STOCHASTIC MODELING TECHNOLOGY FOR GRAIN CROPS STORAGE APPLICATION: REVIEW

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ABSTRACT

Stochastic modeling is a key technique in event prediction and forecasting applications. Recently, stochastic models such as the Artificial Neural Network, Hidden Markov, and Markov Chain have received a significant attention in agricultural application. These techniques are capable of predicting the actions for the better planning and management in various fields. This work comprehensively summarizes and compares their applications such as their processing techniques, performance, as well as their strengths and limitations with regard to event prediction and forecasting. The work ends with recommendations on the appropriate techniques for cereal grain storage application.

KEYWORDS

Grain storage condition, Hidden markov model, Artificial Neural Network, Markov chain & Forecasting

1. INTRODUCTION

Stochastic modeling techniques have been the most significant in prediction and forecasting. These techniques have been used for estimating the probability of outcomes to predict what conditions might be under different situations [1]. Forecasting of unknown features depends on exploitation of these techniques. They largely contribute to better detection and prediction of data. Modeling techniques such as Artificial Neural Networks (ANNs), Hidden Markov and Markov Chain models have become increasingly important methods with the growth of complex computations [2, 3]. Today, we are faced with the crucial problem of inefficient detecting and predicting of condition (variations of moisture contents and temperature) over the entire grain bulk [4] in the storage facility. The aim of this study is to suggest the best technique for forecasting the grain storage conditions under few given states.

2. LITERATURE REVIEW

Hidden Markov (HMMs), Artificial Neural Networks (ANNs), and Markov Chains (MC) models are popular tools for modelling dependent random variables in diverse areas [5] such as speech processing and enhancement [6], audio segmentation [7], DNA recognition [8] , fault [9], and rainfall occurrence [10]. These are based on a stochastic process [11] in which a chain produces an unobservable state that can be inferred only through another set of stochastic process. Previous studies on weather condition and crop activity show that forecasting using stochastic techniques is a highly researched area as shown in Table 1 to 2, though

DOI: 10.5121/ijaia.2016.7603

not enough has been done for crop grain storage. In Figure 1 and 2, the frequency of publications in the area of weather condition and crop activity forecasting published between 2008 and 2016 respectively are demonstrated as reviewed in this study.

2.1. ARTIFICIAL NEURAL NETWORKS (ANNS)

For crop activities as demonstrated in Table 2, the study [12] presented a neural network approach in which the classification of rice varieties was estimated. An overall classification accuracy obtained was 92%. Wheat seeds classification using ANN was also estimated whereby the method was found to be effective for recognizing wheat varieties [13]. The study [14] showed that back propagation neural network (BPNN) provided more correct wheat classification at 90% than discriminant analysis which was at 83.33%. Further [15] illustrated how Multi layer perceptron back propagation with image processing algorithm gave higher wheat seeds classification accuracy which was at 95%. It was presented in [16] that ANN approach was capable of predicting wheat production under different conditions and farming systems using direct and indirect technical factors. Moreover, three terms ANN back propagation network was proposed as a predicting tool for moisture content on maize. The model outweighed the two terms back propagation with the proportional factor which increased the convergence speed and reduced learning stalls [17]. The study [18] presented the artificial neural network method in which the equilibrium moisture content of maize was predicted. Maize needed less energy at higher moisture content (above 11% d.b.) for drying and storing, but at lower moisture contents more energy was needed. Artificial Neural Networks (ANN) analysis was also carried to predict the extent of shelled corn shrinkage. The method was found to be most appropriate for prediction capability of shrinkage [19]. It was also reported in [20] that generic approach for collective prediction of moisture sorption isotherms (MSI) for 12 cereals and 5 legumes using artificial neural networks was an effective, reliable, and fast method for the collective prediction of MSIs for several grains and legumes simultaneously.

For weather condition as shown in Table 1, the study [21] reported the prediction of rainfall over Udupi District of Karnataka in India through artificial neural network. The method used three layered networks of different number of hidden neurons. In [22] rainfall prediction suggested that the ANN model could be an important tool for local rain forecasting, although it cannot replace the forecasters' experience. It was also reported in [23] that rainfall prediction by combining wavelet technique with ANN gave high accuracy. Moreover, the study [24] presented that ANN with linear transfer function (LTF), and fuzzy rule-based techniques was developed for the prediction of rainfall runoff for Narmada catchment up to Manot gauging site. The other study [25] presented the rainfall runoff modeling using Modular ANN with singular spectrum analysis. In the study [26], an artificial neural network (ANN) approach to forecasting future precipitation was proposed. It was done through spatial downscaling and constructing new intensity duration-frequency (IDF) curves with climate change into consideration using a temporal downscaling method. It was reported in [27] that neural network algorithms with wavelet transformation for daily precipitation predictions provided significant advantages for estimation process.

2.2. MARKOV CHAIN (MC)

Few studies have been conducted on crop activities forecasting using Markov chain model as shown in Table 2. Studies reviewed in this work are of between 2008 and 2016. There are few studies that have used Markov chain model for crop activities and average for weather condition are very few as demonstrated in Figure 5 and 6. In this work [28], Markov chain model was used to predict the crop grown on a field when the crops grown in the previous 3–5 years are known. The obtained results showed that the proposed approach was able to predict the crop type of each field, before the beginning of the crop season, with accuracy of 60%, which was better than the results obtained with approaches based on remote sensing imagery. Non-stationary Markov chain with logistic regression was also used to model dynamics of crop rotation [29].

Some of studies presented the weather forecasting as shown in Table 1. Among them include: estimation of the rainfall sequences during the rainy season in Kurdufan [30], rainfall prediction at the Daspalla Region in Odisha, Eastern India [31] for crop planning, daily rainfall occurrence forecasting in Peninsular Malaysia [32], the rainfall estimation during monsoon season over major station in Gangetic West Bengal [33], and a stochastic generator of monthly rainfall series in Tunisia [34]. In the study [35], Markov chain model with weights was applied to predict Standardized Precipitation Index (SPI) drought intensity by using standardized self coefficients as weights. However, the forecasting ability was weak when there was a sharp change or an increase in drought intensity. Analysis of hydrological drought characteristics showed that the expected frequency of drought occurrence was higher for smaller time scales (i.e., 3-month and 6-month) [36]. Moreover, other works presented the wet and dry patterns of daily precipitation in Colombo [37]. The method also can be used to investigate the return periods of long wet and dry spells. However, the accuracy of modeling wet spells found to be high compared to dry spells. Markov chain was also used to know the dry and wet spell distribution at Varanasi in Uttar Pradesh whereby a week period was considered as the optimum length of time [38]. The study [39] presented daily temperature prediction from correlated categorical data sequence in Taipei, Taiwan. The proposed method gave higher average forecasting accuracy.

2.3. Hidden Markov Model (HMM)

For crop activities as shown in Table 2, the study [40] found that the rate for single insect with normal pattern was about 98%, while for lateral position single insect was about 87%. In this work [41], a general framework of Hidden Markov Models (HMMs) based corn progress percentage estimation method was also presented. The results demonstrated the feasibility of proposed solutions on corn progress percentage estimation in the state-level. Moreover, the optimum growth states and atmospheric conditions were determined using the Viterbi algorithm in HMM.

For weather condition as demonstrated in Table 1, the study [42] presented modeling of winter rainfall occurrence using the hidden markov model. The hidden states were assumed to be an unknown random function of slowly varying climatic modulation of the winter jet stream and moisture transport dynamics. In the study [43], modeling of a homogeneous hidden markov model on the northeast rainfall monsoon using 40 rainfall stations in Peninsular, Malaysia for the period of 1975 to 2008 was also presented. The model assessed the behaviour of rainfall characteristics with large scale atmospheric circulation. It was reported in [44] that non-homogeneous hidden Markov model was utilized to investigate potential changes in Indian monsoon summer rainfall, comparing with the 2070–2099 period with the second half of the twentieth century. The persistence level of Kuantan daily rainfall prediction was reported in [45]. It was done using the hybrid of autoregressive fractional integrated moving average (ARFIMA) and hidden Markov model (HMM). Moreover, it was presented in [46] that the hidden markov model was used for analyzing the spatiotemporal characterization of droughts at different severities. Another work [47] presented the development of the hidden markov model for assessing the drought characteristics in India using monthly precipitation and streamflow data. Moreover, Homogenous Hidden Markov Models (HMMs) were also developed for forecasting droughts using the Standardized Precipitation Index, SPI, at short-medium term [48]. Furthermore, the paper [49] reported a constrained Hidden Markov Model for evaluating a session of precipitation series. The method was capable of checking the quality of precipitation series instead of manual way.

Table 1. Key Points of Survey on Weather Condition Forecasting Techniques

Main focus	Method	References
Rainfall runoff modeling	ANN	[24, 25]
Precipitation downscaling forecasting	ANN	[26]
Daily precipitation predictions	ANN	[27]
Rainfall prediction	ANN	[21-23]
Rainfall forecasting	MC	[30-34]
Drought occurrence prediction	MC	[35, 36]
Dry and wet spell distribution	MC	[38]
Description of wet and dry patterns of weather	MC	[37]
Temperature prediction	MC	[39]
Rainfall modeling	HMM	[42-45]
Drought forecasting	HMM	[46-48]
Anomaly detection of precipitation series	HMM	[49]

Table 2. Key Points of Survey on Crop Activities Forecasting Techniques

Main Focus	Method	References
Predicting wheat production	ANN	[16]
Classification of Rice Grains	ANN	[12]
Identification of Stored Grain Age	ANN	[14]
Moisture Prediction in Maize	ANN	[17, 18]
Determining moisture sorption isotherms of cereal grains and legumes	ANN	[20]
Predicting the capability Shelled corn shrinkage	ANN	[19]
Wheat Seeds Classification	ANN	[13, 15]
Predicting the crop type of each field for crop rotation	MC	[28]
Crop rotation modeling	MC	[29]
Stored grain insect Image processing	HMM	[40]
Estimation of Corn Progress Stages	HMM	[41]

2.4. Strengths And Limitation Of Forecasting Techniques

A number of strengths and limitations of forecasting techniques have been identified in this work as summarized in Table 3 [50-69]. Markov Chain Model (especially first order Markov Chain) with some of the data is insufficient to estimate reliable probability. Because it may not be possible to observe sufficient transitions from a given transient set of states to a closed state where this transition is dependent on a rare climatic event, the value of this parameter is of vital importance in the dynamics of the community. Also, validation of the Markov model depends on predictions of system behaviour over time, and it is; therefore, frequently difficult, and may even be impossible for really long period of time [70]. HMM is flexible with fewer computations compared to artificial neural network model [71, 72]. However, HMM algorithm [73, 74] (forward backward or viterbi) presents poor discriminative power because it bases on the Maximum Likelihood (ML) criterion, which is itself non-discriminative. HMM [75] is explainable and has solid statistical foundation. It shows potentials for time series prediction.

Table 3. Strengths and Limitations of Modeling Techniques

	ANN	HMM	MC
Strengths	Independent on the statistical distribution	Performs linear relationship	Effective in modeling time series
	Nonlinearity	Dynamic relationship Powerful optimization algorithms (EM)	Effective in modeling categorical data sequences
	Discriminative	Computational intractability inferring hidden state form observation	Solves several linear programming problems
	Rich in complex computation	Deals well with sequential structures	Evaluates system reliability well
Limitations	Lack of interpretability Lack of a set of methods for optimizing the network structure	Inefficient and difficult to interpret for many states	Does not predict the future from the observed events
	Unable for linear computation Cannot perform better for independent stochastic event	Fully-connected transition diagram can lead to severe overfitting	Computational limitations
	Over training of network	Lack of global context for modeling	Slow convergence rates and very slow
	Extrapolation error A great computation burden overfitting	Require the initial assumption for the statistical distributions	The amount of computations increases rapidly with the amount of states
	Black box in nature Unclear relationships between the outcome and the predictors	The number of hidden states must be set a priori so that model complexity is not inferred from data in a bayesian way	Model is often not structurally similar to the physical or logical organization of the system

3. FORECASTING TECHNIQUES

3.1. ARTIFICIAL NEURAL NETWORKS MODEL

Artificial Neural Networks (ANNs) model is the mathematical tool which is used to simulate and solve complex problems. It is based on the powerful thought ability of the human brain. It is applied to various applications such as industry, health, electronics, finance, chemistry, statistics, agriculture, automotive and cognitive sciences. ANNs are described by their modular structure, learning capability, prediction performance, and internal non-linearity. As human brain, artificial neural network also has neurons with many inputs as human brain synapses as demonstrated in Figure 1. Its neuron has the simple model with three functions such as multiplication, summation, and activation. Each input of a neuron is multiplied by the weight at the entrance. Then, it sums up all weighted inputs and bias. At last, the mathematical model determines the activation level of the neuron using the transfer function as shown in Figure 2. This is done once the activation level exceeds the threshold value [76, 77].

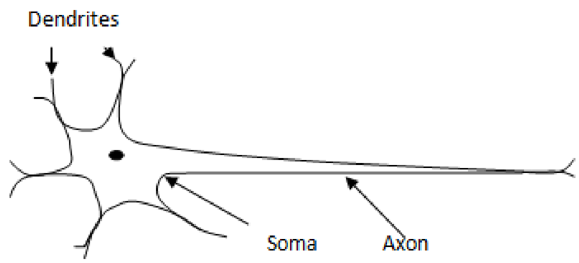

Figure 1. Biology Neuron [78]

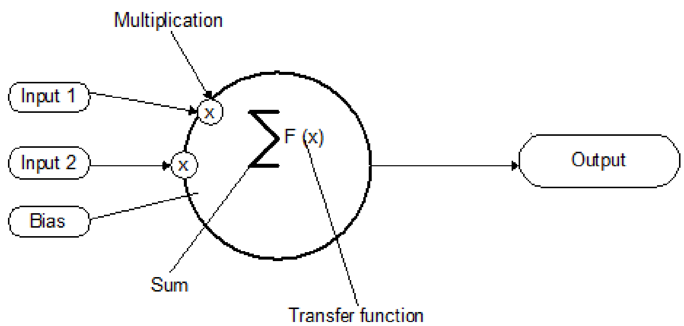

Figure 2. Artificial Neuron [78]

ANN mode has architecture which consists of three neuron layers such as input, hidden and output layers as shown in Figure 3. The first layer has input neurons that send information through synapses to the second layer of neurons. Then, they pass through more synapses to the third layer of output neurons [79, 80].

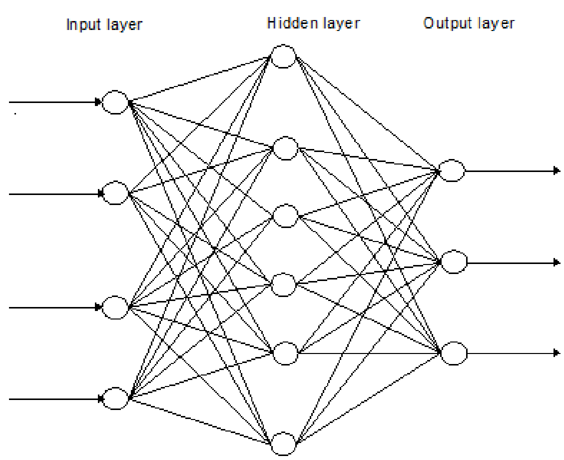

Figure 3. ANN Structure [81]

3.2. MARKOV CHAIN MODEL

A Markov chain is a mathematical model of a random observable fact with time that the past affects the future only through the present. The time can be discrete or continuous. It works basing on Markov property. It has a finite set of possible states and transitions among them. These are governed by a set of conditional probabilities of the next state given the present one [82, 83].

Markov Property: The Markov property states that the conditional probability distribution for the system at the next step depends only on the current state of the system, and not the state of the system at previous steps.

A Markov chain is defined by a transition probability parameter (aij) associated with each transition (arrow) and determines the probability of a certain state (Sj) following another state (Si). The state probabilities are well defined below [84, 85]:

It has a finite set of states, S_1, S_2 ...S_N, a set of transition probabilities:

$$a_{ij} = P(q_{t+1} = S_j | q_t = S_i) \quad (1)$$

The initial state probability distribution is given as:

$$\pi_i = P(q_0 = S_i) \quad (2)$$

3.3. HIDDEN MARKOV MODEL (HMM)

Hidden Markov Model (HMM) is an extension of the Markov Chain. It is the simplest dynamic bayesian distribution over sequences of observations. It is described as a 5-tuple λ = (q, ∑, π, A, B). The states q are hidden. Probabilities A are state transition probabilities that indicate the chance that a certain state change might occur. Probabilities π are the initial state transition probabilities. Each state has a set of possible emissions ∑. Probabilities B are observation probabilities for the emissions. HMM applies the Markovian property. In every state, a Markov chain can be observed directly. But sometimes there is a sequence of a state that wants to be known but cannot be observed directly but through the observable state as shown in Figure 4. That is why it is called the hidden Markov model[86, 87].

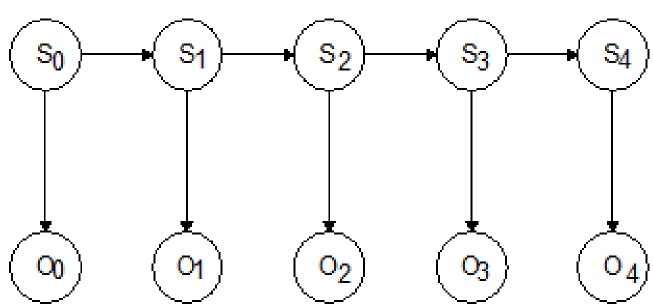

Figure 4. HMM Topology [88]

The HMM states [89, 90] are described as:

N is the number of hidden states in the model. The individual states are denoted as:

$$S = \{s_1, s_2, .., s_N\} \tag{3}$$

This is done at the length t as Qt.

M is the number of distinct observation symbol per hidden state. The individual symbols are denoted as:

$$V = \{v_1, v_2, \dots, v_M\} \tag{4}$$

It is also done at the length t as Qt.

The state transition probability matrix is described as:

$$[A]_{ij} = \{a\}_{ij} \tag{5}$$

Whereas, $a_{ij} = P(Q_{t+1} = s_j | Q_t = s_i)$, $1 \leq i, j \leq N$ (6)

The observation symbol probability in hidden state j is also described as:

$$[B]_{jk} = \{b_j(v_k)\} \tag{7}$$

Where, $b_j(v_k) = P(O_t = v_k | Q_t = s_j)$

$$1 \leq j \leq N,\ 1 \leq k \leq M \tag{8}$$

The initial state distribution is given as:

$$\Pi = \{\pi_i\} \tag{9}$$

Where, $\pi_i = P(Q_1 = s_i)$ $1 \leq i \leq N$ (10)

Once the HMM is given appropriate values of N, M, A, B, and π, it can be used as a generator to a given observation sequence:

$$O = \{O_1 O_2 \dots O_T\} \tag{11}$$

Where, T is the number of observations in the sequence. For simplicity, using the compact notation [86, 87, 91]:

$$\lambda = (A, B, \pi) \tag{12}$$

3.3.1. HMM Main Problem Solving Steps

The HMM architecture usually is automated with integrated stochastic processes using solving techniques such as evolution, decoding and Leaning.

3.3.1.1. Evolution

This is an algorithm process in HMM with a sequence of observations, *P (O | λ).* The probability of the observation sequence given a model can be computed [86, 91]. One of the efficient algorithms for evolution solution is the Forward algorithm.

In evolution if the process in the HMM is a first order Markov Chain, the probabilities of the system in particular state s (t) at time t depends on its state at s (t-1) [86, 87, 91, 92] . The probability of the HMM being in state s_j at time t having generated the first t emission that is the partial probability αj (t) [86, 87, 92]:

$$\alpha_j(t) = \begin{cases} 0 & , t = 0 \text{ and } j \neq \text{initial state} \\ 1 & , t = 0 \text{ and } j = \text{initial state} \\ \left[\sum_i \alpha_i\,(t-1)a_{ij}\right] b_{jk} v(t), & \text{Otherwise} \end{cases} \tag{17}$$

3.3.1.2. DECODING

This is the algorithm that produces the most probable sequence of hidden states given some observations [90, 93]. It applies viterbi algorithm, which is also a trellis algorithm. It is very similar to the forward algorithm, except that the transition probabilities are maximized at each step instead of being summed [90, 93]. It is a simple and efficient decoding technique.

3.3.1.3. LEARNING

Learning is the process that calculates the Markov model on state transition and emission matrices that have generated a sequence of observations. The process has supervised and unsupervised trainings. If the training contains both the inputs and outputs of a process, supervised training can be performed by equating inputs to observations and outputs to states. But if only the inputs are provided in the training data, then unsupervised training is used to guess a model that may have produced those observations [86, 94, 95].

The baum welch algorithm is the mostly used method in the learning technique. This is also known as forward backward algorithm. It gives the probabilities that the model is in state s_i (t) as [87]: These probabilities are the partial in equation (17) and backward probabilities in equation (18).

$$\beta_i(t) = \begin{cases} 0 & , s_i(t) \neq s_0(t) \text{ and } t = T \\ 1 & , s_i(t) = s_0(t) \text{ and } t = T \\ \sum_i \beta_j(t+1) a_{ij} b_{jk} v(t+1), & \text{Otherwise} \end{cases} \tag{18}$$

Since, α_i (t) and β_i (t) are just estimates for the calculation of an improved of these estimates the auxiliary γ_{ij} (t) quantity is introduced [87, 91]:

$$\gamma_{ij}(t) = \frac{\alpha_i(t-1) a_{ij} b_{jk} \beta_j(t)}{p(V^T|\lambda)} \tag{19}$$

Using the auxiliary quantity, an estimated version $\acute{a}_{ij}$ of a_{ij} can now be calculated by [87, 91, 92]:

$$\acute{a}_{ij} = \frac{\sum_{t=1}^{T} \gamma_{ij}(t)}{\sum_{t=1}^{T} \sum_k \gamma_{ik}(t)} \tag{20}$$

Similarly, an estimated version $\acute{b}_{jk}$ of b_{jk} can be given as [87, 91, 92]:

$$\acute{b}_{jk} = \frac{\sum_{t=1, v(t)}^{T} \sum_l \gamma_j l(t)}{\sum_{t=1}^{T} \sum_l \gamma_j l(t)} \tag{21}$$

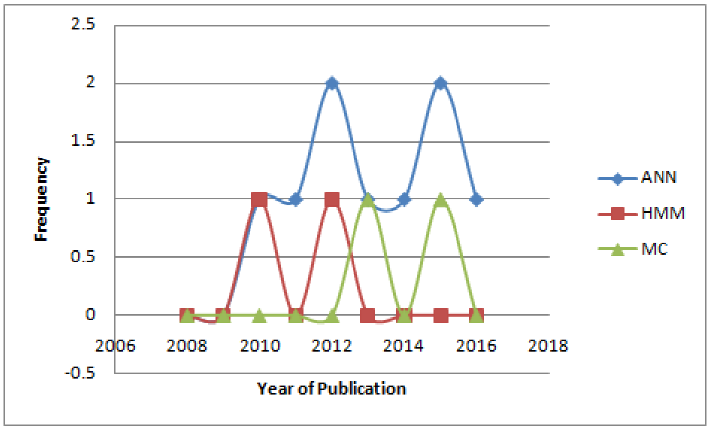

Figure 5. Studies of Modeling Techniques on Crop Activities

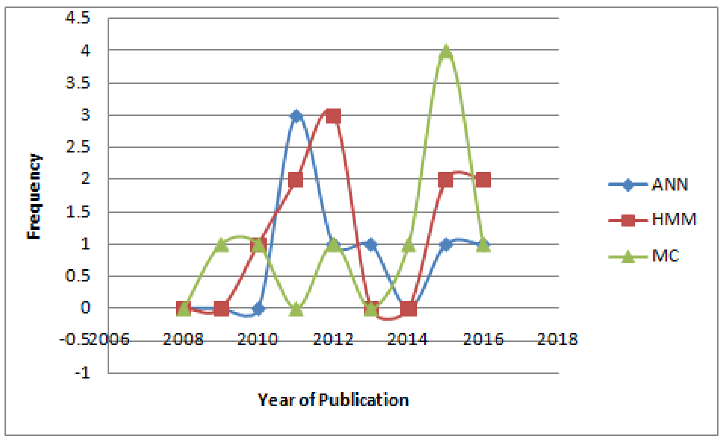

Figure 6. Studies on Weather Condition Analysis

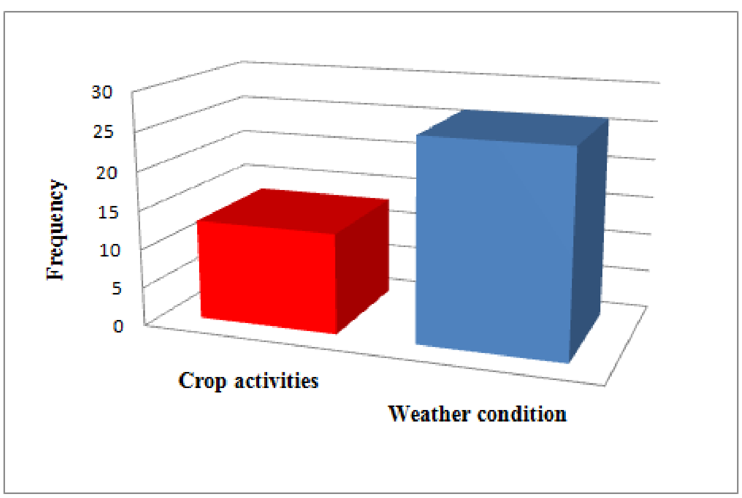

Figure 7: Activities Forecasted using Modeling Techniques Between 2008 and 2016

4. DISCUSSION AND CONCLUSION

From literature and as reviewed in this work, the weather condition forecasting dominates crop activities as demonstrated in Figure 7. This indicates a positive of stochastic models for environment monitoring. Table 3 indicates that Artificial Neural Network (ANN) is applied only to non-linearly separable classes. It has the black box nature that causes greater computation burden on the hardware infrastructure available for the analysis. This is a great disadvantage to many systems. Unlike the Hidden Markov Model, it predicts not yet observed states. However, it has a superior capability over other models in complex computations and convergence. The Markov Chain Model (MC) does not allow the prediction of hidden states since it is limited to emission probability. The Hidden Markov Model (HMM) allows different types of states to be defined such as hidden states and observation states in connection with the normal and emission probabilities. It always models conditional dependencies of (predicts) hidden states from observed states. Therefore, the sequence of states visited is hidden. Unlike in the Markov Chain, there is no longer a one to one correspondence between states and output symbols. In the HMM, the same symbol may be emitted by more than one state and a state can emit more than one symbol.

The published papers with applications of ANN, HMM, and MC for weather condition and crop activities were reviewed in this work. All these technologies proved to have given solutions for crop planning, weather prediction, moisture detection, temperature estimation, as well as crops and seeds classification. But, the reviewed studies have confirmed that the condition forecasting of crop storage is not yet seriously researched. For this reason, these modeling techniques can be introduced in grain storage application whereby the storage condition must be forecasted basing on the variations of temperature and moisture contents. Artificial Neural Network and Hidden Markov models have enormous advantages over other models, like Markov Chain Model for their ability to learn the environment. Hence they are better models. Either ANN or HMM or both are highly recommended to be applied in grain storage condition forecasting. Since the HMM is a less computational and flexible model, it might be the best option for the grain storage condition when few states are needed to be computed.

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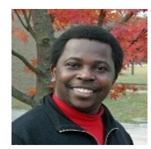

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