International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies

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PAPER ID: 11A9Q

AN INVESTIGATION OF CAPABILITY OF ARTIFICIAL INTELLIGENCE APPROACH IN DROUGHT FORECAST

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ARTICLE INFO

Article history:
Received 16 December 2019
Received in revised form 28 February 2020
Accepted 09 March 2020
Available online 31 March 2020

Keywords:
Deep neural network; Rainfall forecasting; Large-scale atmospheric variables; Drought forecasting modelling; Klong Yai river basin; Thailand.

ABSTRACT

In Thailand, droughts frequently occur during the last 5 decades with increases in frequency of occurrence and their impact on the agricultural sector as well as human economic activities, in recent decades due to climate change. It is necessary to develop drought forecasting models for efficient water resources management. Rare drought forecast models, with high accuracy, are developed in Thailand. The study aims to investigate the capability of an Artificial Intelligence Approach in drought forecasting by using Deep Learning Neural Network (DNN) for monthly rainfall forecast. Eastern river basin in Thailand was selected as a case study, due to its frequent occurrence of drought. Monthly rainfall from Plauk Daeng station during 1991-2016 was collected for analysis of drought situations. Drought in the study is defined as low rainfall than normal conditions leading to insufficient water to meet normal needs. The percentile range method was adopted in the study for drought identification when monthly rainfall is lower than the 40th percentile then drought condition is classified. Monthly rainfall during 1991-2010 was used for the training process of the DNN model while monthly rainfall during 2011-2016 was used for the validation process. Drought forecast during the validation process reveals that Artificial Intelligence Approach can predict drought situations with acceptable accuracy for only three months ahead with 60% accuracy. When the leading time of the forecast increases to be 6 months, the accuracy of the forecast decreases to be only 55%. Further study to improve model performance will be conducted using the Input Selection Technique so that the model is applicable in engineering practice.

Disciplinary: Water Resources Engineering.

1. INTRODUCTION

During the last five decades, Thailand frequently experiences drought phenomena in almost all regions in the country. The frequency of drought occurrence, as well as their impacts on agricultural

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sectors and human economic activities, is increasing in the last two decades due to climate change. To reduce the drought damage, an early drought warning is required. An attempt of developing drought forecast model was conducted in this study. In Thailand, a rare drought forecast model with high accuracy of the forecast was developed. Firstly, the drought situation definition is difficult to explain. Secondly, it is hard to collect ground truth data. The definition of drought is categorized in the four types namely meteorological, agricultural, hydrologic, and economic considerations (Rasmussen et al., 1993). Meteorological (climatological) drought is described as a time interval during that the supply of moisture at a given place cumulatively is less than the climatologically appropriate moisture supply (Palmer, 1965). Agricultural drought is considered for a time interval that soil moisture cannot meet the evapotranspiration demand for crop initiation, to sustain crops and pastures or supply water for irrigation crops or livestock (Rasmussen et al., 1993). Hydrological drought is a condition of a time interval of less than normal streamflow or depleted reservoir/groundwater storage. Socio-economics drought is the effects of physical processes on human economic activities due to drought.

In this study drought is defined as low rainfall than normal conditions, leading to insufficient water to meet average water requirements. This study investigates whether Artificial Intelligence approach is able to forecast drought situation or not.

2. STUDY AREA AND DATA COLLECTION

Based on the National Economics and Social Development Plan of Thailand, the eastern region will be developed to be Eastern Economics Corridor which certainly has high water demand in the near future. The Klong Yai river basin, situated in the eastern region, was chosen as a study case. Klong Yai river basin covers the drainage area 1800 square kilometers. Monthly rainfall data during 1991-2016 from Pluak Daeng station, see Figure 1, was used for analysis and model simulation.

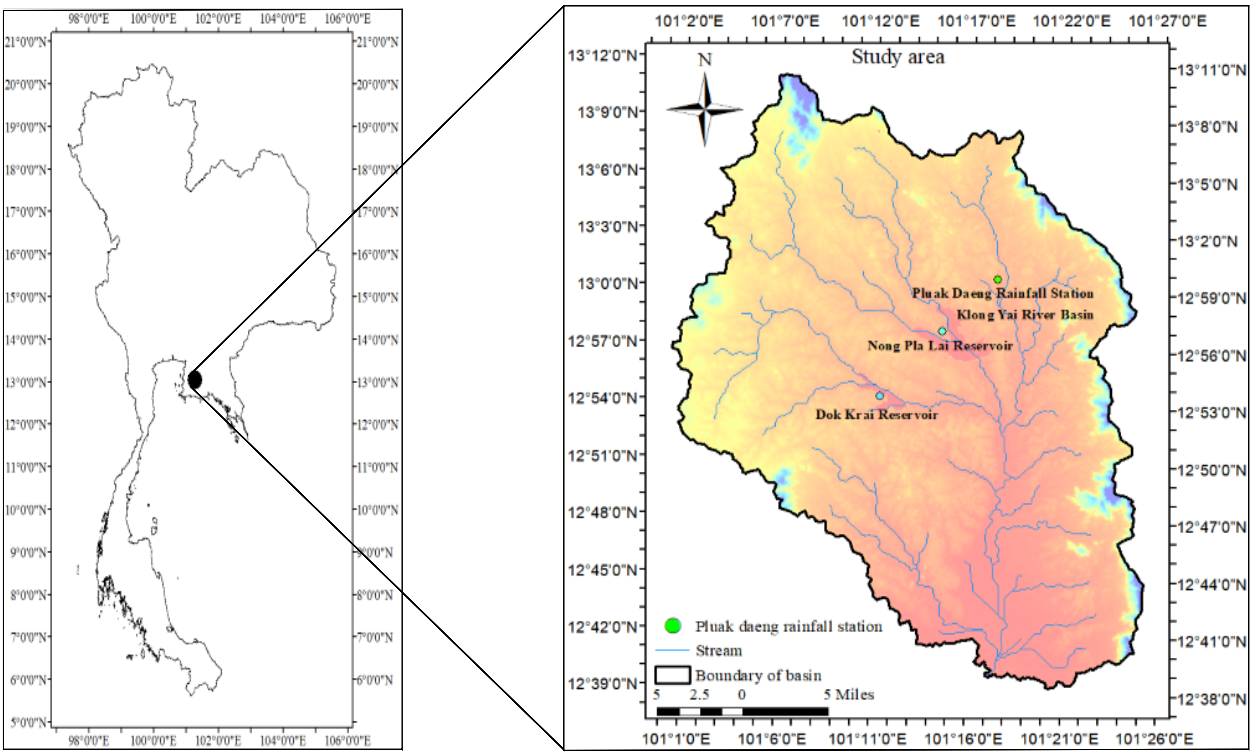

Figure 1: The study area.

3. IDENTIFICATION OF ATMOSPHERIC PREDICTORS FOR RAINFALL FORECAST

It has been revealed by several previous studies (Weesakul et al., 2013a, 2013b, 2013c, 2013d; Weesakul and Yodpongpiput, 2015; Weesakul et al., 2013e, 2014, 2016) that seasonal rainfall in different parts of Thailand was influenced by Large-scale Atmospheric Variables (LAV). However, the correlation between LAV and seasonal rainfall varied from region to region as well as varied from season to season (Weesakul et al., 2013a, 2013b, 2013c, 2013d; Weesakul and Yodpongpiput, 2015; Weesakul et al., 2013e, 2014, 2016). For seasonal rainfall, four Atmospheric Predictors for rainfall forecast are Sea Level Pressure (SLP), Sea Air Temperature (SAT), Surface Zonal wind (u) and Surface Meridian Wind (υ) (Weesakul et al., 2013a, 2013b, 2013c, 2013d; Weesakul and Yodpongpiput, 2015; Weesakul et al., 2013e, 2014, 2016). To develop a rainfall forecast model for water resources management, monthly rainfall should be accurately forecasted instead of seasonal rainfall. Weesakul et al. (2018) investigate the correlation between LAV in different layers and monthly rainfall over the study area to identify predictive Large-Scale Atmospheric Variables for monthly rainfall forecast over the eastern river basin in Thailand. Table 1 presents the influential LAV predictors used to forecast monthly rainfall in this study.

Table 1: Large-scale Atmospheric Variables (LAV) used in the study.

Variable abbreviation	Variable Name	Height Based on atmospheric pressure (millibar)	Latitude	Longitude
AT1	Air Temperature	400	25° to 30° N	175° to 180° E
AT2			0° to 5° S	210° to 218° E
AT3		850	12° 30’ to 17° 30’ N	157° 30’ to 167° 30’ E
AT4		2000	3° S to 3° N	250° to 260° E
AT5		50	9° to 14° N	110° to 120° E
GH1	Geopotential Height	250	7° to 12° N	180° to 185° E
GH2		600	0° to 5° N	135° to 140° E
GH3		850		240° to 250° E
MW1	Meridional Wind	10	12° to 20° N	180° to 190° E
MW2		150	10° to 15° N	207° 30’ to 212° 30’ E
MW3		200	0° to 5° S	155° to 160° E
O1	Omega	500	11° to 16° N	207° 30’ to 212° 30’ E
O2		925	5° to 10° N	155° to 160° E
OLR1	Outgoing Longwave Radiation	2000	0° to 5° S	255° to 260° E
P1	Pressure			220° to 225° E
PR1	Precipitation Rate		2° S to 3° N	255° to 260° E
PR2			0° to 5° N	202° to 207° E
PW1			5° to 10° S	180° to 190° E
PW2			7° 30’ S to 2° 30’ N	105° to 115° E
RH1	Relative Humidity 28up to 300mb only	925	2° to 7° N	135° to 140° E
RH2		400	5° to 10° N	202° to 207° E
SH1		500	12° 30’ to 17° 30’ N	205° to 210° E
SH2			0° to 5° N	180° to 185° E
SH3		400	7° to 15° N	120° to 130° E
SH4			0° to 5° S	110° to 120° E
SH5			0° to 5° N	110° to 115° E
SH6		600	2° 30’ S to 2° 30’ N	217° 30’ to 222° 30’ E
SLP1	Sea Level Pressure	2000	2° to 7° S	255° to 260° E
SLP2			0° to 5° S	207° 30’ to 212° 30’ E
SST1	Sea Surface Temperature			255° to 260° E
ZW1	Zonal Wind	30	10° to 16° N	85° to 95° E
Irf	Monthly Rainfall at Pluak Daeng Station (mm)		13° N	101° 18’ E

4. MODEL FORMULATION BASED ON ARTIFICIAL INTELLIGENCE APPROACH

Recently, Artificial Neural Network (ANN) was used to forecast monthly rainfall in this eastern region river basin (Thammakul and Kaewprapha, 2017). Yet, the forecast accuracy was not sufficient enough for practical use in water resources management, particularly for reservoir operation. Presently new advanced calculation techniques, particularly AI techniques (Hochreiter and Schmidhuber, 1997; Cho et al., 2014; Donahue et al., 2015; Sutskever et al., 2014; Karpathy and Fei-Fei, 2017; Ranzato et al., 2014; Srivastava et al., 2015; Xu et al., 2015; Klein et al., 2015; Xingjian et al., 2015) are capable of improving the accuracy of the forecast. The monthly rainfall forecast model was therefore developed based on this new AI technique like Deep Learning Neural Network (DNN) technique (Weesakul et al., 2018), using influential LAV as predictors as shown in Table 1. In this study, such a DNN model was applied to forecast monthly rainfall which is a water availability indicator for drought classification. The formulation of Deep Learning Neural Network based on the Artificial Intelligence approach is represented in Figure 2.

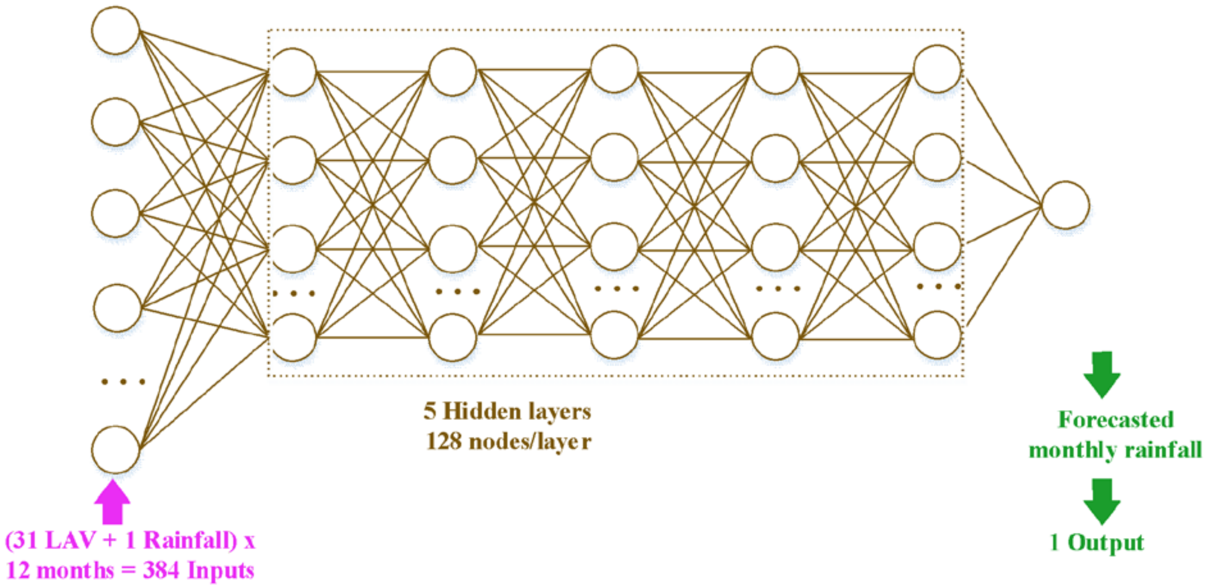

Figure 2: DNN architecture developed with 384 inputs to predict the monthly rainfall forecast.

Generally, a simple neural network consists of three layers i.e. input, hidden, and output layers. The principle of calculation of the output layer is to minimize the errors (ERR) between Observed output (O) and Predicted output (P) by using quadratic loss function as presented in Equation (3). The procedure of manipulation can be summarized as

$$r_j = \delta\left(net_j\right) = \delta\left(B_j + \sum_{i=1}^{N} I_{ij} F_{ij}\right) \tag{1}$$

where I_{ij} is the input at i value hidden node j;

F_{ij} is the weight for i value hidden node j;

B_j is the bias on hidden node j;

r_j is the output on hidden node j;

δ is activation function

net_j is network node input of sigmoid function on the hidden node j.

$$\delta(net_j) = \frac{1}{1+e^{-net_j}} \quad (2),$$

where $\delta(net_j)$ is the sigmoid function output on the hidden node j.

$$\text{ERR} = \frac{1}{2}(\text{Obs} - \text{Pre})^2 \quad (3),$$

where ERR is the error,

Obs is the observed output,

Pre is the predicted output.

In the process of minimizing errors, partial derivatives (Equation (4)) and chain rules were used as techniques in back-propagation (second step of the calculation) to find the best weights (F_{ij}) at each node. Summary of manipulation can be written as

$$\varepsilon_{F_{ij}} = \frac{\partial ERR}{\partial F_{ij}} = (\text{Obs-Pre})r_j' = (\text{Obs-Pre})net_j(1 - net_j)net_j' \quad (4),$$

where

$\varepsilon_{F_{ij}}$ is weight change of weights i at the hidden node j;

r_j' is a derivative activation function at the hidden node j;

net_j is network node input of sigmoid function at the hidden node j;

net_j' is a derivative of the network at the hidden node j;

and

$$F_{newij} = F_{oldij} + \varepsilon_{F_{ij}} \quad (5),$$

F_{newij} is a new weight of i value at the hidden node j

F_{oldij} is an old weight of i value at the hidden node j

In this study, 31 Large Scale Atmospheric Variables and one monthly rainfall, for 12 months 32x12 = 384 input variables were used to forecast one output monthly rainfall. Several simulations in the training process of the model revealed that 5 hidden layers with 128 nodes provide the minimum error of forecast (see Figure 2).

5. DROUGHT INDICATION

In this study, drought is defined as low rainfall than normal conditions, leading to insufficient water to meet the average water requirement. Rainfall is major water resources in this area, therefore amount of rainfall is reasonable to be a good indicator of water availability for all kinds of water demand.

There are a variety of drought indices using the amount of rainfall as important variables, for example, the Palmer drought severity index (Palmer, 1965), Standardized Precipitation Index (Mckee et al, 1993), the decile method (White and O'Meagher, 1995), etc.

This study preliminary investigates the capability of the AI approach in drought forecast, therefore, in this study drought is simply defined by using the Percentile range. Based on UNESCO report criteria (White et al., 1999), drought condition is defined as shown in Table 2.

Table 2: Drought Identification defined by Percentile Range.

Percentile Range	Drought condition
0-10	Severe drought
11-40	Drought
41-100	Normal to wet

The Percentile range method was used in this study to identify drought conditions in the study area. The monthly rainfall of Plauk Daeng station during 1991-2010 was analyzed and ranking percentile for each month. Table 3 shows the amount of monthly rainfall in each month for each level of water availability.

Table 3: Drought Identification using Percentile Range of monthly rainfall (mm) at Plauk Daeng rainfall station during 1991-2010.

Drought condition	Percentile Range	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
Severe drought	0	0	0	0	0	0	0	0	0	0	0	0	0
	10	0	6	9	29	78	55	37	76	97	129	0	0
Drought	11	1	7	10	30	79	56	38	77	98	130	1	0
	40	14	14	43	110	116	93	87	120	198	171	13	0
Normal to wet	41	15	15	44	111	117	94	88	124	199	172	14	1
	100	76	83	167	193	262	335	273	192	423	315	142	63

6. PERFORMANCE OF DROUGHT FORECAST MODEL

To investigate the capability of the DNN model in the forecasting of drought situation in the study area, firstly monthly rainfall of the study area was forecasted, from 2011-2016. Secondly, the forecasted monthly rainfall was ranked in the Percentile range which indicates the drought situation of that month (Table 3). The forecast accuracy was calculated by comparison between forecasted and observed drought situation, which can be expressed as

$$\text{Accuracy of Forecast} = \frac{N_{CF}}{N_T} * 100 \qquad (6),$$

where N_{CF} is the number of months that forecasted drought situation is correct, based on observed drought situation

N_T is the total number of months which is simulated by DNN model (in this particular case, N_T is 72 months i.e. 2011-2016).

Evaluation of the performance of the drought forecast model was conducted during 2011-2016 with three scenarios, which are three months leading time of the forecast, six months leading time of forecast and 12 months leading time of forecast. Figure 3 shows the DNN model performance in the forecasting of the drought situation, revealing that model can forecast drought situation with acceptable accuracy for only three months leading time of the forecast, while a one-year leading time of forecast provides unsatisfactorily accuracy of the forecast.

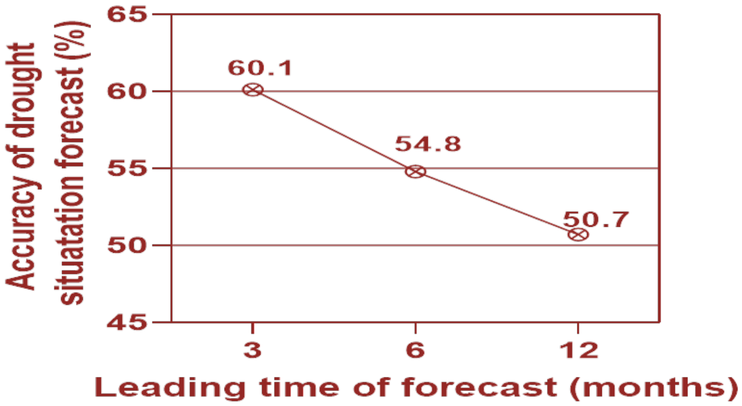

Figure 3: Performance of DNN model in drought forecast in the eastern river basin of Thailand.

7. CONCLUSION

An attempt to investigate the capability of the Artificial Intelligence approach in drought forecast was conducted. The selected river basin is in the eastern region of Thailand due to its frequent experiences in lacking water resources in the area. Deep Learning Neural Network (DNN) was selected as an Artificial Intelligence tool for forecasting of monthly rainfall. The monthly rainfall at Plauk Daeng rainfall station during 1991-2010 was analyzed and used in the training process of the DNN model while time series during 2011-2016 was used in the validation process. Correlation analysis between monthly rainfall over the river basin and Large Atmospheric Variables in various layers around the study area revealed that there are 31 influential LAV that can be predictors for forecasted monthly rainfall. The percentile range method was adopted in the study to identify drought situation. When monthly rainfall is lower than the 40th percentile, the drought situation is identified. Comparison between forecasted drought based on DNN model and observed drought during 2011-2016 revealed that the DNN model is capable of forecasting drought for three months leading time with acceptable accuracy of about 60%. However, the accuracy of forecast decreased to 55% and 51% when the leading time of forecast increases to 6 months and one year, respectively. It is necessary to further study to improve the performance of the DNN model in forecast monthly rainfall, which may be the improvement in the process of input selection technique to identify the most predictable predictors, consequently providing more satisfactorily result which can be used in real engineering practice.

8. AVAILABILITY OF DATA AND MATERIAL

Data can be made available by contacting the corresponding authors.

9. ACKNOWLEDGEMENT

This research has been financially supported by the Faculty of Engineering, Thammasat University.

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