 \end{bmatrix} \tag{22}$$

Transition Probability Matrix

$$A = \begin{bmatrix} 0.7407 & 0.2222 & 0.0370 \\ 0.5555 & 0.2222 & 0.2222 \\ 0.2500 & 0.5000 & 0.2500 \end{bmatrix} \tag{23}$$

Observation Count Matrix

$$C = \begin{bmatrix} 4 & 6 & 8 & 6 \\ 3 & 2 & 0 & 2 \\ 1 & 0 & 0 & 0 \end{bmatrix} \tag{24}$$

Pseudo count Observation Matrix

$$S = \begin{bmatrix} 5 & 7 & 9 & 7 \\ 4 & 3 & 1 & 3 \\ 2 & 1 & 1 & 1 \end{bmatrix} \tag{25}$$

Observation Probability Matrix

$$\mathrm{B} = \begin{bmatrix} 0.4545 & 0.6363 & 0.8181 & 0.6363 \\ 0.3636 & 0.2727 & 0.0909 & 0.2727 \\ 0.1818 & 0.0909 & 0.0909 & 0.0909 \end{bmatrix} \tag{26}$$

Initial State Probability

$$\pi = \begin{bmatrix} 0.75 & 0.2187 & 0.0312 \end{bmatrix} \tag{27}$$

$$\lambda_2 = (A, \quad B, \quad \pi) \tag{28}$$

After 900 iteration of Baum Welch Algorithm, equation (28) stabilized to (29)

$$\lambda^* = \left(\hat{A}, \quad \hat{B}, \quad \hat{\pi} \right) \tag{29}$$

Where

$$\hat{A} = \begin{bmatrix} 0.5333 & 0.4667 & 0.0000 \\ 0.0000 & 0.0000 & 1.0000 \\ 1.0000 & 0.0000 & 0.000 \end{bmatrix} \tag{30}$$

$$\hat{B} = \begin{bmatrix} 0.0000 & 0.0000 & 0.6000 & 0.4000 \\ 1.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 1.0000 & 0.0000 & 0.0000 \end{bmatrix} \tag{31}$$

$$\hat{\pi} = \begin{bmatrix} 0.75 & 0.2187 & 0.0312 \end{bmatrix} \tag{32}$$

Prediction for 2021 and 2022

Following similar method of predictionprocedures andusing equation(30) to (32)the results for 2021 and 2022 predictions are presented in the table 7 below

Table 7:The Result for 2021 and 2022Number OfFireAccident OccurrenceBased on Viterbi Algorithm Prediction

Year	2020	2021				2022			
States:	1	2	3	1	1	2	3	1	1
Observation:	Q_4	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4

DISCUSSION OF RESULTS

The parameter of the validity test model was determined usingfire Accident Occurrencedata from 2013 to 2017. After 1000 iterations of the Baum Welch Algorithm, λ_1 stabilised to a new model $\lambda_1^\bullet$, Viterbi Algorithm was then used to make a prediction for Fire Accident Occurrence for 2018, 2019, and 2020. From the table 1, the HMM1 was in state 1 at 2017last Quarter(Q_4), It make transition to state 2 in 2018emitting observation(Q_1),then it make move to state 3 emitting observation(Q_2),at that point, it also make move to state 1emitting observation(Q_3),it then make move to state 1emitting observation(Q_4). The Validity test for the Quarters of 2018 shows 75% Accuracy.

Similarly in 2019 the process is in state 2first Quarter (Q_1), then make move to state 3 emitting observation(Q_2), at that point, it also make move to state1emitting observation (Q_3),it also make move to state 1emitting observation(Q_4).The validity test for 2018 and 2019 Quarters showed 62.5% Accuracy.

Similar interpretation is given in 2020, the process is in state 2at first Quarter of 2020 (Q_1). then it make move to state 3 emitting observation(Q_2),at that point, it also make move to state 1emitting observation(Q_3),it also make move to state 1emitting observation at (Q_4),The validity test for 2018, 2019 and 2020 shows 50% Accuracy.

Generally, the result for the validity test showed that the model perform better for short time prediction and performed fairly for long time prediction.

For the Future predictionthe parameter of the HMM were estimated usingFire Accident Occurrencedata from 2013 to 2020. After 900 iteration of the Baum Welch algorithm λ_2, stabilised to another model $\lambda_2^\bullet$, the Viterbi Algorithmwas then used to make a prediction for future Quarters. From the table1, the HMM wasin

Scientia Africana, Vol. 21 (No. 1), April, 2022. Pp 207-222 https://dx.doi.org/10.4314/sa.v21i1.18
© Faculty of Science, University of Port Harcourt, Printed in Nigeria ISSN 1118 – 1931

state 2last Quarter of 2020, then it make move to state 2 emitting observation(Q_1)in 2021, at that point, it also make move to state 3emitting observation(Q_2),it also make move to state 1emitting observation(Q_3)it also make move to state 1emitting observation(Q_4) at 2021.

Similar interpretation is given to the movement instate 2 emitting observation(Q_1), at 2022at that point, it also make move to state 3emitting observation(Q_2),it also make move to state 1emitting observation(Q_3), it also make move to state 1emitting observation(Q_4)at year 2022.

CONCLUSION

The study has developHidden Markov Model that predicts the number of fire accident occurrence in Niger State using Viterbi Algorithm. The Validity test for the model showed 75% accuracy for short time prediction and shows 50% accuracy for long time prediction. The result indicates that the model is more reliable and dependable for only short time prediction. Information for this study could serve as a guide to the government in policy formulation that might assist in curbing the number of fire accident occurrences in Niger State.

REFERENCES

Ardianto, R. &Chhetri, P. (2019).Modeling Spatial–Temporal dynamics of urban residential fire risk using a Markov Chain technique.*International Journal of Disaster Risk Science*, 4(3), 45 - 98.

Asgary, A., Ghaffari, A. & Levy, J. (2010). Spatial and temporal analyses of structural fire incidents and their causes: A case of Toronto, Canada. *Fire Safety Journal*, 45(1), 44-57.

Ceyhan, E., Ertuğay, K. &Düzgün, Ş. (2013). Exploratory and inferential methods for spatio-temporal analysis of residential fire clustering in urban areas.*Fire Safety Journal*, 58,226-239.

Charles, J. (2000). Fire Technology. Malaysia International Conference, 35, 13- 89.

Chhetri, P., Corcoran, J., Stimson, R. &Inbakaran, R. (2010).Modelling potential socio-economic determinants of building fires in South East Queensland.*Geographical Research*, 48(1), 75-85.

Corcoran, J. & Higgs, G. (2013).Special issue on spatial analytical approaches in urban fire management.*Fire Safety Journal*, 6(2), 1-2.

Corcoran, J., Higgs, G., Brunsdon, C., Ware, A. & Norman, P. (2007). The use of spatial analytical techniques to explore patterns of fire incidence: A South Wales case study. Computers, Environment and Urban Systems, 31(6), 623-647.

Corcoran, J., Higgs, G., Rohde D. & Chhetri, P. (2011b).Investigating the association between weather conditions, calendar events and socio-economic patterns with trends in fire incidence: an Australian case study. *Journal of Geographical Systems*, 13(2), 193-226.

Durbin, R., Eddy, S.Y., Krogh. A., & Mitchison,.G. (1998). Biological Sequence Analysis: Probabilistic Models of Proteins and Nucleic Acids. Cambridge, UK: Cambridge University Press.

Enza, M., & Daniele, T.(2007). Hidden Markov models for scenario generation. *Journal of Management Mathematics*, 19, 379-401.

Fink,G.A.(1989). Markov Models for Pattern Recognition. From Theory to Applications Second Edition. London, UK: Springer.

Guldåker, N. &Hallin, P-O., Nilsson, J. &Tykesson, M. (2018).Spatio-temporal patterns of intentional fires, social stress and socio-economic determinants: A case study of Malmö, Sweden. *Fire Safety Journal*, 7(3), *71-80.*

Jennings, C. (2013). Social and economic characteristics as determinants of residential fire risk in urban neighbourhoods: a review of the literature and commentary. *Fire Safety Journal,* 6(2), 13-19.

Lawal Adamu (2018). "Hidden Markov Model and its Application in Rainfall Pattern Prediction" (A Monograph in Mathematics) LAP Lambert Academic Publishing: ISBN: 978-613-4-98532-1

Pantousa,D. E. M. (2017). Interface modelling between CFD and FEM analysis: the dual-layer post-processing model. *Engineering Computations Journal Impact,* 3(1), 45 -133.

Rabiner, L.R. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. Proc. IEEE, 77, 257-286.

Robert Mattila (2020). Hidden Markov Models: Identification, Inverse Filtering and Applications Doctoral Thesis in Electrical Engineering KTH Royal Institute of Technology Stockholm, Sweden

Sakurahara, T., Mohaghegh, Z. &Reihani, S. (2018). An integrated methodology for spatio-temporal incorporation of underlying failure mechanisms into fire probabilistic risk assessment of nuclear power plants. *Journal of Statistical Scholar.* 3(2), 121 – 145.

Špatenková, O. & Virrantaus, K. (2013). Discovering spatio-temporal relationships in the distribution of building fires. *Fire Safety Journal, 62, pp. 49-63.*

Sun, T. M., & Mao S. W. (2011). Optimal Simultaneous Delivery of siRNA and Paclitaxel via a "Two-in-One" Micelleplex Promotes Synergistic Tumor Suppression. *Engineering Computations Journal Impact,* 3(1), 65 -73.

Wuschke, K., Clare, J. & Garis, L. (2013). Temporal and geographic clustering of residential structure fires: A theoretical platform for targeted fire prevention. *Fire Safety Journal, 62, pp. 3-12.*

Yahaya, M and **Lawal**. A (2020) "A Stochastic Model for Rice Yields Forecast"*Lapai Journal of Applied and Natural Sciences,*5(1): 16-25.

Yusuf, O. (2012). A literature review of fire incidence with an emphasis on urban residentialfires. 8, 116-130.