RESEARCH PAPER | International Journal of Agricultural Engineering | Volume 12 | Issue 2 | October, 2019 | 177-185

ISSN–0974–2662 ■ Visit us : *www.researchjournal.co.in* ■ **DOI: 10.15740/HAS/IJAE/12.2/177-185**

Hidden markov modeling for sorghum crop production

M. Thirunavukkarasu

Received : 26.04.2019; **Revised :** 15.08.2019; **Accepted :** 01.09.2019

Author for Correspondence :

M. Thirunavukkarasu
Department of Community Medicine, Sri Venkateshwaraa Medical College Hospital and Research Centre, **Ariyur (Puducherry) India**
Email : thirustat10@gmail.com

■ **ABSTRACT :** This study presents of a hidden markov model (HMM) based on technique to classify agricultural crops time series and identify better sequence. The objective is to figure out the hidden state sequence given the observation sequence so that the trend can be analyzed using the steady state probability distribution values. The probability of Markov process generated one year difference in time series value when considered is found to give the best optimum state sequence then other difference sequence. These numerical results clearly show an improved forecasting accuracy compared to all difference fitness value and highest fitness value is well fitted sequence in sorghum production using MATLAB coding programme.

■ **KEY WORDS :** Markov chain, Hidden sequence, Observation sequence, Transition, Emission probability matrix

■ **HOW TO CITE THIS PAPER :** Thirunavukkarasu, M. (2019). Hidden markov modeling for sorghum crop production. *Internat. J. Agric. Engg.*, **12**(2) : 177-185, **DOI: 10.15740/HAS/IJAE/12.2/177-185.**

A hidden markov model (HMM) is a classic approach for time series phenomena analysis and prediction. It has been widely used in the fields like DNA sequencing and speech recognition. A significant hypothesis on HMM is based on the relationship between the attributes of particular data items in the dataset considered (Zamani *et al.*, 2010). A process in which the state sequence that the process passes through is not known but can only be guessed through a sequence of observations of the dynamics of the process. A hidden Markov model assumes that the underlying process is a Markov chain whose internal states are hidden from the observer. It is usually assumed that the number of states of the system and the state-transition probabilities are known. Thus, there are two parameters associated with each states of the Markov chain: Emission probabilities that describe the probabilities of the different possible outputs from the state. Transition probabilities that explain the probability of entering a new state from the current state. The visible Markov models have limited power in modeling many applications. Their limitation arises from the fact that they assume perfect knowledge of the system's internal dynamics or that a decision maker can control the system evolution through some well-defined policy. Unfortunately, many applications do not conform to either of these two assumptions. For such applications the HMM can be used. By considering the above facts in mind the present chapter was aimed to carry out the trend analysis of the sorghum crop production based on hidden Markov model by considering different lag values. The trend once followed over a particular period would sure to repeat in future. For a given observation sequence, the hidden sequence of states and their corresponding probability values were found. The probability values of Π gave the trend percentage. Decision makers make decisions in case of uncertainty. This approach gives a platform for decision makers to make decisions on the basis of the percentage probability values obtained from the steady state probability distribution.

■ METHODOLOGY

The present study have been carried out on the basis of sorghum crop production time-series data pertaining to the period 1959-60 to 2012-13. Data have been collected through the Indian government of United States Department of Agriculture. The production trend was obtained using HMM by considering year to year variations. For a given production sequence, the hidden sequence of states and their corresponding probability values were found. The probability values gave the trend percentage of the production. The various computations are discussed in sequence as under. The MATLAB function "Hmm generate" was used to generate a random sequence of emission symbols and states. The length of both sequence and states to be generated is denoted by L.

Methodology for hidden markov model:

HMM is a stochastic model where the system is assumed to be a Markov process with hidden states. HMM gives better accuracy than other models. Using the given input values, the parameters of the HMM (ª) denoted by A, B and ® were found out.

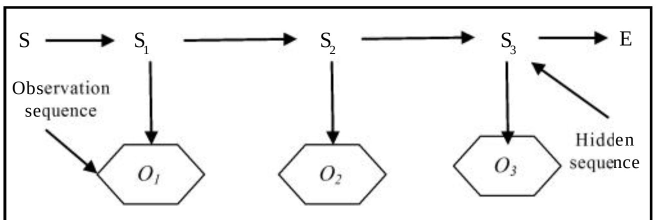

Fig. A : General structure of a hidden markov model

HMM consists of a set of hidden or latent states (S), a set of possible output symbols (O), a state transition probability matrix (A). Probability of making transition from one state to each of the other states, observation emission probability matrix (B). Probability of emitting/observing a symbol at a particular state, prior probability matrix (®). Probability of starting at a particular state an HMM is defined as ª $=(S,O,A,B,$®$)$; $S=\{s_1,s_2,...,s_N\}$ is a set of N possible states; $O=\{o_1,o_2,...0_M\}$ is a set of M possible observation symbols; A is an $N \times N$ state transition probability matrix (TPM); B is an NM observation or Emission probability matrix (EPM); ® is an N dimensional initial state probability distribution vector and A,B and® should satisfy the following conditions:

$$\sum_{j=1}^{N} a_{ij} = 1 \text{ where } 1 \le i \le N; \ \sum_{k=1}^{M} b_{ij} = 1$$

$$\text{where } 1 \le i \le N; \ \sum_{j=1}^{N} \pi_i = 1 \text{ where } \pi_i \ge 0.$$

The main problems of HMM are: Evaluation, decoding, and learning.

Evaluation problem:

Given the HMM model λ={A,B,π} and the observation sequence $O=o_1o_2...o_M$, the probability that model λ has generated sequence *O* is calculated. Often this problem is solved by the Forward Backward Algorithm (Rabiner, 1989) and (Rabiner and Juang, 1993).

Decode problem:

Given the HMM λ={A,B,π} and the observation sequence $O=o_1o_2...o_M$, calculate the most likely sequence of hidden states that produced this observation sequence *O*. Usually this problem is handled by Viterbi Algorithm (Rabiner, 1989) and (Rabiner and Juang, 1993).

Learning problem:

Given some training observation sequence $O=o_1o_2...o_M$, and general structure of HMM (number of hidden and visible states), determine HMM parameters λ={A,B,π} that best fit training data. The most common solution for this problem is Baum-welch algorithm (Rabiner, 1989 and Rabiner and Juang, 1993). which is considered as the traditional method for training HMM. Two observing symbols "I"and "D" have been used: "I indicate increase", "D indicates decrease". If the current year production value –previous year production value > 0, then observing symbol is I otherwise it is D. There are six hidden states assumed and are denoted by the symbol is S_1,S_2,S_3,S_4,S_5,S_6. Where, S_1 indicate "very low"; S_2 indicates "low"; S_3 indicates "moderate low"; S_4 indicates "moderate high"; S_5 indicates "high"; S_6 indicates "very high". The states are not directly observable. The situations of the crop production are considered hidden. Given a sequence of observation one can find the hidden state sequence that produced those observations.

■ RESULTS AND DISCUSSION

Computation of hidden Markov model parameters for the sorghum crop production. Different lag values of the sorghum productions have been calculated and given in the Table 1. Six optimal hidden states sequences were generated and compared. The findings are discussed as under. The probability values of transition probability matrix (A), Emission probability matrix (B) and for lag one to lag six values on sorghum production were calculated and given below.

Probability values of TPM, EPM and ® for the lag 1sorghum production:

$$\begin{array}{ccccccc} & S_1 & S_2 & S_3 & S_4 & S_5 & S_5 \\ S_1 & 0 & 0 & 0.333 & 0.333 & 0 & 0.333 \\ S_2 & 0.154 & 0.077 & 0.231 & 0.539 & 0 & 0 \\ S_3 & 0 & 0.316 & 0.526 & 0.105 & 0.053 & 0 \\ S_4 & 0.071 & 0.214 & 0.429 & 0.214 & 0.071 & 0 \\ S_5 & 0 & 0.5 & 0 & 0.5 & 0 & 0 \\ S_6 & 0 & 1 & 0 & 0 & 0 & 0 \end{array} \quad \begin{array}{ccc} & I & D \\ S_1 & 0 & 1 \\ S_2 & 0 & 1 \\ S_3 & 0.4 & 0.6 \\ S_4 & 1 & 0 \\ S_5 & 1 & 0 \\ S_6 & 1 & 0 \end{array}$$

Probability values of TPM, EPM and ® for the lag 2 sorghum productions:

$$\begin{array}{ccccccc} & S_1 & S_2 & S_3 & S_4 & S_5 & S_5 \\ S_1 & 0 & 0 & 0.5 & 0 & 0.5 & 0 \\ S_2 & 0 & 0 & 0.5 & 0 & 0.5 & 0 \\ S_3 & 0 & 0.154 & 0.154 & 0.462 & 0.231 & 0 \\ S_4 & 0 & 0 & 0.35 & 0.45 & 0.1 & 0.1 \\ S_5 & 0.111 & 0 & 0.222 & 0.333 & 0 & 0.333 \\ S_6 & 0.333 & 0 & 0 & 0.333 & 0.333 & 0 \end{array} \quad \begin{array}{ccc} & I & D \\ S_1 & 0 & 1 \\ S_2 & 0 & 1 \\ S_3 & 0 & 1 \\ S_4 & 0.429 & 0.571 \\ S_5 & 1 & 0 \\ S_6 & 1 & 0 \end{array}$$

Probability values of TPM, EPM and ® for the lag 3 sorghum productions:

$$\begin{array}{ccccccc} & S_1 & S_2 & S_3 & S_4 & S_5 & S_5 \\ S_1 & 0.143 & 0.143 & 0.571 & 0.143 & 0 & 0 \\ S_2 & 0.167 & 0.5 & 0.083 & 0.25 & 0 & 0 \\ S_3 & 0.077 & 0.231 & 0.385 & 0.077 & 0.154 & 0.077 \\ S_4 & 0.1 & 0.3 & 0.2 & 0.2 & 0.2 & 0 \\ S_5 & 0.286 & 0 & 0 & 0.429 & 0.286 & 0 \\ S_6 & 0 & 0 & 0 & 0 & 1 & 0 \end{array} \quad \begin{array}{ccc} & I & D \\ S_1 & 0 & 1 \\ S_2 & 0 & 1 \\ S_3 & 0.154 & 0.846 \\ S_4 & 1 & 0 \\ S_5 & 1 & 0 \\ S_6 & 1 & 0 \end{array}$$

Probability values of TPM, EPM and ® for the

Table 1: Values of sorghum production at different lags

Sr. No.	Sorghum	Lag 1 values	Lag 2 values	Lag 3 values	Lag 4 values	Lag 5 values	Lag 6 values
1.	9814						
2.	8026	-1788					
3.	9744	1718	-70				
4.	9195	-549	1169	-619			
5.	9681	486	-63	1655	-133		
6.	7581	-2100	-1614	-2163	-445	-2233	
7.	9224	1643	-457	29	-520	1198	-590
8.	10048	824	2467	367	853	304	2022
9.	9804	-244	580	2223	123	609	60
10.	9721	-83	-327	497	2140	40	526
11.	8105	-1616	-1699	-1943	-1119	524	-1576
12.	7722	-383	-1999	-2082	-2326	-1502	141
13.	6968	-754	-1137	-2753	-2836	-3080	-2256
14.	9097	2129	1375	992	-624	-707	-951
15.	10414	1317	3446	2692	2309	693	610
16.	9504	-910	407	2536	1782	1399	-217
17.	10524	1020	110	1427	3556	2802	2419
18.	12064	1540	2560	1650	2967	5096	4342
19.	11436	-628	912	1932	1022	2339	4468
20.	11648	212	-416	1124	2144	1234	2551

Table 1: Contd……….

Table 1: Contd………

21.	10431	-1217	-1005	-1633	-93	927	17
22.	12062	1631	414	626	-2	1538	2558
23.	10753	-1309	322	-895	-683	-1311	229
24.	11919	1166	-143	1488	271	483	-145
25.	11402	-517	649	-660	971	-246	-34
26.	10197	-1205	-1722	-556	-1865	-234	-1451
27.	8866	-1331	-2536	-3053	-1887	-3196	-1565
28.	9500	634	-697	-1902	-2419	-1253	-2562
29.	10170	670	1304	-27	-1232	-1749	-583
30.	12914	2744	3414	4048	2717	1512	995
31.	11681	-1233	1511	2181	2815	1484	279
32.	8100	-3581	-4814	-2070	-1400	-766	-2097
33.	12806	4706	1125	-108	2636	3306	3940
34.	11410	-1396	3310	-271	-1504	1240	1910
35.	9200	-2210	-3606	1100	-2481	-3714	-970
36.	9550	350	-1860	-3256	1450	-2131	-3364
37.	11088	1538	1888	-322	-1718	2988	-593
38.	7982	-3106	-1568	-1218	-3428	-4824	-118
39.	8710	728	-2378	-840	-490	-2700	-4096
40.	8860	150	878	-2228	-690	-340	-2550
41.	7716	-1144	-994	-266	-3372	-1834	-1484
42.	8390	674	-470	-320	408	-2698	-1160
43.	7060	-1330	-656	-1800	-1650	-922	-4028
44.	6680	-380	-1710	-1036	-2180	-2030	-1302
45.	7240	560	180	-1150	-476	-1620	-1470
46.	7630	390	950	570	-760	-86	-1230
47.	7150	-480	-90	470	90	-1240	-566
48.	7930	780	300	690	1250	870	-460
49.	7250	-680	100	-380	10	570	190
50.	6700	-550	-1230	-450	-930	-540	20
51.	7000	300	-250	-930	-150	-630	-240
52.	6030	-970	-670	-1220	-1900	-1120	-1600
53.	5300	-730	-1700	-1400	-1950	-2630	-1850
54.	5500	200	-530	-1500	-1200	-1750	-2430

Table 2: Sorghum production of state and observing symbol

Sr. No.	Sorghum	O.S	State	O.S	State	O.S	State	O.S	State	O.S	State	O.S	State
1.	9814												
2.	8026	D	S_2										
3.	9744	I	S_4	D	S_4								
4.	9195	D	S_3	I	S_5	D	S_3						
5.	9681	I	S_3	D	S_4	I	S_5	D	S_3				
6.	7581	D	S_2	D	S_3	D	S_1	D	S_3	D	S_2		
7.	9224	I	S_4	D	S_4	I	S_3	D	S_3	I	S_4	D	S_3
8.	10048	I	S_4	I	S_6	I	S_3	I	S_4	I	S_4	I	S_5
9.	9804	D	S_3	I	S_4	I	S_5	I	S_4	I	S_4	I	S_3
10.	9721	D	S_3	D	S_4	I	S_4	I	S_5	I	S_3	I	S_4
11.	8105	D	S_2	D	S_3	D	S_2	D	S_2	I	S_4	D	S_2
12.	7722	D	S_3	D	S_3	D	S_1	D	S_1	D	S_3	I	S_3
13.	6968	D	S_3	D	S_3	D	S_1	D	S_1	D	S_2	D	S_2
14.	9097	I	S_5	I	S_5	I	S_4	D	S_3	D	S_3	D	S_3
15.	10414	I	S_4	I	S_6	I	S_5	I	S_5	I	S_4	I	S_4
16.	9504	D	S_2	I	S_4	I	S_5	I	S_5	I	S_4	D	S_3
17.	10524	I	S_4	I	S_4	I	S_4	I	S_6	I	S_5	I	S_5
18.	12064	I	S_4	I	S_6	I	S_5	I	S_6	I	S_6	I	S_6
19.	11436	D	S_3	I	S_5	I	S_5	I	S_4	I	S_5	I	S_6
20.	11648	I	S_3	D	S_4	I	S_4	I	S_5	I	S_4	I	S_5
21.	10431	D	S_2	D	S_3	D	S_2	D	S_3	I	S_4	I	S_3
22.	12062	I	S_4	I	S_4	I	S_4	D	S_3	I	S_4	I	S_5
23.	10753	D	S_2	I	S_4	D	S_2	D	S_3	D	S_3	I	S_4
24.	11919	I	S_4	D	S_4	I	S_4	I	S_4	I	S_4	D	S_3
25.	11402	D	S_3	I	S_4	D	S_3	I	S_4	D	S_3	D	S_3
26.	10197	D	S_2	D	S_3	D	S_3	D	S_2	D	S_3	D	S_2
27.	8866	D	S_2	D	S_2	D	S_1	D	S_2	D	S_1	D	S_2
28.	9500	I	S_4	D	S_3	D	S_2	D	S_1	D	S_3	D	S_2
29.	10170	I	S_4	I	S_5	D	S_3	D	S_2	D	S_2	D	S_3
30.	12914	I	S_5	I	S_6	I	S_6	I	S_6	I	S_4	I	S_4
31.	11681	D	S_2	I	S_5	I	S_5	I	S_6	I	S_4	I	S_4
32.	8100	D	S_1	D	S_1	D	S_1	D	S_2	D	S_3	D	S_2
33.	12806	I	S_6	I	S_5	D	S_3	I	S_6	I	S_5	I	S_6
34.	11410	D	S_2	I	S_6	D	S_3	D	S_2	I	S_4	I	S_5
35.	9200	D	S_1	D	S_1	I	S_4	D	S_1	D	S_1	D	S_3
36.	9550	I	S_3	D	S_3	D	S_1	I	S_5	D	S_2	D	S_1
37.	11088	I	S_4	I	S_5	D	S_3	D	S_2	I	S_5	D	S_3
38.	7982	D	S_1	D	S_3	D	S_2	D	S_1	D	S_1	D	S_3
39.	8710	I	S_4	D	S_2	D	S_2	D	S_3	D	S_2	D	S_1
40.	8860	I	S_3	I	S_5	D	S_1	D	S_3	D	S_3	D	S_2
41.	7716	D	S_2	D	S_3	D	S_3	D	S_1	D	S_2	D	S_2
42.	8390	I	S_4	D	S_4	D	S_3	I	S_4	D	S_2	D	S_3
43.	7060	D	S_2	D	S_4	D	S_2	D	S_2	D	S_3	D	S_1

Table 2 : Conted……….

Table 2: Contd…………..

44.	6680	D	S_3	D	S_3	D	S_2	D	S_2	D	S_2	D	S_2
45.	7240	I	S_3	I	S_4	D	S_2	D	S_3	D	S_2	D	S_2
46.	7630	I	S_3	I	S_5	I	S_4	D	S_3	D	S_3	D	S_3
47.	7150	D	S_3	D	S_4	I	S_4	I	S_4	D	S_3	D	S_3
48.	7930	I	S_4	I	S_4	I	S_4	I	S_5	I	S_4	D	S_3
49.	7250	D	S_3	I	S_4	D	S_3	I	S_3	I	S_4	I	S_3
50.	6700	D	S_3	D	S_3	D	S_3	D	S_3	D	S_3	I	S_3
51.	7000	I	S_3	D	S_4	D	S_2	D	S_3	D	S_3	D	S_3
52.	6030	D	S_2	D	S_4	D	S_2	D	S_2	D	S_3	D	S_2
53.	5300	D	S_3	D	S_3	D	S_2	D	S_2	D	S_2	D	S_2
54.	5500	I	S_3	D	S_4	D	S_2	D	S_2	D	S_2	D	S_2

O.S - Observing symbol

Table 3: Probability values for lag 1 sorghum production value

States with	S_1		S_2		S_3		S_4		S_5		S_6	
observing symbol	I	D	I	D	I	D	I	D	I	D	I	D
S_1	0	0	0	0	0.333	0	0.333	0	0	0	0.333	0
S_2	0	0.154	0	0.077	0	0.231	0.539	0	0	0	0	0
S_3	0	0	0	0.312	0.312	0.211	0.11	0	0.053	0	0	0
S_4	0	0.071	0	0.214	0.071	0.357	0.214	0	0.071	0	0	0
S_5	0	0	0	0.5	0	0	0.5	0	0	0	0	0
S_6	0	0	0	1	0	0	0	0	0	0	0	0

Table 4: Probability values for lag 2 sorghum production value

States with	S_1		S_2		S_3		S_4		S_5		S_6	
observing symbol	I	D	I	D	I	D	I	D	I	D	I	D
S_1	0	0	0	0	0	0.5	0	0	0.5	0	0	0
S_2	0	0	0	0	0	0.5	0	0	0.5	0	0	0
S_3	0	0	0	0.154	0	0.154	0.154	0.308	0.231	0	0	0
S_4	0	0	0	0	0	0.35	0.25	0.2	0.1	0	0.1	0
S_5	0	0.111	0	0	0	0.222	0	0.333	0	0	0.333	0
S_6	0	0.2	0	0	0	0	0.4	0	0.4	0	0	0

Table 5: Probability values for lag 3 sorghum production value

States with	S_1		S_2		S_3		S_4		S_5		S_6	
observing symbol	I	D	I	D	I	D	I	D	I	D	I	D
S_1	0	0.143	0	0.143	0.143	0.429	0.143	0	0	0	0	0
S_2	0	0.167	0	0.5	0	0.083	0.25	0	0	0	0	0
S_3	0	0.077	0	0.231	0.077	0.308	0.077	0	0.154	0	0.077	0
S_4	0	0.1	0	0.3	0	0.2	0.2	0	0.2	0	0	0
S_5	0	0.286	0	0	0	0	0.286	0	0.429	0	0	0
S_6	0	0	0	0	0	0	0	0	1	0	0	0

Table 6: Probability values for lag 4 sorghum production value												
States with	S_1		S_2		S_3		S_4		S_5		S_6	
observing symbol	I	D	I	D	I	D	I	D	I	D	I	D
S_1	0	0.167	0	0.167	0	0.333	0.167	0	0.167	0	0	0
S_2	0	0.364	0	0.364	0	0.091	0	0	0	0	0.182	0
S_3	0	0.071	0	0.071	0	0.429	0.214	0	0.071	0	0	0
S_4	0	0	0	0.25	0.125	0	0.25	0	0.375	0	0	0
S_5	0	0	0.2	0	0.2	0.2	0	0	0.2	0	0.2	0
S_6	0	0	0	0.4	0	0	0.2	0	0	0	0.4	0

Table 7 : Probability values for lag 5 sorghum production value												
States with	S_1		S_2		S_3		S_4		S_5		S_6	
observing symbol	I	D	I	D	I	D	I	D	I	D	I	D
S_1	0	0	0	0.667	0	0.333	0	0	0	0	0	0
S_2	0	0	0	0.3	0	0.4	0.2	0	0.1	0	0	0
S_3	0	0.067	0	0.333	0	0.267	0.267	0	0.067	0	0	0
S_4	0	0.067	0	0	0.067	0.333	0.467	0	0.067	0	0	0
S_5	0	0.25	0	0	0	0	0.5	0	0	0	0.25	0
S_6	0	0	0	0	0	0	0	0	1	0	0	0

Table 8 : Probability values for lag 6 sorghum production value												
States with	S_1		S_2		S_3		S_4		S_5		S_6	
observing symbol	I	D	I	D	I	D	I	D	I	D	I	D
S_1	0	0	0	0.667	0	0.333	0	0	0	0	0	0
S_2	0	0	0	0.462	0.077	0.385	0	0	0	0	0.077	0
S_3	0	0.167	0	0.167	0.111	0.222	0.167	0	0.167	0	0	0
S_4	0	0	0	0.333	0	0.333	0.167	0	0	0	0.167	0
S_5	0	0	0	0	0.5	0.25	0.25	0	0	0	0	0
S_6	0	0	0	0	0	0	0	0	0.667	0	0.333	0

Table 9 : Comparison of 6 optimum state sequences and performance of fitness value			
Sr. No.	Comparison of 6 lag sequence of states	Computed value	**Fitness value** $\frac{1}{\dot{g}\ \text{compare}(i, j)}$
1.	Lag 1 value of sorghum production	1	1
2.	Lag 2 value of sorghum production	1.36	0.735
3.	Lag 3 value of sorghum production	1.91	0.524
4.	Lag 4 value of sorghum production	1.52	0.658
5.	Lag 5 value of sorghum production	2.56	0.391
6.	Lag 6 value of sorghum production	2.44	0.409

lag 4 sorghum productions:

$$\begin{array}{cc} & \begin{array}{cccccc} S_1 & S_2 & S_3 & S_4 & S_5 & S_5 \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{array} & \left[\begin{array}{cccccc} 0.167 & 0.167 & 0.333 & 0.167 & 0.167 & 0 \\ 0.364 & 0.364 & 0.091 & 0 & 0 & 0.182 \\ 0.071 & 0.071 & 0.571 & 0.214 & 0.071 & 0 \\ 0 & 0.286 & 0 & 0.286 & 0.429 & 0 \\ 0 & 0.333 & 0.333 & 0 & 0.167 & 0.167 \\ 0 & 0.2 & 0.2 & 0.2 & 0 & 0.4 \end{array}\right] \end{array} \begin{array}{cc} & \begin{array}{cc} I & D \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{array} & \left[\begin{array}{cc} 0 & 1 \\ 0 & 1 \\ 0.071 & 0.929 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \end{array}\right] \end{array}$$

Probability values of TPM, EPM and ® for the lag 5 sorghum productions:

$$\begin{array}{cc} & \begin{array}{cccccc} S_1 & S_2 & S_3 & S_4 & S_5 & S_5 \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{array} & \left[\begin{array}{cccccc} 0 & 0.667 & 0.333 & 0 & 0 & 0 \\ 0 & 0.3 & 0.4 & 0.2 & 0.1 & 0 \\ 0.067 & 0.333 & 0.267 & 0.267 & 0.067 & 0 \\ 0.067 & 0 & 0.4 & 0.467 & 0.067 & 0 \\ 0.25 & 0 & 0 & 0.5 & 0 & 0.25 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{array}\right] \end{array} \begin{array}{cc} & \begin{array}{cc} I & D \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{array} & \left[\begin{array}{cc} 0 & 1 \\ 0 & 1 \\ 0.067 & 0.933 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \end{array}\right] \end{array}$$

Probability values of TPM, EPM and ® for the lag 6 sorghum productions:

$$\begin{array}{cc} & \begin{array}{cccccc} S_1 & S_2 & S_3 & S_4 & S_5 & S_5 \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{array} & \left[\begin{array}{cccccc} 0 & 0.667 & 0.333 & 0 & 0 & 0 \\ 0 & 0.5 & 0.417 & 0 & 0 & 0.083 \\ 0.158 & 0.158 & 0.368 & 0.158 & 0.158 & 0 \\ 0 & 0.4 & 0.4 & 0.2 & 0 & 0 \\ 0 & 0 & 0.6 & 0.2 & 0 & 0.2 \\ 0 & 0 & 0 & 0 & 0.667 & 0.333 \end{array}\right] \end{array} \begin{array}{cc} & \begin{array}{cc} I & D \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{array} & \left[\begin{array}{cc} 0 & 1 \\ 0 & 1 \\ 0.263 & 0.737 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \end{array}\right] \end{array}$$

Steady state probability distribution of lag1 values:

$$\pi = [0.058 \quad 0.25 \quad 0.365 \quad 0.269 \quad 0.039 \quad 0.019]$$

Steady state probability distribution of lag 2 values:

$$\pi = [0.039 \quad 0.039 \quad 0.255 \quad 0.392 \quad 0.157 \quad 0.118]$$

Steady state probability distribution of lag 3 values:

$$\pi = [0.14 \quad 0.24 \quad 0.26 \quad 0.2 \quad 0.14 \quad 0.02]$$

Steady state probability distribution of lag 4 values:

$$\pi = [0.122 \quad 0.225 \quad 0.286 \quad 0.143 \quad 0.122 \quad 0.102]$$

Steady state probability distribution of lag 5 values:

$$\pi = [0.063 \quad 0.208 \quad 0.313 \quad 0.313 \quad 0.083 \quad 0.021]$$

Steady state probability distribution of lag 6 values:

$$\pi = [0.064 \quad 0.255 \quad 0.404 \quad 0.106 \quad 0.106 \quad 0.064]$$

Generate sequence of HMM:

The MATLAB function Hmm generate is used to generate a random sequence of emission signs and states. The length of both sequence and states to be generated is denoted by L.

The HMM MATLAB toolbox syntax is:

[Sequence, states] = HMM generate (L, TPM, EPM), see (White, 1998).

For instance, if the input is given as :

TPM=[0 0 0.333 0.333 0 0.333; 0.154 0.077 0.231 0.539 0 0; 0 0.316 0.526 0.105 0.053 0; 0.071 0.214 0.429 0.214 0.071 0; 0 0.5 0 0.5 0 0; 0 1 0 0 0 0;];

EPM = [0 1; 0 1; 0.4 0.6; 1 0; 1 0; 1 0];

[Sequence states] = hmm generate (7, TPM, EPM)

‘ Sequence symbols ‘ , { ‘ I ‘, ‘ D ‘} , . . . ‘ State names ‘, { ‘ very low ‘ ; ‘ low ‘ ; ‘ moderate low ‘ ; ‘ moderate high ‘ ; ‘ high ‘ ; ‘ very high ‘ }.

Then the output of few randomly generated sequences and states is given below:

Sequence: $\varepsilon \rightarrow I \rightarrow D \rightarrow D \rightarrow I \rightarrow D \rightarrow D \rightarrow D$

States : $S_6 \quad S_2 \quad S_1 \quad S_6 \quad S_2 \quad S_1 \quad S_3$

Sequence: $\varepsilon \rightarrow I \rightarrow D \rightarrow D \rightarrow I \rightarrow I \rightarrow I \rightarrow I$

States : $S_6 \quad S_2 \quad S_3 \quad S_4 \quad S_4 \quad S_5 \quad S_4$

Sequence: $\varepsilon \rightarrow I \rightarrow D \rightarrow I \rightarrow D \rightarrow I \rightarrow D \rightarrow D$

States : $S_4 \quad S_2 \quad S_4 \quad S_1 \quad S_3 \quad S_2 \quad S_1$

Using the Iterative procedure, for each TPM and EPM framed we get an optimum sequence of states generated. The length of the sequence generated is taken as L=7, for instance.

The optimum sequence of states obtained from the lag 1 TPM and EPM is :

– $\varepsilon \rightarrow I \rightarrow D \rightarrow D \rightarrow D \rightarrow I \rightarrow D$
$S_3 \quad S_4 \quad S_2 \quad S_4 \quad S_3 \quad S_5 \quad S_2$

– $\varepsilon \rightarrow I \rightarrow D \rightarrow D \rightarrow D \rightarrow D \rightarrow I$
$S_3 \quad S_4 \quad S_2 \quad S_4 \quad S_3 \quad S_5 \quad S_2$

– $\varepsilon \rightarrow D \rightarrow D \rightarrow I \rightarrow I \rightarrow D \rightarrow D$
$S_1 \quad S_3 \quad S_5 \quad S_5 \quad S_1 \quad S_3 \quad S_3$

– $\varepsilon \rightarrow I \rightarrow D \rightarrow D \rightarrow D \rightarrow I \rightarrow I$
$S_4 \quad S_2 \quad S_2 \quad S_2 \quad S_6 \quad S_6 \quad S_6$

– $\varepsilon \rightarrow D \rightarrow D \rightarrow D \rightarrow D \rightarrow I \rightarrow D$
$S_2 \quad S_2 \quad S_2 \quad S_3 \quad S_4 \quad S_1 \quad S_2$

– $\varepsilon \rightarrow D \rightarrow I \rightarrow D \rightarrow I \rightarrow D \rightarrow I$
$S_3 \quad S_1 \quad S_2 \quad S_3 \quad S_4 \quad S_4 \quad S_3$

From the Table 9 it is clear that as the lag increases, the fitness values were found to be decreasing. The highest is the fitness value, the better is the performance of the particular sequence and hence, the best optimum sequence is the lag 1 sequence. Similar work related to the present investigation was also carried out by Albert (1991); Churchill (1992); Elliott and Van (1997); Juang and Rabiner (1991); Krogh *et al*. (1994); Leroux and Puterman (1992) and Turin and Sondih (1993).

Conclusion:

In this paper, results are presented using the HMM-based framework and methodology to find the best optimum sorghum production sequence (trend). Six optimal hidden states sequences were generated and compared. The results revealed that lag 1 difference when considered was found to give the best optimum state sequence.

Acknowledgement:

The author expresses his gratitude to the UGC for providing fellowship to carry out this work under scheme of BSR- Fellowship.

■ REFERENCES

Albert, P.S. (1991). A two-state markov mixture model for a time series of epileptic seizure counts. *Biometrics,* **47**: 1371-1381.

Churchill, G.A. (1992). Hidden markov chains and analysis of genome structure. *Computers & Chemistry,* **51** : 107-115.

Elliott, R.J. and Van, de Hoek J. (1997). An application of hidden markov models to asset allocation problems. *Finance & Stochastic,* **1**: 229-238.

Juang, B.H. and Rabiner, L.R. (1991). Hidden markov models for speech recognition. *Technometrics,* **33**: 251-272.

Krogh, A., Brown, M., Mian, I.S., Sjolander, K. and Haussler, D. (1994). Hidden markov models in computational biology: Applications to protein modeling. *J. Molecular Biology,* **235**: 1501-1531.

Leroux, B.G. and Puterman, M.L. (1992). Maximum-penalized-likelihood estimation for independent and markov-dependent mixture models. *Biometrics,* **48**: 545-558.

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

Rabiner, L. and Juang, B. (1993). *Fundamentals of speech recognition.* Prentice-Hall, Englewood Cliffs,NJ.

Turin, W. and Sondih, M.M. (1993). Modeling error sources in digital channels. *IEEE J. Selected Areas in Communications,* **11**: 340-347.

Zamani, Behzad, Akbari, Ahmad, Nasersharif, Babak, Mohammadi, Mehdi and Jalalvand, Azarakhsh (2010). Discriminative transformation for speech features based on genetic algorithm and HMM likelihoods. *IEICE Electronic Express,* **7** (4): 247-253.