IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2019, 9(4), 110-114.

Application of the Stochastic Markov Model in Predicting the Volume of Oil Spill in Nigeria: A Case of the Niger-delta Region

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Received: 22 February 2019 **Accepted:** 12 May 2019 **DOI:** https://doi.org/10.32479/ijeep.7744

ABSTRACT

Oil spillage in the Niger Delta region of Nigeria and its associated hazard is on the increase and there is urgent need to combat its increasing volume by predicting the volume in the future thus, the objective of this study is on the prediction of the volume of oil spill in Nigeria via the Stochastic Markov Model. Two States Markov analysis were employed and it was discovered that the volume of oil spill incident were mostly maintained in a high state than in a low state and the predicted values were approximately steady at a probability value of 0.519 which is in favour of the high state. The study concluded that for the Nigerian Federal government to combat the volume of oil spill, she should in addition to enforcing the laws governing the volume of oil spill incident, employ remediation process that would help clean up the mess caused the spillage

Keywords: Occurrence, Oil Spill, Niger Delta
JEL Classifications: P28, Q53, Q56

1. INTRODUCTION

Nigeria, the giant of Africa is a country that is blessed with both human and natural resources, natural resources such as crude oil, rubber, lime stone are amongst the numerous gifts from God Almighty. Amidst these precious gifts, Nigeria is yet to be called "a developed country" irrespective of the name, "the giant of Africa." Nigeria has all she needs and takes to make her great in all ramifications. One of the blessings given to Nigeria has turned to be her greatest nightmare and that is crude oil but it is pertinent to say that the natural resources endowed to our country Nigeria is more of a resource curse than a blessing. Nigeria's major source of income is crude oil and most of her problems have their origins emanating from the so called crude oil. The major issue is that instead of the natural resources to bring about the needed gains or say blessings to both the country and her citizens, the feedback is a "resource curse."

The discovery of oil and oil on a commercial basis was in the Niger Delta region of Nigeria at Oloibiri (the present day Bayelsa state) in the year 1956, although more oil discoveries were made after that of Olobiri and exports began in the year 1958 almost 2 years after discovery at Olobiri. It was only in the year 1965 that it became significant and the reason for that was because the Bonny Island terminals at Rivers State and the necessary pipelines to feed the terminal were completed. The Nigerian export was put at an average of 2.5 million barrels each day in the year 2004 and its reserve at 35 billion barrels (CAB, 2005). Subsequent discoveries of oil in other parts of the country gave rise to diverse problems that are harmful to man and development. Problems such as pipe line vandalization, oil bunkering and siphoning, oil theft are some of the problems facing the country and depriving her of the necessary and supposed growth. When it comes to oil in the Niger Delta, oil spillage or oil spill incident has become a household name. It is rather imperative to think that it is a recent issue. Oil spillage in Nigeria is on the increase and its associated harm on the environment is also on the increase. The problem is now on the volume of oil spill, how can the Nigerian government tackle this problem?, or one can say in a lighter mood, how can its remediation process work if the quantity or volume lost is not modelled and predicted.

The main aim of this paper is on how the volume of oil spill can be predicted via the stochastic Markow model and thus if this is achieved, the remediation process can also be readily achieved because one can thus have a rough idea of what the volume of oil spill would look like in years to come and thus work ahead of time.

2. LITERATURE REVIEW

Previous stochastic Markow analysis literature were mainly on risks disruptions due to Maritime, risk of workers that are exposed to oil and gas industry, there are also studies that are not Markov oriented, studies such as that by Mode et al. (2013), they predicted the rate and volume of oil spill on both vertical and horizontal pipelines with a high correlation coefficient value of 0.978. It was realized that the model should be utilized with a high degree of confidence so that the bioremediation project was used for proper assessment. Another study developed a guerrilla movement that observed oil pipeline attack decision, although the Markov Decision Process was modelled as an infinite horizon that chooses each period either to attack or not to attack the pipeline. Parameters were also compared when the discount factor changed (Offstein, 2002). Offstein (2002) discovered that a zero discount factor hypothesis implies that the movement or attack behaviour is very much compatible with extortionary behaviour. Bam (2015) examined the effects of oil spill and recovery of terrestrial arthropods in Louisiana Saltmarsh ecosystem. Ten sites were sampled, that is, these sites were along the Louisiana coast. Amongst the ten sites that were sampled, 4 were heavily oiled, 3 were lightly oiled and the last 3 unoiled. It was discovered that the terrestrial arthropods were affected by oil and hurricane Isaac and up till today, the oil contamination effects still persist today (Bam, 2015).

Rico et al. (2008) viewed the effects of the prestige oil spill on macroalgal assemblages via a large scale comparison, they compared data obtained before the spill and after the spill. They sampled 4 zones in the North and North West coast of Spain and discovered that differences in abundance were observed but they did not display any significant pattern. They concluded that the causes of the assemblages after spill were the limited use of aggressive cleanup methods and fuel deposition on the shores that weren't intense but rather extensive. Rutherford et al. (2015) examined how the stochastic prediction of oil spill transport can be improved using the approximation methods. Their sole aim was on how they can identify parameters that could further improve the forecasting algorithms. Rutherford et al. (2015) focused on the CranSLIK functionality as one of its approximation methods and concluded that the CranSLIK v2.0 which was a revised model was validated against the MEDSLIK-II and it was discovered that the new version of CranSLIK was better in forecasting improvements by its ability to capture the oil spill accurately than the other.

There are also studies that were just on oil spill incident; studies such as (Cekirge, 2013; Mba et al., 2019; Ndeh et al., 2017; Ohanmu et al., 2018). Mba et al. (2019) examined oil spillage causes and terrain in the Niger-Delta region of Nigeria, they employed a two way analysis of variance approach and thus concluded that sabotage was the major cause of oil spillage in the Niger Delta followed by operational and mystery spill. Ohanmu et al. (2018) examined if the changes in physicochemical properties and heavy metals would affect two species of pepper. They employed the randomized block design and discovered that crude oil spill actually affects the soil properties and nutrients. Ndeh et al. (2017) investigated crude oil spillage in Upenekang village in Ibeno local government area of Akwa Ibom state in Nigeria, they looked at the effect of crude oil spill on the underground and surface stream water. They employed a one way analysis of variance approach and their sresult showed that there are no significant influence of distance away from spill on the level of heavy metals in the water samples collected.

Cekirge (2013) employed methods in determining the volume of oil spill. These methods were based on ascertaining the thickness of oil on water surface by employing usual observations, an algorithm and model were thus developed using optimization techniques and software. They concluded that the method would give a positive result if it is employed on actual oil spill.

3. METHODOLOGY

The monthly oil spill data ranging from January 2015 to December 2018 was used and the source of the data is from Shell Nigeria database[1].

The Stochastic Markov Chain (SMC) model.

The monthly observed oil spill data will follow two (2) states, S_t; where S_t=1, which would be referred to as a "high" state of the volume of oil spill incident in Nigeria.

S_t=2, would henceforth be referred to as a "low" state of the volume of oil spill incident in Nigeria.

Thus, whether states S_t=1,2; the process respectively would switch states such that the change observed from a past state t to a new state t+1 is from a normal distribution and thus is a random draw. Thus Y_t is the observed change and the distribution would thus be:

$$Y_t \sim \left(\mu_1 \sigma_1^2\right) \text{ distribution for the "high" state} \quad (1)$$

$$Y_t \sim \left(\mu_1 \sigma_1^2\right) \text{ distribution for the "low" state} \quad (2)$$

From expressions (1) and (2), there exist switches from one state to the other and thus the probabilities (P_{ij}) of the switches between the two states is given as:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} \text{which can also be written as } P_{ji} = \begin{bmatrix} P_{hh} & P_{hl} \\ P_{lh} & P_{ll} \end{bmatrix} \quad (3)$$

1 https://www.shell.com.ng/sustainability/environment/oil-spills.html

Expression (3) is referred to as the transition probability matrix. Therefore, the transition probability state can be switched between the two states or that a particular state (i) be followed by another state (j) or vice versa. Thus, the current volume of oil spill incident depends on the preceding and not on the past volume of oil spill incident.

Therefore the SMC Model is given as;

$$SMC=P(Xt+1=x/X1=x1, X2=x2,\ldots,Xt=xt) \quad (4)$$

Where t is an element of N and N is the total number of oil spill incident in a year.

X is the volume of oil spill incident at different time period.

Note that the sum of the probabilities row wise cannot exceed 1.

$$\text{Thus, } P_{11}+P_{12}=1 \quad (5)$$

The N-step transition probabilities.

Thus, the probability that a SMC would be in state j (say a high state or a low state) after n periods is given as:

$$\Pr(X_{t+n}=j/X_t=i)=\Pr(X_n=j/X_1=i)=Pij(n) \quad (6)$$

Where $P_{ij}(n)$ is called the n-step probability of a transition from state i to state j.

For the N-step transition probabilities to be achieved, the years under study would be pooled and their frequencies and transition probabilities thus would be calculated.

Therefore the observed frequency Fij table for the two states is given in Table 1.

Where Fij is the observed frequency from the volume of oil spill incident and thus the F_{HH} simply implies that the switches are from a high state to another high state and F_{HL} implies that it is from a high state to a low state and F_{LH} shows that it is from a low state to a high state and lastly F_{LL}; a low state to another low state.

4. ANALYSIS AND INTERPRETATION OF RESULTS

From the Table 2, it can be seen that in the year 2015, from January to December, that the total switches from a high volume of oil spill to another high volume of oil spill is twenty-one (21). The highest switches was witnessed still in the year 2015 with a total frequency of 38 and the switches was from a low state to a high state followed by 37 in the year 2017, that is from a high state to a low state and 36, from a low state to a high state. In 2016, it was discovered that switches from a low state to another low state was 7 in total frequency followed by 14, that is, a low state to another low state.

Table 1: Observed frequency F_{ij}

Switching states	Frequency (Fij)
HH	F_{HH}
HL	F_{HL}
LH	F_{LH}
LL	F_{LL}

Table 2: Observed frequency table for 2 states volume of oil spill

Year	Switching states	Frequency (Fij)
2015	HH	21
	HL	37
	LH	38
	LL	24
2016	HH	17
	HL	23
	LH	24
	LL	7
2017	HH	16
	HL	37
	LH	36
	LL	23
2018	HH	30
	HL	32
	LH	32
	LL	14

Source: Authors' computations

It can be seen that in the year 2016, the volume of oil spill will switch from a low state to another low state with a probability value of 0.226 that is 23%, which is very low (Table 3). Thus from year 2015 to 2018, the switches were mainly from high state to low state and from low state to high state. This simply implies that the volume of oil spill would always switch majorly between a low to high states or vice versa.

The probability of the volume of spill remaining in the same state, that is, from a high state to a high state or low state to a low state are usually insignificant in value but the switches from one state to another; say a high state to a low state or from a low state to a high state are significant in value, thus, there is always transition or movement from one state to another. It takes 39% in 2015, 23% in 2016, 39% in 2017 and 30% in 2018 for the volume of oil spill to remain in a low state and 36% in 2015, 43% in 2016, 30% in 2017 and 48% in 2018 for the volume of oil spill to remain in high state but for switches from high to low, it takes 64% in 2015, 58% in 2016, 69% in 2017 and 52% in 2018 and finally low to high shows 61%, 77%, 61% and 70% for years 2015 through 2018 respectively. Thus the switches is more from the low state of oil spill incident to a high state than the other way. It simply implies that the volume of oil spill incident usually is high as regards the volume of its spillage. Thus, the volume of oil spilled is more in quantity as shown by the probability values indicating the low state of oil spill to a high state of oil spill.

The Pooled Frequency and Transition Probability Matrices from 2015-2018 is given as:

$$\begin{bmatrix} 84 & 129 \\ 128 & 68 \end{bmatrix} = \begin{bmatrix} 0.394 & 0.606 \\ 0.653 & 0.347 \end{bmatrix}$$

Table 3: The transition probability matrices for the different years with respect to volume of oil spill

Year	Switching states	TP	TPM
2015	HH	0.36	$\begin{bmatrix} 0.36 & 0.64 \\ 0.61 & 0.39 \end{bmatrix}$
2015	HL	0.64	
2015	LH	0.61	
2015	LL	0.39	
2016	HH	0.425	$\begin{bmatrix} 0.425 & 0.575 \\ 0.774 & 0.226 \end{bmatrix}$
2016	HL	0.575	
2016	LH	0.774	
2016	LL	0.226	
2017	HH	0.301	$\begin{bmatrix} 0.301 & 0.698 \\ 0.610 & 0.390 \end{bmatrix}$
2017	HL	0.698	
2017	LH	0.610	
2017	LL	0.390	
2018	HH	0.484	$\begin{bmatrix} 0.484 & 0.516 \\ 0.696 & 0.304 \end{bmatrix}$
2018	HL	0.516	
2018	LH	0.696	
2018	LL	0.304	

Source: Authors' computations, TP: Transition probabilities, TPM: Transition probability matrices

The pooled transition probability (PTP) value for the oil spill incident with respect to the switches between high to low and low to high are 0.606 and 0.653 respectively which shows that it takes 61% for the volume of oil spill incident to switch from a high state to a low state and then 65% for the volume of oil spill incident to switch from a low state to a high state. Thus, one can see that the switches from a low state volume of oil spill to a high state volume of oil spill is more, that is, from 2015 to 2018, it can still be seen that the volume of oil spill is on a high state than any other state. The table below shows the iteration table of the N-step transition probability that shows the prediction of the oil spill incident in Nigeria.

The table below shows the N-step iteration for the PTP from 2015 to 2018 and the corresponding predicted years from 2019 through 2023.

From the Table 4, the N-step PTP matrices show that even in the long run, the high state to high state in the year 2019 is 0.550954 approximately 0.551; in 2020, 0.5103029 approximately 0.510. Thus, there was a decrease in the probability value and in 2021, 0.5181046 approximately 0.518, 0.5188109 approximately 0.519 in 2022 and in 2023, 0.5186280 approximated to 0.519. Recall also that the PTP from 2015 to 2018 is 0.394. From the matrices, we can see that there was a tremendous increase and in the year 2022 and 2023, the probability value remained unchanged with probability values approximated at 0.518. The low state to low state had 0.347 and had an increase but from 2020 to 2023, the probability value reduced ranging from 0.516127 in 2019, 0.4723231 in 2020 and approximately a steady value of 0.4807299 approximated to 0.481 (in 2021), 0.4814910 approximated to 0.481 (in 2022) and 0.4812938 approximated to 0.481 (in 2023).

Switches from a high state to a low state can also be seen to increase from 0.449046 in 2019 to 0.4896971 in 2020 and later decreased to 0.4818954 approximately 0.482 and maintained a steady probability value of 0.481 for 2022 and 2023 respectively. Switches from a low state to a high state also increased from 2019

Table 4: N-step pooled transition probability matrices

Year	PTP^N	N-step PTP matrices
2015-2018	PTP^1	$\begin{bmatrix} 0.394 & 0.606 \\ 0.653 & 0.347 \end{bmatrix}$
2019	PTP^2	$\begin{bmatrix} 0.550954 & 0.449046 \\ 0.483873 & 0.516127 \end{bmatrix}$
2020	PTP^3	$\begin{bmatrix} 0.5103029 & 0.4896971 \\ 0.5276769 & 0.4723231 \end{bmatrix}$
2021	PTP^4	$\begin{bmatrix} 0.5181046 & 0.4818954 \\ 0.5192701 & 0.4807299 \end{bmatrix}$
2022	PTP^5	$\begin{bmatrix} 0.5188109 & 0.4811891 \\ 0.5185090 & 0.4814910 \end{bmatrix}$
2023	PTP^6	$\begin{bmatrix} 0.5186280 & 0.4813720 \\ 0.5187062 & 0.4812938 \end{bmatrix}$

Source: Authors' computations

with probability value of 0.483873 to 0.5276769 in 2020 and later reduced in the probability value to 0.5192701 to a steady probability value of 0.5185090 in 2022 and 0.5187062 in 2023 approximately 0.519. Thus, a high state volume of oil spill incident has been predicted to occur more than the low state and the switches from even the low state to the high state is also with an increased value but the values housing the low state or switches from a high state to a low state is also reduced since the volume of oil spill incident state is switching from a state of high to low and not the other way. This implies that even in the future, the predicted probability values of the PTP matrices shows that a high state of the volume of oil spill incident will keep increasing and at a point would be maintained and the only way to combat the situation is to apply remediation processes that would bring about the reverse state, that is, from the state of high volume of oil spill incident to a low state and also maintain it so that there are no longer switches.

5. CONCLUSION AND RECOMMENDATION

The Stochastic Markow model was applied in predicting the volume of oil spill in Nigeria so as to know how best to tackle the unending problems that are caused by the spillage. The volume of oil spill has remained in a high state than in a low state. The switches from one state to the other has also proved that the volume of oil spill is in a high state than in a low state. The volume of oil spill was also predicted and from the results, it showed that even in the future, the state of high volume of oil spill has a steady state probability value of 0.519 which was seen from the high state to a high state and from a low state to a high state. Thus, the volume of oil spill incident are in the high state with a steady state probability value of 0.519 (52%) approximately. Subsequently, for Nigeria to combat the high state of oil spill, there is need for her to know if the oil spillage is actually in a high state or low state.

Thus, from this study, it can be seen that the volume of oil spill is actually in the high state most times. Conclusively, the Nigerian government can now apply a remediation process on time since it has been predicted via the Stochastic Markov analysis that the volume of oil spill is actually in a high state than in the low state. The Nigerian Federal government can also enforce laws that govern the volume of oil spill incident and treat offenders without mercy.

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